

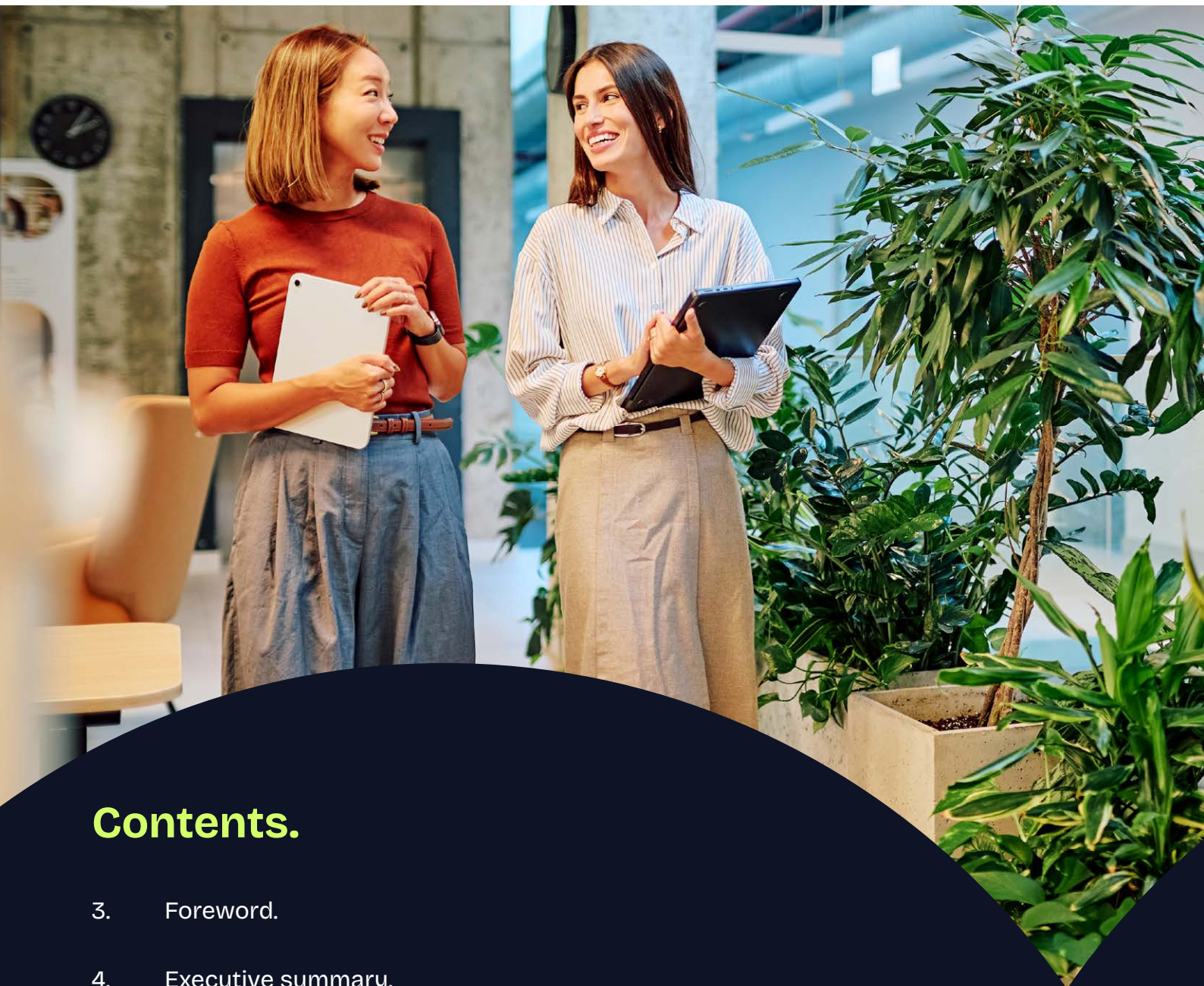
The **AI** ambition gap.

Aligning capabilities
for productivity.



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The Productivity Institute • The University of Manchester

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Foreword.

Turning AI Ambition into measurable, lasting productivity at speed.

Written by Sam Mudd, CEO, Bytes Technology Group (BTG)



This AI cycle runs on a striking tension: it takes extraordinary capital to build and almost nothing to try. At the frontier, chips, data centres and specialist talent demand investment at enormous scale.

Inside most organisations, AI simply arrives – through browsers, APIs and features switched on in software already in use – and it changes from one release to the next.

So employees are using powerful AI tools long before their company has a policy or a plan. One in three European workers now use generative AI at work. The productivity gains have been far harder to find.

The research shows AI delivering remarkable gains in individual tasks – writing, analysis, software development, customer support. Yet those gains leak as you zoom out, from a single task to a job, a team, and the organisation as a whole.

And the clock is running. Leaders who once worked to multi-year adoption cycles are being asked to respond in weeks and months, often to tools their people already rely on – and every new release widens the gap between the organisations realising productivity gains and those still working out where to start.

For leaders, this creates urgent questions: is your organisation among the early adopters, or beginning to fall behind? Are employees already using AI in ways the business understands and supports? Are isolated efficiencies translating into stronger processes and better outcomes? What separates the organisations creating measurable value from those accumulating licences, pilots, and fragmented use cases?

These questions sit at the heart of this research. Bytes commissioned The Productivity Institute at the University of Manchester to answer them independently. This research examines what AI can achieve, what the evidence says about its effect on productivity, and why promising gains leak as AI moves through an organisation.

This matters because adoption figures only tell part of the story. Across our customer base, organisations in the same sector are taking markedly different approaches. Some leaders invest in licences for every individual employee, while others invest in nothing at all.

The risks run in both directions. Move quickly ahead of governance and you take on legitimate concerns around data, security, cost and regulation. Move slowly, and competitors build the experience, processes and workforce capability you'll need to catch up. Leaders need a clearer basis for judging where their organisation stands, and where focused action makes the greatest difference.

The AI ambition gap: aligning capabilities for productivity provides that basis. It brings together current evidence and expert insight to show where AI is producing value, where that value is leaking away, and what separates access and experimentation from productive integration. Then it turns to the question that matters most to the leaders reading this: what does it take to turn AI ambition into measurable, lasting productivity?



Executive Summary.

This report examines why the rapid advance and growing adoption of AI have not yet translated into broad-based productivity gains, and sets out what business leaders, people managers and policymakers can do to close this **AI ambition gap**.

The gap refers to the divide between the aspirations for AI, as defined by its technical and economic potential, and its ultimate realisation into sustained, widely shared productivity gains across organisations, the economy and society.

The scale of the AI ambition gap is increasingly apparent at successive levels of aggregation. While task-level studies commonly report double-digit productivity gains, evidence of organisation-wide improvements is more limited and generally points to smaller gains. Realising AI's potential at scale requires complementary investments in skills, management, data, workflow

redesign, and measurement. This needs to be supported by institutions that facilitate effective adoption and diffusion.

Closing the AI ambition gap requires action across **four connected imperatives** that should be on the radar of CEOs, COOs and Chief Transformation or Digital Officers:

The four connected imperatives

1

attention to the most strategically relevant uses of AI;

2

incentives to act;

3

capabilities to adopt AI effectively;

4

execution to redesign work, scale successful applications and sustain change.



Seven key enablers define the practical actions that can be undertaken to close the AI ambition gap, and turn the technical and economic potential of AI into productivity.

Four of them are primarily directed to business leaders focusing on the organisational actions needed to turn AI adoption into productivity gains: redesign, and measurement. This needs to be supported by institutions that facilitate effective adoption and diffusion.

The remaining **three** enablers point to the wider systemic action needed beyond individual organisations and leaders:

1

Use **leadership and management** to set direction and allocate resources and ensure AI delivers measurable value.

2

Build **worker capabilities** which create the skills and judgement needed to use AI effectively.

3

Assess **technical feasibility against economic viability** by evaluating costs, returns and whether to scale, revise or stop applications.

4

Develop **adaptive capacity** to redesign work and sustain organisational change.

5

Strengthen **AI governance** to provide trusted, adaptive and sector-sensitive rules.

6

Facilitate **regional ecosystems** to connect firms to trusted support and shared learning.

7

Enable both **frontier innovation and diffusion capabilities** to turn frontier advances into widely used applications.



Closing the AI ambition gap requires coordinated action by business leaders, people managers and policymakers.

Business leaders should focus organisational attention on high-value use cases linked to strategy, customer value and operational bottlenecks. They also need to strengthen the business case through clear accountability and outcome ownership, build the managerial, workforce, data and organisational capabilities needed for adoption, and ensure that AI initiatives are evaluated and scaled according to measurable productivity, quality or service outcomes.

People managers should treat AI as a work redesign and capability-building agenda. They should involve workers early in identifying use cases, embed training in real work, and use worker voice, job redesign and benefit-sharing to build trust, durable expertise and better working conditions.

Policymakers should help firms identify relevant opportunities, reduce adoption risks and uncertainty, strengthen incentives through competition, infrastructure and adaptive regulation, and support the regional, institutional and data infrastructures needed for broad-based diffusion.





AI PRODUCTIVITY GAINS DECLINE WITH AGGREGATION

- 1 **Tasks**
Strongest evidence: sizeable gains under controlled conditions show AI's potential more than typical use.
- 2 **Jobs & Occupations**
AI reshapes bundles of tasks; judgement, coordination and complementary work become binding constraints.
- 3 **Organisations**
Value depends on workflow redesign, management, skills, data and absorptive capacity—not adoption alone.
- 4 **Sectors & Economy**
Uneven diffusion, resource reallocation and institutions determine whether firm-level gains scale.

FOUR IMPERATIVES TACKLE THE AI AMBITION GAP

The divide between AI's technical and economic potential and sustained, widely shared productivity gains.

FOUR IMPERATIVES

- 1 **Attention**
Focus high-value uses
- 2 **Incentives**
Create confidence to act
- 3 **Capabilities**
Build skills, data and systems
- 4 **Execution**
Redesign, scale and sustain

CONNECTED SEQUENCE

Value is lost when any step breaks.

SEVEN ENABLERS FOR CLOSING THE AI AMBITION GAP

BUSINESS ENABLERS

- 1 **Leadership & Management**
Turn strategic intent into coordinated process change and measurable value.
- 2 **Workforce Skills**
Combine domain expertise and judgement with responsible experimentation and organisational learning.
- 3 **Technical & Economic Alignment**
Align technical feasibility with shared functional ownership, measurable outcomes, lifecycle costs and economic viability.
- 4 **Transition Capability**
Reorganise workflows and business models through managed experimentation before external pressure forces change.

SYSTEM ENABLERS

- 5 **Governance & Regulation**
Build adaptive, sector-sensitive governance that strengthens trust, regulatory clarity and cross-government coordination.
- 6 **Regional Ecosystems**
Extend absorptive capacity beyond leading firms and diffuse knowledge across regional value chains.
- 7 **Innovation & Diffusion**
Connect frontier advances to applications firms can commercialise and scale.

Firm-level capabilities need to be complemented with a supportive and resilient ecosystem for AI adoption and productivity gains.

ADOPTION ALONE IS NOT ENOUGH



... REINFORCING LOOPS CLOSE THE AMBITION GAP



Introduction.

Closing the AI ambition gap.



Rapid advances in artificial intelligence (AI) since the early 2010s, and especially the rise of generative AI (GenAI) since 2022, mark a new phase in the digitalisation of the economy and AI has the potential to reshape the long-term trajectory of productivity growth.

Earlier waves of digital technology have already delivered substantial productivity gains. Most notably, the diffusion of ICT — including personal computers, software and the internet — is estimated to have added roughly 0.5–1 percentage points per year to productivity growth in the late 1990s and early 2000s, with the higher end applying particularly to the United States and the lower end to Europe, where digital technologies were adopted and used less effectively than in the United States.¹

Since the mid-2000s, annual labour productivity growth across advanced economies has slowed markedly from around 2 to about 1 per cent, although the timing and scale of the decline vary across countries.²

Reviving productivity growth is increasingly important because employment growth—the other main source of economic growth—is unlikely to remain a major driver of rising living standards amid adverse demographic trends, especially population ageing.

AI has the potential to reshape the long-term trajectory of productivity growth, but whether it can restore economic growth to the rates achieved in earlier decades remains uncertain. Much will depend on whether AI delivers more than one-off efficiency gains for firms and becomes a sustained source of innovation, helping economies to tackle major economic and societal challenges ranging from climate change to the continued provision of high-quality public services.



As AI ambition is high, what is holding firms back?

This report looks at what prevents organisations and the economy as a whole from capturing AI's productivity opportunities, and how adoption can be accelerated to deliver faster, broader and better gains. We show that while ambition to adopt AI is widespread, **adoption alone is not enough to obtain broad-based productivity gains**. We define the **AI ambition gap** as the divide between the aspirations for AI, shaped by its technical and economic potential and its ultimate realisation into sustained, widely shared productivity gains across the economy and society.

Closing the ambition gap requires organisations to meet **four connected imperatives**. First, they must recognise and prioritise the AI opportunities most relevant to their strategy, operations and customers (**attention**). Second, they must ensure that leaders, managers and workers have sufficient reason, confidence and pressure to act on those opportunities (**incentives**). Third, they need to build the organisational resources, process knowledge and ability to integrate new technologies needed to implement them effectively (**capabilities**). And finally, they need to coordinate, scale and sustain the organisational changes required to realise value from AI (**execution**).

Productivity gains are strongest at the task level

Drawing on an extensive review of the current evidence, the first part of this report examines how the ambition gap widens as the analysis moves from individual tasks to broader levels of people's occupations, entire organisations, production sectors and the economy as a whole.

Evidence of productivity gains is strongest at the task level. The challenges increase at the level of jobs and occupations which combine multiple tasks, and rise further within teams, business functions and organisations, where adaptable systems of tasks and jobs must be coordinated.

The productivity effects are least visible at the sector and macroeconomic levels, where outcomes depend on the wider ecosystem in which firms operate. At each successive level, the translation of technical potential into measurable productivity becomes more difficult because complementary capabilities and coordination requirements become more demanding. This helps explain the recurring productivity paradox: **despite the availability of a powerful, widely applicable technology, AI's measured productivity effects remain modest so far.**

four

connected imperatives

1 recognise
and **prioritise**
relevant ai opportunities

2 ensure workers have the
confidence to **act**
on those opportunities

3 build the resources to
implement those
new technologies effectively

4 coordinate, scale and sustain
changes to **realise**
value from AI

Firm-level and system-level enablers of AI productivity

The second part of the report identifies seven key enablers that can help to close the ambition gap. Some are business enablers and operate mainly at the level of tasks, jobs and organisations, including **leadership and management, workforce capabilities, the alignment of technical feasibility with economic viability and adaptive capacity**. Others are primarily system-level enablers, including **adaptive and sector-sensitive**

governance, regional ecosystems for AI and a well-connected pipeline linking **frontier innovation to diffusion** with strong demand-driven feedback loops. Together, these enablers show that closing the ambition gap requires both firm-level capabilities to turn AI into measurable organisational value and wider institutional conditions that support diffusion, trust, coordination and productive use across sectors and the economy.



Actions for business, people and policy leaders

The report concludes with recommendations for business, policy and people leaders to close the AI ambition gap across four connected imperatives.

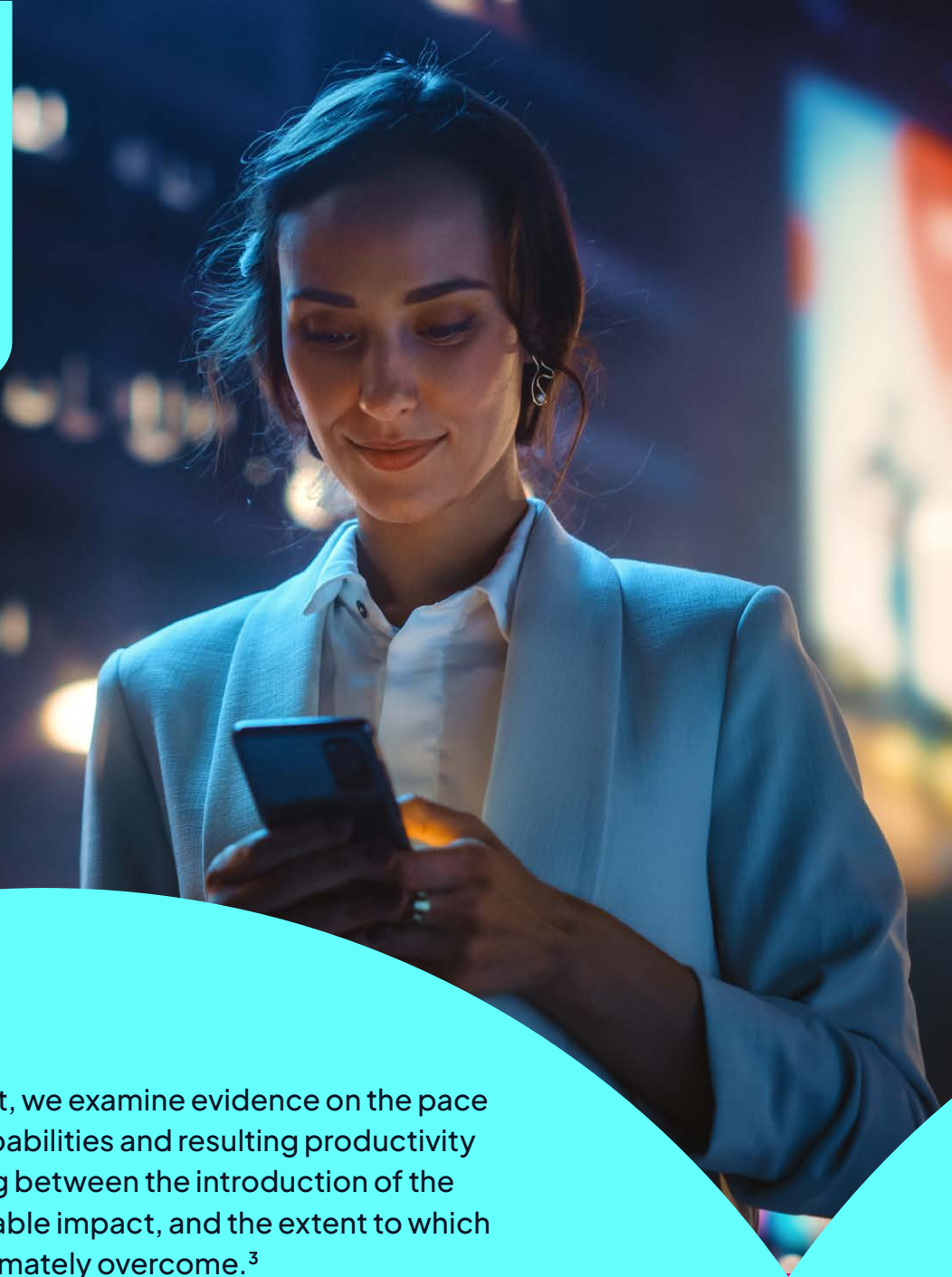
Business leaders need to focus organisational attention on high-value use cases, strengthen the business case for action, build the managerial, workforce and data capabilities required for adoption, and execute the workflow redesign needed to turn AI use into measurable performance. **People managers** should ensure that workers are involved early in

identifying use cases, that training is embedded in real work, and that job redesign, worker voice and benefit-sharing help turn AI adoption into durable expertise, better working conditions and broadly shared productivity gains. Finally, **policymakers** should help firms identify relevant opportunities, reduce adoption risks and uncertainty, strengthen incentives through competition, infrastructure and adaptive regulation, and support the capability-building institutions needed for diffusion.



Part One.

AI adoption and productivity at successive levels of aggregation.



In the first part of this report, we examine evidence on the pace of adoption, the critical capabilities and resulting productivity effects at each level, the lag between the introduction of the technology and its measurable impact, and the extent to which barriers to adoption are ultimately overcome.³

Task-level effects of AI adoption

Evidence that AI raises productivity is strongest at the level of individual tasks. A frequently cited study shows that generative AI increased customer-support productivity by about 14 per cent, with the largest benefits accruing to less experienced workers because the system helped transmit tacit knowledge from more skilled colleagues.⁴ Other studies report similarly substantial effects at task level, especially when conducted in controlled settings holding the worker,

firm and organisational context constant:⁵ software developers using GitHub Copilot completed around 26 per cent more tasks;⁶ professionals using ChatGPT for routine writing and analysis reduced completion time by 40 per cent while improving quality by 18 per cent;⁷ human-AI marketing teams achieved productivity gains of as much as 73 per cent;⁸ and individuals using AI in product development matched the performance of two-person teams without AI.⁹



professionals using ChatGPT for routine writing and analysis reduced completion time by

40% while improving quality by **18%**



80% of workers could have at least
10% of their tasks affected by large language models.

GenAI broadens the range of exposed cognitive tasks

Compared with earlier AI versions, GenAI performs particularly well across a wider set of non-routine cognitive activities, including those involving language, code, drafting, summarisation and information synthesis. This has broadened the range of tasks exposed to automation or augmentation. US evidence suggests that 80 per cent of workers could have at least 10 per cent of their tasks affected by large language models, while around one fifth could see more than half of their tasks affected.¹⁰ AI is becoming capable of handling longer, more complex, multi-step activities rather than only short, discrete tasks. For example, the duration of tasks that leading AI models can complete successfully in at least half the time has doubled roughly every four months since 2023, reaching more than 16 hours.¹¹ However, exposure to GenAI is concentrated in information processing, drafting and routine analysis rather than physical or interpersonal activities.

Evidence from thousands of text-based tasks suggests that AI capabilities are improving gradually across a broad range of tasks, which can be referred to as a “rising tides” pattern. This differs from “crashing waves”, where new models suddenly automate whole groups of previously inaccessible tasks. More gradual change may give workers more time to adapt and reduce the risk of sudden disruption.¹²

The duration of tasks that leading AI models can complete successfully in at least half the time has doubled roughly every four months since 2023, reaching more than 16 hours.

Task gains do not automatically translate into organisational productivity

Strong task-level results from AI should nevertheless be interpreted with caution. Surveys of worker- and firm-level AI adoption generally find AI adoption rates between 20 and 40 per cent, although estimates vary considerably because studies define and measure adoption differently, as discussed below in more detail.¹³ These figures are not adjusted for differences in worker, firm or survey characteristics and vary considerably with how adoption is defined and measured. Experimental studies, which typically hold workflows, management incentives, complementary technologies and data availability constant, demonstrate what AI can achieve under favourable conditions, rather than what organisations necessarily realise in practice.¹⁴

AI changes not only how tasks are performed but also the human role

As AI takes on more activities, productivity increasingly depends on how organisations redefine human work around it. In design, for example, workers may shift from solving pre-defined problems towards determining which problems are worth solving, favouring organisations already equipped for data-intensive, iterative development.¹⁵ A similar pattern is evident in software: evidence from more than 500,000 GitHub developers shows that adoption across successive generations of AI coding tools increased coding activity by approximately 240 per cent. However, the corresponding increases were around 80 per cent for the number of projects and only 30 per cent for releases. Although these gains remain substantial for any workplace technology, human bottlenecks in reviewing, integrating, testing and releasing software absorb much of AI’s potential productivity gain.¹⁶



Job-level effects of AI adoption

High task exposure to AI does not automatically make a job more productive. Jobs combine automatable activities with tasks requiring judgement, coordination, client interaction and critical thinking. The more likely outcome is therefore not the wholesale automation of jobs, but the augmentation of occupations as AI takes

on selected information-processing tasks while human work shifts towards other complementary activities. As AI removes or accelerates some activities, these complementary human tasks may become the binding constraint, limiting both time savings and the translation of task-level gains into job-level productivity.

When automation removes tasks requiring less expertise, the remaining job requires greater expertise, raising wages but reducing the pool of qualified workers.



Job outcomes depend on task composition and complementary expertise

Combining occupational data at firm level with occupational-level measures of AI exposure allows the computation of a firm-specific indicator of AI exposure. This measure suggests that the benefits of AI can be unlocked by firms with higher existing capabilities, such as human capital and complementary assets.¹⁷ For example, two firms may have similarly AI-exposed workforces, but the firm with stronger employee skills, data assets and digital systems is likely to be better placed to translate that exposure into productivity gains.

This implies that technology may in part displace labour from existing tasks while also creating new tasks in which workers retain comparative advantage.¹⁸ Employment, productivity and wage outcomes therefore depend on the balance between displacement and reinstatement. This makes the composition of jobs, including the

identification of substituted, complemented and newly created tasks, more informative than task exposure alone.

Compositional effects depend on who holds the complementary expertise and organisational authority needed to use AI effectively. For example, when automation removes tasks requiring less expertise, the remaining job requires greater expertise, raising wages but reducing the pool of qualified workers. When it removes expert tasks, the remaining work becomes less demanding. This potentially lowers wages but expands employment by allowing more workers to perform the role. Outcomes therefore depend less on the intensity of automation than on the expertise content of the remaining tasks for humans to perform. This also explains why routine-task automation can raise wages in some occupations and lower them in others.¹⁹



AI exposure and complementarity vary across countries and occupations

Workers in advanced economies initially appear more exposed to AI than workers in emerging markets because professional and managerial occupations account for a larger share of employment in the former. However, the difference from emerging economies narrows when exposure is separated into tasks that AI may substitute and tasks where AI is more likely to complement human expertise.²⁰

Among six countries (US, UK, Brazil, Colombia, India and South Africa), the UK has the highest share of workers in occupations with both high exposure and high complementarity.²¹ This is in part related to its large financial and professional business service sectors, characterised by a high share of cognitive occupations. High complementarity is more common in those occupations than in jobs with many routine and manual tasks. For example, lawyers and judges, despite their high AI exposure, can implement AI as a supporting tool for cognitive tasks requiring judgement, accountability, advice and extensive training. Consequently, workers in such occupations may therefore be better positioned to benefit from AI and may face lower displacement risk, provided they have the skills and organisational support needed to use it effectively. This mix of tasks within an occupation appears associated with the most favourable outcomes from AI adoption. In contrast, telemarketers, despite sharing similar high AI exposure metrics with lawyers, display low complementarity. Many of their duties involve tasks like capturing customer data or detailing products that can be easily replaced by AI.

Other evidence reinforces the observations that worker demographics, occupational and industrial structure, and firm characteristics matter for AI adoption. For example, across countries, jobs held by women and university graduates tend to face greater exposure, while highly paid workers are more likely to occupy jobs combining high exposure with high complementarity.²² Those kinds of characteristics account for about 55 per cent of the US/European gap in workplace AI adoption. The explained share of different AI adoption rates even rises to around 80 per cent when differences in

Lawyers and judges, despite their high AI exposure, can implement AI as a supporting tool for cognitive tasks requiring judgement, accountability, advice and extensive training.

management practices, particularly in terms of whether employers actively encourage and support employees' use of AI, are included. The gap therefore reflects not only the composition of workers and firms, but also whether organisations legitimise experimentation, provide appropriate tools and guidance, and adapt workplace practices to facilitate AI use.²³



The UK has the highest share of workers in occupations with both high exposure and high complementarity.

AI could reshape more than **15%** of working time for



72% of US workers by 2035.



Exposure is high, but intensive use remains limited

So far, however, AI use within jobs remains limited, with little measurable effect on firm-level productivity. For example, 43 per cent of US workers and 32 per cent of European workers use GenAI at work.²⁴ These figures are generally higher than the firm-level adoption rates which we discuss below, even though a recent survey of senior business executives in the United States, United Kingdom, Germany and Australia found that as many as 69 per cent of firms use AI in some form. Use remains limited in intensity: more than two thirds of executives reported an average usage amounts of only around 1.5 hours per week. Adoption is also concentrated among younger and already more productive firms.²⁵ (see also box on “reported AI adoption rates”).

Other evidence highlights that 30 per cent of US workers who used AI at work saved three or more hours per week, but AI could reshape more than 15 per cent of working time for 72 per cent of US workers by 2035.²⁶ Finally, expectations about future trajectories seem to differ between workers and employers. While employees expect AI to increase employment in their firms by 0.5 per cent over three years, executives only anticipate effects in the medium term, including productivity growth of 1.4 per cent and employment reductions of 0.7 per cent. This gap may reflect different assumptions about whether AI augments workers or reorganises jobs around fewer employees.²⁷



As many as

69%

of firms use AI
in some form.



More than **two thirds** of executives
reported an average usage
amount of only around

1.5 hours per week.



Reported AI adoption rates and performance measures

Measures of AI adoption vary widely because surveys differ in who they ask, how they define AI and how they frame adoption questions:¹

- **First, respondent type matters.**
Senior executives and managers often report higher adoption than frontline workers, reflecting strategic intent or awareness rather than actual use, while worker surveys can capture informal or task-level use that firm surveys miss. Large firms also report higher adoption than SMEs because they have stronger digital capabilities and organisational readiness.
- **Second, how AI is defined is equally important.**
Estimates further differ depending on whether surveys focus narrowly on GenAI or advanced AI, or include broader tools such as machine learning, automation and data analytics.
- **Third, question wording matters too.**
Surveys that include embedded AI or employee-driven “bring-your-own AI” practices report much higher rates than those focused on deliberate firm-level implementation.
- **Finally, it is important to note that most measures capture only the extensive margin: whether AI is used at all.** These measures say much less about intensity, workflow integration or organisational change.
- **The 43 per cent US and 32 per cent European estimates in row two** capture individual workers’ self-reported use of generative AI, irrespective of whether their employer has formally adopted the technology.
- **The 69 per cent estimate in row four** captures firms reporting any AI use at all, a threshold broad enough to include firms where average use amounts to only around 1.5 hours per worker per week.
- **The 14 per cent productivity gain in customer-support work using GenAI in row six** is a performance effect, not an adoption rate, and therefore should not be interpreted as evidence on the prevalence of AI use.

Across the wider literature, reported adoption rates for similar periods range from single digits to more than 80 per cent. As discussed above, this divergence reflects differences in survey definitions, question wording, sample composition and target populations, rather than a single underlying rate of AI adoption.

For this reason, the definitions underpinning each measure are essential for interpreting the figures used in this report. The absence of a consistent adoption measure complicates efforts to track progress, compare countries and evaluate policy. It also strengthens the case for the UK to participate in a harmonised AI survey series, while retaining complementary national surveys that can capture sectoral, regional and organisational detail.

The table compares several AI adoption and performance measures cited in this report. These figures are not directly comparable because they refer to different units of observation, definitions of AI use and measurement thresholds. For instance:

- **The 20–40 per cent range in the top row** refers to task-level adoption or use observed in experimental and controlled settings, rather than adoption under normal operating conditions.

1. For a more detailed discussion, see B. van Ark (2026), “Rewiring Europe’s Productivity Framework: Aligning Investment, Innovation, and Diffusion”, Productivity Insights Paper No. 096, The Productivity Institute.



AI adoption-related estimates across different studies

ESTIMATE	STUDY	WHY IT DIFFERS FROM OTHER STUDIES
ADOPTION		
20–40%	Crane, Green and Soto (2025) (footnote 14)	Employee- and firm-level surveys measuring the share of workers who report any use of AI at work. Adoption varies substantially across occupations and is particularly high in fields such as programming.
43% (US) 32% (Europe)	Bick, Blandin, Deming, Fuchs-Schündeln and Jessen (2026) (footnote 21)	Individual worker self-reported GenAI use; a survey of people, independent of formal employer adoption.
69%	Yotzov, Barrero, Bloom et al. (2026) (footnote 26)	Firms reporting any AI use at all. A low bar that includes firms averaging just 1.5 hours of use per week.
Single digits to >80%	No dedicated source; draws on Crane et al. (footnote 14) and Bick et al. (footnote 21)	The range across all surveys, driven by differing definitions, question wording, samples and target populations.
EXPLANATION OF DIFFERENCES IN ADOPTION		
55% to 80%	Same study: Bick et al. (2026) (footnote 21)	The share of the US–Europe gap in adoption explained by demographics and by management practices.
PERFORMANCE EFFECTS		
40% faster / 18% higher quality	Noy, S. and Zhang, W. (2023) (footnote 7)	Time and quality improvement for professionals using ChatGPT on writing/analysis tasks. Two figures from one controlled experiment.
14%	Brynjolfsson, E., Li, D. and Raymond, L.R. (2023) (footnote 4)	Productivity gain in customer support work using GenAI, largest for less-experienced workers. Performance gain is not a rate of adoption.



Organisational-level effects of AI adoption

Complementary organisational investment is a key mechanism through which firms can limit the leakage of AI-enabled task-level gains before they translate into organisational productivity.²⁸ Firms with stronger organisational capital, including effective management,

adaptable processes, workforce skills, data capabilities and trusted workplace relationships, are therefore better positioned both to realise productivity gains and to improve job quality.



Only

46%

of firms progressed
beyond tool pilots



Although

89%

use AI in at least

one business function

Potential and realised absorptive capacity

The returns from a new technology depend on a firm's absorptive capacity, defined as the ability to recognise, assimilate and commercially exploit external knowledge.²⁹ Absorptive capacity is firm-specific and path-dependent. Organisations build it from existing knowledge, so early underinvestment can restrict later use of a technology even when that technology is widely available.

The distinction between potential absorptive capacity—the ability to acquire and understand knowledge—and realised absorptive capacity, which transforms and exploits that knowledge through routines and production processes, is especially important for AI.

For example, licensing a tool does not mean that a firm can integrate it productively.³⁰

Recent research found that only 46 per cent of firms progressed beyond pilots, although 89 per cent use AI in at least one business function. However, just one-quarter of respondents reported redesigning workflows around AI rather than adding it to existing processes. “AI high performers” (organisations that attribute at least 5 per cent of EBIT to AI and report a significant overall organisational impact) represented only 6 per cent of the sample.³¹ Recognising use cases, experimenting with workflows and deciding whether to deploy tools all depend on organisational and project capabilities.³²

Firms with stronger organisational capital, including effective management, adaptable processes, workforce skills, data capabilities and trusted workplace relationships, are therefore better positioned both to realise productivity gains and to improve job quality.

The productivity J-curve

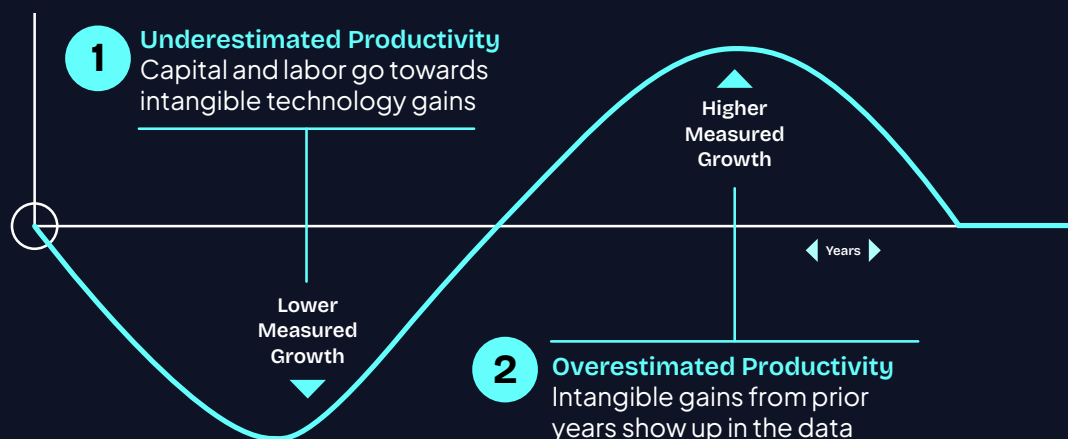
The importance of absorptive capacity for productivity can be illustrated by the productivity J-curve.³³ During the adoption of a new technology, firms devote labour and capital to intangible assets, such as redesigned processes, training, data and software integration, that conventional performance measures do not fully incorporate. Productivity, measured as output per unit of input, may therefore initially be

understated because the expenses are recorded as costs while the resulting capital stock is not. Later, measured productivity may rise as services from this hidden stock generate observable output. The measurement error is thus first biased downwards and then biased upwards as accumulated organisational capital begins to contribute to productivity. (Figure 1)

Figure 1 – Productivity J-Curve / Source: Authors' construction.

Productivity J-Curve

Skewed measurement of productivity growth after a **major new technology** is introduced



Redrawn from the article "Why Artificial Intelligence isn't Boosting the Economy - Yet"

Organisational capability is capital

Pre-GenAI evidence already points to complementarity between ICT intensity and intangible capital rather than simple addition. Non-R&D intangibles and workforce skills contribute more to output than their cost shares would predict, suggesting spillovers beyond the individual firm.³⁴ Complementarity also extends beyond the firm. For instance, productivity gains may depend

on whether input suppliers and connected sectors also innovate, easing bottlenecks in the supply or value chain that prevent concentrated advances from becoming industry-wide gains.³⁵ Organisational capability is therefore capital in its own right and interacts with technology adoption.



AI-using firms hold
market shares up to

7.5

times larger
than non-users



UK firms with
stronger
management
scores in

20
20

were more likely
to adopt AI by

20
23

AI-specific studies broadly support the importance of complementary capabilities. For example, analysis of representative firm-level microdata across 15 OECD countries finds that adopters tend to have stronger human capital and digital capabilities. Once these characteristics are controlled for, the AI-related productivity advantage for adopters largely disappears, suggesting that what appears to be a return to AI may partly be a return to the capabilities that make effective use possible.³⁶

Moreover, recent evidence from the OECD showed that AI-using firms hold market shares up to 7.5 times larger than non-users and are more productive on average. However, this advantage loses statistical significance once digitalisation intensity and lagged productivity are controlled for, suggesting that it reflects pre-existing capability rather than AI use itself.³⁷

Similarly, UK firms with stronger management scores in 2020 were more likely to adopt AI by 2023, even after accounting for size, age, sector and location. The same management advantage predicts other technologies

far less strongly, suggesting that data management and coordination are particularly important for AI.³⁸

Following this, AI adoption across two-digit sectors in the EU in 2025 correlates positively with sector-average managerial-practice quality as measured by the World Management Survey, reinforcing the finding that management capability and not just technology access predicts AI uptake.³⁹

Qualitative evidence from FinTech illustrates the same point at the level of implementation. Firms differ in their ability to convert AI investment into market-ready products because adoption depends on business stage, reliance on third-party platforms, data availability, investment, organisational agility and product novelty. Some firms make substantial investments in AI without converting AI concepts or prototypes into market-ready products. This is a firm-level version of the aggregation paradox: spending and technical potential are insufficient when the organisational configuration does not support implementation.⁴⁰



Technical feasibility versus economic viability

The gap between potential and realised absorptive capacity is often reflected in the difference between the technical feasibility and economic viability of AI adoption.

A study of US firms developing computer-vision technology estimates that automated tasks represent only about a quarter of wages paid for vision-related work, despite a much larger technically automatable share.⁴¹ Expected savings must justify the fixed costs of development, deployment and integration. Recurring inference costs, including per-query or per-token charges, create an additional constraint because they may offset efficiency gains as usage intensifies. The business case must consequently cover both one-off integration expenditure and continuing operating costs. AI-as-a-service may narrow this gap by spreading fixed costs across users.

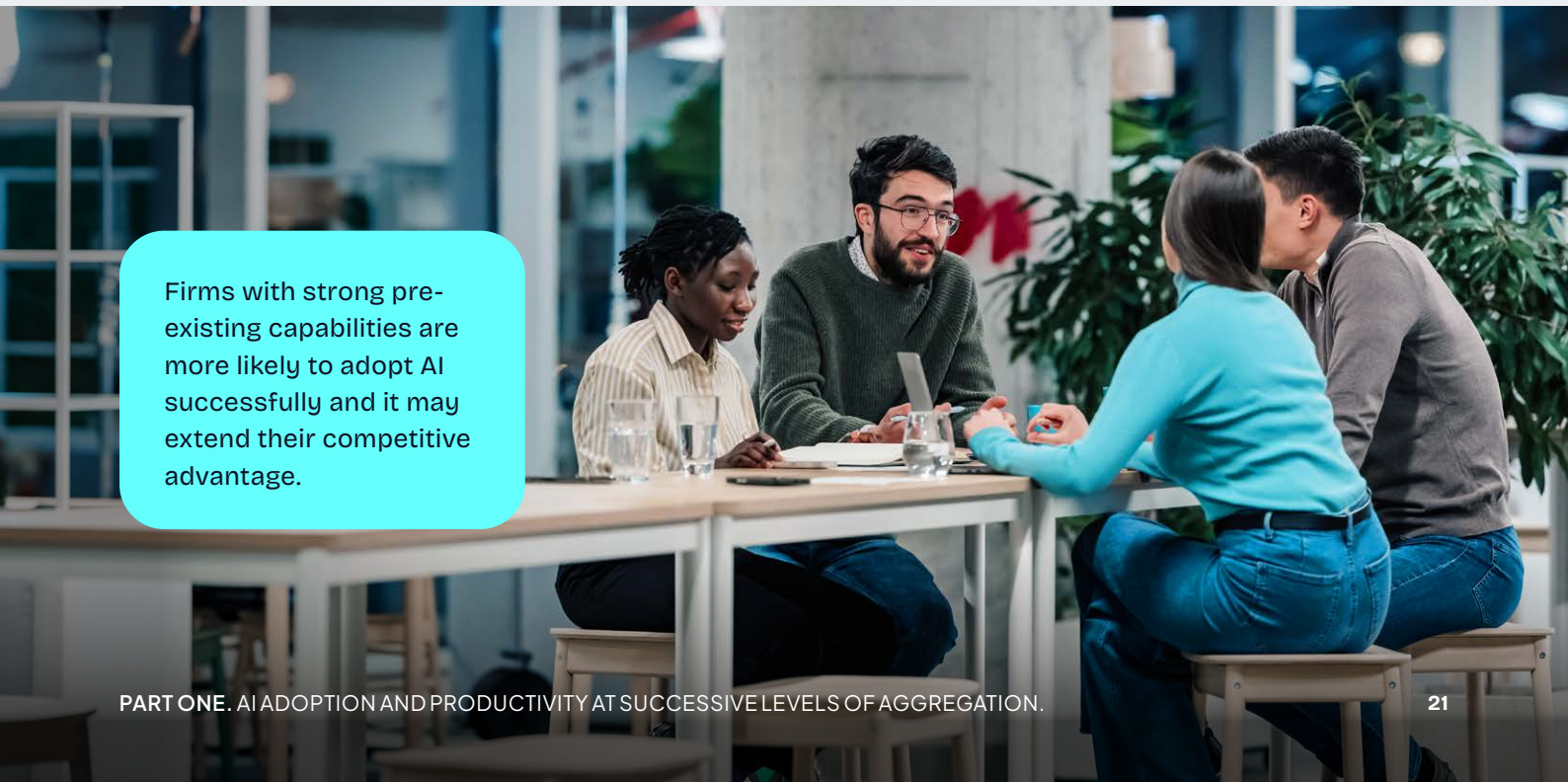
Absorptive capacity is not an entirely internal affair to the organisation. Realised absorptive capacity depends partly on the quality, stability and accessibility of the surrounding innovation ecosystem. However, these barriers tend to change in nature as adoption matures. Legal and ethical uncertainty weighs most heavily on first-time adopters, whereas extensive users are more constrained by expected costs. ICT skills raise adoption, while restrictive labour market and competition policies reduce it.⁴²

Evidence from Chinese manufacturing reaches similar conclusions to studies of US, UK and European firms.

Robot adoption – an AI-adjacent form of automation – can stimulate firm innovation, including sustainability-oriented innovation, with absorptive capacity serving as an important transmission mechanism. However, gains in innovation efficiency vary considerably, tending to be concentrated among state-owned enterprises, traditional manufacturers and firms located in more economically developed cities.⁴³

Digital investment and capacity utilisation also appear to follow an inverted-U relationship: additional investment eventually produces diminishing or even negative returns unless labour relations, industry conditions and regional markets are sufficiently supportive. Absorptive capacity is therefore necessary, but firms cannot productively absorb unlimited investment.⁴⁴

Across UK and EU surveys, OECD microdata, Chinese manufacturing panels and qualitative evidence, the central conclusion is that **AI is not a plug-and-play technology**.⁴⁵ Its productivity return depends on complementary investment in skills, data, management and organisational redesign. These investments are path-dependent, costly and subject to diminishing returns. Firms with strong pre-existing capabilities are therefore more likely to adopt AI successfully and it may extend their competitive advantage. Widespread awareness, limited intensive use and modest measured productivity effects are not contradictory, but symptoms of the AI ambition gap that task-level potential alone cannot overcome.



Firms with strong pre-existing capabilities are more likely to adopt AI successfully and it may extend their competitive advantage.



Sector-level and macroeconomic effects of AI adoption

Moving beyond the firm raises two distinct questions.

1

How do adoption, constraints and productivity effects differ across sectors?

2

How much of these sector-level gains can apply to the macroeconomy, given uneven adoption, differences in organisational capability, limited labour and capital mobility, and the economic weight of the activities transformed by AI?

Sectoral productivity gains differ in nature

A synthesis of more than 150 peer-reviewed studies and 30 corporate reports across three sectors – FinTech, retail and advanced manufacturing – finds a broadly positive relationship between AI adoption and productivity, although the mechanisms and constraints are often sector-specific.⁴⁶

For example, in FinTech AI supports fraud detection, credit-risk assessment, labour allocation and more responsive services, while regulatory uncertainty and consumer trust constrain deployment. In retail, personalisation, demand forecasting and inventory

optimisation can improve customer retention, employee efficiency and resource allocation, even though privacy concerns can offset these gains. In advanced manufacturing, AI strengthens automation, resilience, energy efficiency, supply-chain performance and green innovation, yet skill shortages, integration costs and displacement risks weigh particularly heavily on smaller firms. Sectoral productivity gains are therefore conditional on institutional context, firm capability and resource endowment rather than being an automatic result of exposure.

Uncertain paths to macroeconomic productivity gains

Macroeconomic estimates vary widely because they rest on different assumptions about task exposure, achievable cost savings, spillovers and innovation. A cautious estimate projects gains in total factor productivity (TFP) for the US of no more than 0.7 per cent over ten years. This approach combines the share of exposed tasks with the expected savings on those activities. However, as discussed above, both metrics are highly uncertain. Indeed, the TFP gain might fall to 0.53 per cent when greater weight is placed on complex tasks for which outcomes are more difficult to evaluate.⁴⁷

These cautious estimates assume that AI mainly delivers limited efficiency gains within existing activities. More optimistic estimates of productivity gains assume that AI also creates new markets, improves business processes across value chains and supports continuing innovation. Estimates based on historical comparisons

with earlier technological revolutions, and revised assumptions within the same task-based framework, yield a median estimate of about 0.7 percentage points of productivity growth per year – which is about 10 times larger than the cautious estimate.⁴⁸

Intermediate estimates for the US, combining task-level performance gains with exposure and adoption data, suggest annual TFP growth rates of 0.25–0.6 percentage points and labour-productivity growth of 0.4–0.9 points.⁴⁹ However, aggregate productivity gains may be much smaller if AI benefits are concentrated in only a few sectors, while demand, labour and investment remain tied to activities that AI transforms less. Aggregate productivity therefore depends not only on the size of sectoral improvements, but also on substitution in consumption and the reallocation of productive resources.



The US–Europe and US–UK gaps reflect upstream innovation and downstream diffusion

As with earlier waves of digital technology, AI is expected to deliver larger productivity gains in the United States than in Europe, partly because US firms and technology sectors are better positioned to develop, commercialise and scale AI-enabled innovations.

A useful distinction is between an upstream channel, through which AI raises productivity by accelerating software innovation, and a downstream channel, through which firms in other sectors turn AI-related intangible capital into broad-based productivity gains.

The United States derives significantly larger productivity gains from the upstream AI channel. AI software production, use and related R&D accounted for around half of the acceleration in US labour productivity growth, which rose from 0.8 per cent in 2012–2017 to 2.0 per cent in 2017–2024. Software-producing industries alone contributed roughly 40 per cent of the acceleration in US TFP growth, which increased from 0.4 to 0.9 per cent over the same period.⁵⁰ Overall, this suggests that a 1 percentage-point annual improvement in US labour productivity is within reach.

For the European Union, estimated productivity gains amount to around 0.3 per cent per year. However, these gains vary substantially across countries and are generally expected to be larger in Europe's higher-income economies.⁵¹

Europe's smaller AI-software sector means it captures less of the upstream productivity benefit from developing and commercialising AI technologies. European innovation evidence reinforces this concern. AI patenting depends heavily on prior capability in

adjacent technologies, such as communications, computing and large-scale data processing, while knowledge flows disproportionately to firms already at the technological frontier.⁵² Fragmented R&D policies and limited collaboration between universities and business in Europe and the UK make it harder to direct resources towards firms able to develop, absorb and scale frontier technologies. As a result, European economies are likely to rely more heavily on downstream diffusion, where productivity gains rely on complementary skills, data, management capabilities and organisational capital. These gains may therefore take longer to spread from individual tasks to firms, sectors and the wider economy.

The UK sits towards the upper end of the European range. Its AI sector is relatively large by European standards, giving it greater access to the upstream channel than most other European economies. Recent OECD evidence estimates that high-exposure economies such as the UK and the US could see annual aggregate labour-productivity gains of between 0.4 and 1.3 percentage points.⁵³ By contrast, IMF model-based scenarios put the UK's annual productivity gains over the coming decade at between 0.9 and 1.5 percentage points, a range that appears optimistic.⁵⁴

Given historical experience and the implementation challenges discussed in this report, we regard the lower half of the 0.4 to 1.5 percentage points range of additional annual labour productivity growth in the UK as most plausible. Even an annual uplift of around 0.5–0.7 percentage points, if sustained, would represent a significant step change relative to the UK's productivity performance over the past decade.



The UK's AI sector
is relatively large by
European standards...



...giving it greater access to the
upstream channel than most
other European economies.

Four Imperatives to Close the Ambition Gap

The evidence across the four levels of this review shows that AI's productivity potential is real but progressively harder to realise as the level of aggregation increases.

Task-level experiments often generate sizeable gains, but these gains may be diluted within jobs when complementary human activities become binding constraints. At the organisational level, adoption produces sustained returns only when firms can redesign workflows, develop skills, integrate data and systems, measure outcomes and

mobilise effective management and employee engagement. At the sectoral and macroeconomic levels, uneven diffusion, limited resource reallocation, institutional differences and weaknesses in innovation ecosystems create further leakage.

This points to a central implication that adoption alone will not close

the ambition gap. Organisations and economies must also recognise where AI can create value, have sufficient incentives to act, build the capabilities required for productive use, and execute the changes needed to turn potential into measurable productivity gains. The four imperatives below set out these conditions in more detail.

1 Attention

The attention imperative helps firms recognise and prioritise the AI opportunities most relevant to their strategy, operations and customers. This means creating the managerial bandwidth, practical use-case discovery, external advice and business support needed to translate AI's general potential into concrete opportunities for value creation.⁵⁵

2 Incentives

The incentives imperative ensures that leaders, managers and workers have sufficient reason, confidence and pressure to act on recognised AI opportunities. This means clarifying expected returns, reducing transition costs and implementation risks, aligning benefits and incentives, strengthening competitive pressure, and building the regulatory clarity and trust needed to support action.

3 Capabilities

The capabilities imperative builds the skills, data, systems, finance, managerial competence, technical support, process knowledge and absorptive capacity needed to act on AI opportunities effectively. This means investing in the complementary assets and organisational know-how that enables firms to move from recognised opportunities to practical implementation.

4 Execution

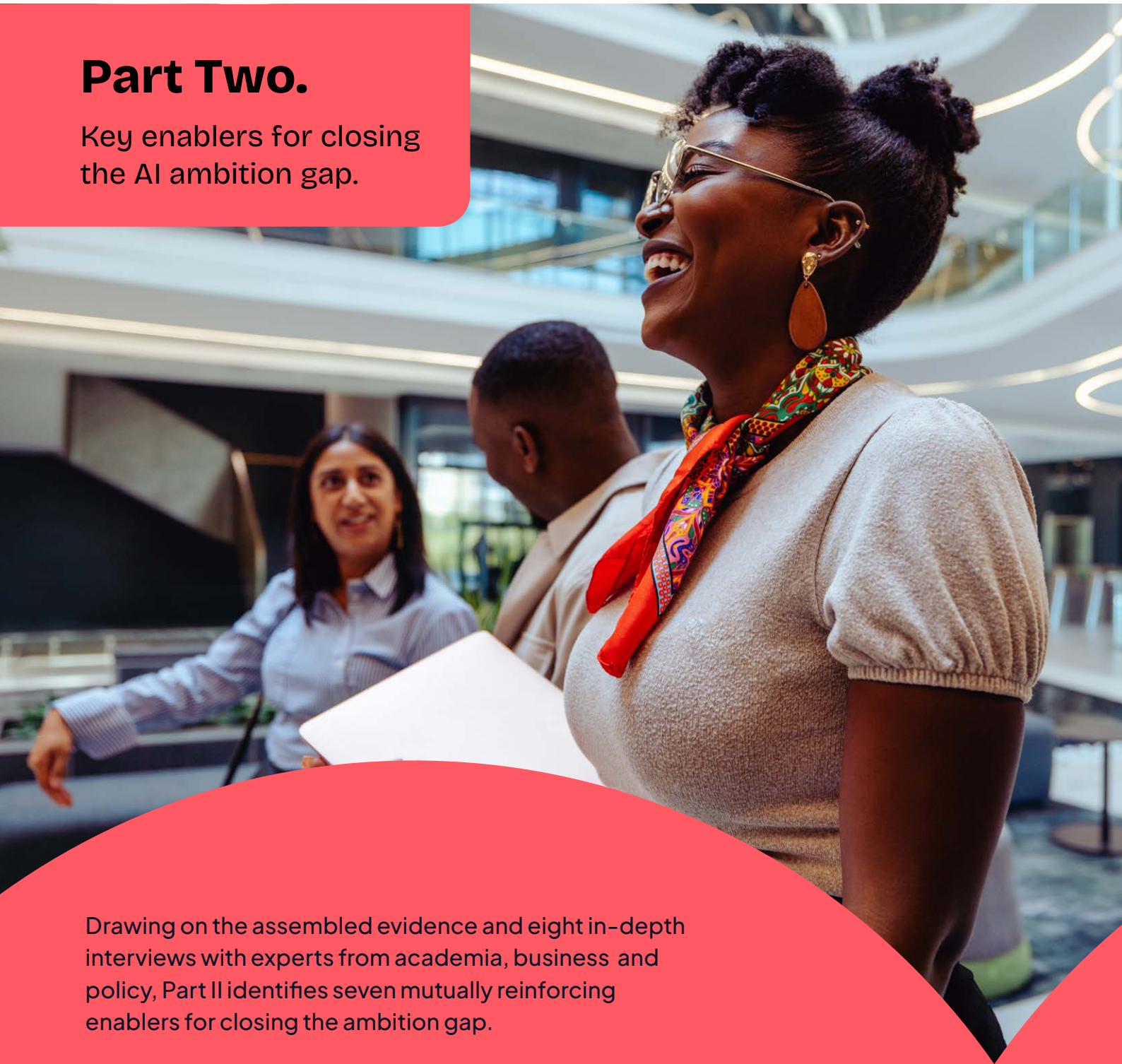
The execution imperative is to coordinate, scale and sustain the organisational changes needed to realise value from AI. This means establishing clear ownership, resource discipline, process redesign, pilot scaling, accountability, learning loops and persistence over time.

The four imperatives should be understood not as separate conditions, but as a connected sequence through which AI opportunities are either converted into productivity gains or lost.



Part Two.

Key enablers for closing the AI ambition gap.



Drawing on the assembled evidence and eight in-depth interviews with experts from academia, business and policy, Part II identifies seven mutually reinforcing enablers for closing the ambition gap.

Part I of this report showed that the ambition gap widens as AI moves from individual tasks to jobs, organisations and the wider economy. Closing it requires more than faster adoption: firms and economies must build the enablers that convert access to AI into redesigned processes, new products, better jobs and measurable productivity gains.

Drawing on the assembled evidence and eight in-depth interviews with experts from academia, business and policy, Part II identifies seven mutually reinforcing enablers for closing the ambition gap.⁵⁶

The seven enablers are ordered from the organisation-level conditions most directly within the control of business leaders (i.e., four business enablers) to the wider institutional and innovation-system conditions needed for broad-based diffusion (i.e., three system enablers).

Four business enablers

At the firm level, the sequence starts with leadership attention: identifying where AI is strategically relevant, testing whether technically feasible applications are economically viable, and assigning clear ownership for outcomes. It then depends on the leaders and managers, the workforce, and business functions

working together to redesign processes, build skills, evaluate results and scale only those applications that create measurable value. Adaptive capacity is the organisational ability to move beyond established routines and turn this sequence into sustained change.

1 Leadership and management: Set strategic direction, define the “North Star”, allocate resources, coordinate implementation and evaluate whether AI applications generate measurable value.

2 Worker capabilities: Strengthen domain knowledge, judgement, data literacy and responsible experimentation, which help organisations turn individual use into shared learning and improved work design.

3 Alignment of technical feasibility with economic viability: Clarify lifecycle costs and expected returns, establish shared metrics and outcome ownership, and guide decisions to scale, revise or stop AI applications.

4 Adaptive capacity: Help firms move beyond existing routines and business models by building the willingness and ability to redesign workflows, reallocate tasks, consult affected stakeholders and sustain change.

Three system enablers

At the system level, policy and institutions must make this operating model easier for many more firms to follow. Governance should provide trust, regulatory clarity and sector-sensitive guidance. Regional ecosystems should extend practical support and absorptive capacity beyond leading firms. And innovation policy should connect frontier advances to downstream application and diffusion.

Taken together, the seven enablers should not be read as a checklist of separate capabilities, but as an operating model for moving from AI potential to productivity outcomes. The common objective is to move from isolated experiments, uneven adoption and fragmented responsibility towards a system in which AI-enabled innovation is translated into broad-based productivity, better work and resilient growth.

5 AI governance provides clear, adaptive and sector-sensitive rules, builds trust and regulatory confidence, and offers standards, guidance and institutional support for responsible AI deployment.

6 Regional ecosystems help firms identify relevant opportunities, access trusted support and diffuse learning across suppliers, customers and local value chains.

7 Frontier innovation and diffusion turn technological possibility into usable applications by connecting upstream innovation with downstream institutions, business practice and diffusion across the economy.



Leadership and management

Leadership and management lie within the organisation's direct remit and are central to all four imperatives in our framework. This enabler strongly depends on organisational capital, namely the coordination routines, knowledge-sharing mechanisms, data practices and management systems that allow organisations to integrate and operationalise new knowledge.

Management quality as a precondition for AI adoption

Leadership and management capabilities appear especially important for AI. For example, cross-sectional evidence shows that UK firms in the top quartile of management practice scores adopt technology, including AI, at substantially higher rates than firms in the bottom quartile. Longitudinal evidence strengthens this association. Firms with stronger management practices three years earlier are more likely to adopt AI subsequently, even after differences in size, age, sector and location are taken into account.⁵⁷

Management quality also predicts AI adoption more strongly than the uptake of other technologies, suggesting that AI places distinctive demands on data management, cross-functional coordination and organisational learning. This helps explain why productive and already well-managed firms often adopt AI first. Adoption reflects an accumulated endowment of measurement systems, change-management experience and prior technology investment, rather than the effect of AI alone. In this sense, downstream investment in organisational and managerial capital may be the binding constraint on firms' ability to exploit upstream technological advances (see also the 'frontier innovation and diffusion' enabler).

Leadership across the AI adoption lifecycle

Leadership and management matter at every stage of the adoption process. Before adoption, senior leaders must set a clear 'North Star' - what AI is expected to achieve, which business outcomes it should improve, who owns those outcomes, what resources are available and what return is required.

Firms that acquire licences without this leadership plan risk stalling at the boundary between formal adoption and value maximisation. During experimentation and implementation, middle managers become the operational hinge. They allocate tasks between people and AI, redesign workflows, coordinate training and create a controlled environment in which employees can experiment and fail safely within agreed governance parameters, positioned between unrestricted use and an outright ban. As evidence and organisational confidence accumulate, managers can widen the boundary of permitted use while preserving accountability.

After adoption, leaders and managers must measure results, scale successful applications and stop those that do not generate value. Policy support should go beyond adoption grants. It should also provide management diagnostics, leadership training, implementation coaching and post-adoption evaluation. Where feasible, grants should be conditional on firms completing this follow-through.



My view on all of this is that if you're running your business well, you will be using AI and you will get a lot out of it. The issue is kind of upstream of AI itself: knowing what good looks like, having the KPIs and measurement tools to figure out how you're doing operationally, and knowing how to run change management programmes with people. If you have those things, and are focused on performance improvement, you almost can't avoid using AI well.

Tera Allas, CBE
Senior Advisor, McKinsey Company



Worker capabilities

Worker capabilities are central to whether AI adoption improves productivity and job quality. As AI changes tasks and occupations, organisations need workers who can use the technology critically, apply it to business problems and help redesign workflows.

Skills for AI-augmented work

Workforce skills primarily support the capability and execution imperatives at each organisational level: tasks, occupations and the organisation as a whole. Yet these skills cannot be reduced to generic AI literacy, basic training in how to operate a tool, or better prompt-writing. Employees need sufficient domain knowledge to frame problems, judge the quality of outputs and recognise when human verification is essential, particularly as tasks become longer and more complex.

Employees also need data literacy, critical thinking, communication and the confidence to experiment responsibly. The skills required will vary with the way AI recomposes work. For instance, when AI automates routine or inexperienced tasks, the expertise content of

the remaining work may increase. In contrast, when it automates expert tasks, skills may instead be devalued.⁵⁸ Training should therefore align with the organisation's business strategy, and prepare workers for changing responsibilities, including problem framing, verification and judgement.

Because AI exposure is higher in many jobs held by women and university graduates, capability-building should not be treated as a generic training agenda but targeted towards the occupations and functions where work is most likely to be augmentable, ensuring that exposed workers gain the judgement, verification and redesign skills needed to benefit from AI rather than simply absorb its risks.

When AI automates routine or inexperienced tasks, the expertise content of the remaining work may increase. In contrast, when it automates expert tasks, skills may instead be devalued.

From individual learning to organisational capability

The larger challenge is converting individual learning into organisational knowledge. Skills are changing with AI and digital technologies in ways that extend well beyond narrowly defined digital skills and depend on organisational, industry and institutional context.⁵⁹ Effective implementation therefore requires coordinated training for managers and workers, embedded in real business processes. Cross-functional teams can document successful use cases, share practices across the organisation and capture lessons from experimentation, turning individual experience into repeatable organisational capability.

Worker voice is important because employees may identify viable use cases and begin using low-cost tools before formal policy exists. Consultation, transparency, training rights and clear data protections can convert this shadow adoption into governed learning while improving job quality.⁶⁰ For SMEs, training support should be combined with retention, progression and good-work practices; otherwise the firms with the greatest skills gaps may train workers only to lose them to larger employers.



Technical feasibility and economic viability

The gap between potential and realised absorptive capacity is often reflected in the difference between the technical feasibility and economic viability of AI adoption.⁶¹ When business leaders consider both, they clarify lifecycle costs and expected returns, establish shared metrics and outcome ownership, and guide decisions on whether to scale, revise or stop AI applications. This enabler therefore bridges the incentive, capability and execution imperatives.

From technical pilots to business-process value

AI programmes can create a separation between organisational functions responsible for technology adoption (such as IT, data, digital innovation or procurement) and those accountable for outcomes (operations, finance, risk, human resources, sales and customer service). This creates a problem because technology teams can deliver licences and pilots without changing the process that determines productivity, revenue, service quality or job design. The appropriate intermediate unit is often the end-to-end business process rather than the individual task or the organisational unit. Processes cross functional boundaries, require multidisciplinary expertise and expose where coordination, data access and decision rights become binding constraints.

Measuring value and lifecycle costs

Coordination is the mechanism through which technical capability, economic viability and organisational change become measurable performance. Each priority use case should therefore have joint ownership by a technology lead and an operational outcome owner, supported by finance, workforce and risk expertise.

Before deployment, teams should establish a baseline and specify expected productivity, quality, revenue and job-related outcomes, alongside a timetable for evaluation. Shared metrics should connect operational changes to firm-level outcomes, enabling managers to distinguish individual time savings from genuine organisational value. They also provide the evidence needed to scale successful applications, revise underperforming ones and stop those that do not create value.

The business case should distinguish one-off costs of development, integration, workflow redesign and training from recurring costs of model access, inference, monitoring and human verification. Technical feasibility does not imply economic viability: deployment is justified when expected benefits are likely to exceed full lifecycle costs by a sufficient margin. This assessment should be repeated as the application scales, because per-query or per-token charges can rise with usage and offset apparent efficiency gains. Cost per successful outcome is therefore more informative than model or token cost in isolation.

Firms should also compare proprietary deployment with AI-as-a-service options, which can spread fixed costs across users but may introduce trade-offs involving data control, dependence on external providers and long-run operating costs.



In truth, it's really always about processes, not individual tasks or roles or even teams. And that's why it's so difficult to get value out of AI, because you have to redesign processes and then lead and manage the change across functions and organisational boundaries.

Tera Allas, CBE
Senior Advisor, McKinsey Company



If change is going to occur, it's because the pressures force a change in risk attitudes... risk attitudes don't change just because business leaders wake up one day and say, you know what, we've been much too risk averse. We got to do something. They wake up and realise they're in serious trouble and have to do something different... It's the pressure that gets created. And part of it's social, part of it's cultural. You have to give up on tradition, be willing to give up on traditional ways.

Martin Fleming
Research Scientist, MIT FutureTech

Adaptive capacity

Closing the ambition gap also requires firms to move from established success towards future opportunity. A firm may possess strong management practices, skilled workers and a viable business model, yet still lack the resilience and flexibility to reorganise around AI while its existing model continues to perform well.

Adaptive capacity is therefore distinct from general absorptive capacity. It concerns the willingness and ability to alter workflows, team structures, task allocation and, where necessary, the business model before external pressures make change unavoidable. The evidence suggests that intensive AI adoption produces productivity gains when it is accompanied by this reorganisation, rather than when firms merely acquire licences or run isolated pilots.

Adaptive capacity must also account for the risks and incentives associated with changing a successful model. Existing success can delay adjustment by reducing the perceived need to alter established routines, while cost pressures and competitive threats may eventually make experimentation unavoidable.

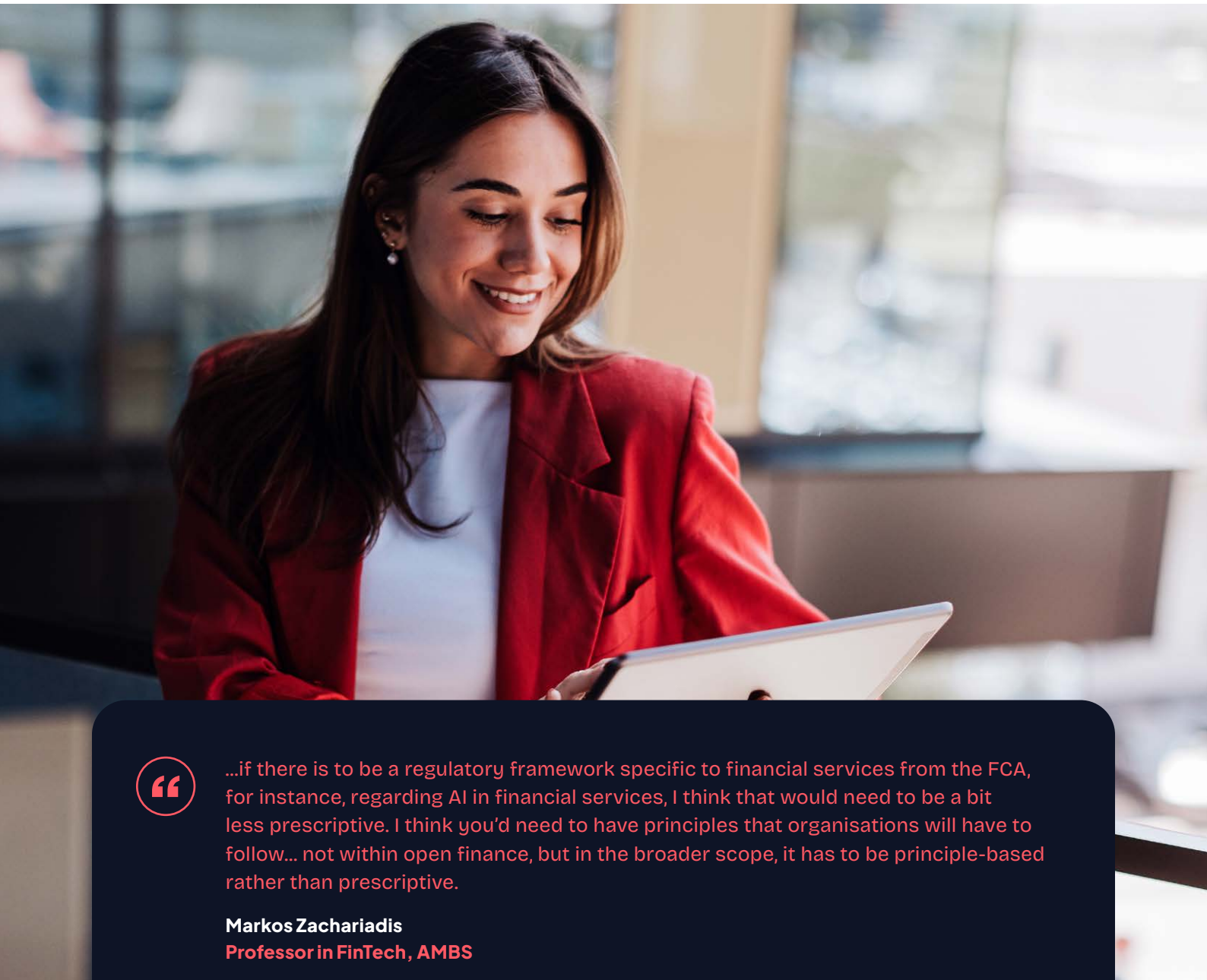
In the UK investment context, weak investment may reflect insufficient risk tolerance rather than a lack of ambition, a distinction that matters for closing the ambition gap. Risk tolerance should therefore be understood as one element of adaptive capacity, alongside organisational capability, complementary investment and coordination.

Adaptive capacity therefore involves both the willingness to depart from inherited practices and the ability to manage implementation through staged experimentation, transparent decision-making and consultation with affected stakeholders. It mainly addresses the incentive, capabilities and execution imperatives.



I think this comes back to the [productivity] J-curve type argument, that I think we're only seeing productivity gains where firms are intensively adopting and reorganising workflow. So they're probably changing the structure of teams and ..., getting people to do different tasks along the workflow so that AIs can do more of that work. There seems to be evidence that that type of reorganisation is required just to get actual productivity gains.

Policy Official



...if there is to be a regulatory framework specific to financial services from the FCA, for instance, regarding AI in financial services, I think that would need to be a bit less prescriptive. I think you'd need to have principles that organisations will have to follow... not within open finance, but in the broader scope, it has to be principle-based rather than prescriptive.

Markos Zachariadis
Professor in FinTech, AMBS

Governance

Beyond the organisational level, governance capability concerns the capacity of government to regulate, coordinate and set standards without unnecessarily slowing or freezing adoption. It mainly supports the attention, incentive and capability imperatives.

Legal, ethical and privacy concerns weigh most heavily on early adopters, whereas the constraints on more mature users increasingly concern productive

integration: shortages of expertise and suitable data, weak system compatibility and uncertainty about implementation.⁶²

As adoption matures, the emphasis in governance may therefore shift from encouraging willingness to adopt towards building the institutional and firm-level capabilities needed to integrate AI safely and productively.



Adaptive governance and sector-specific trust

Building trust is a core pillar of effective AI governance. Given the diverse characteristics of implementing AI across sectors, an explicitly sector-differentiated approach is needed within a coherent national framework, rather than a uniform policy applied across all activities. Financial services, as a heavily regulated sector, illustrates the resulting design tension between prescriptive and principles-based regulation. Prescriptive rules can provide clarity but may struggle to keep pace with rapid technological change.

A lighter, principles-based approach is more adaptable, but may itself create implementation uncertainty when firms lack sufficient guidance to act with confidence. Governance capability should therefore focus less on identifying a universally correct regulatory style than on building the institutional capacity to interpret principles, update guidance, support experimentation and help firms adjust as technologies and risks evolve. Such adaptive governance is itself resource-intensive and requires sustained expertise within regulators and the institutions that support implementation.



Innovation in regulation might make it easier to adopt in certain sectors that are heavily regulated. It hasn't really started yet, but I'd say that's going to be quite an important policy mechanism.

Policy Official



Targeted regulation requires cross-government coordination

The AI Growth Lab, a new UK government initiative, is intended to test whether targeted regulatory adjustments can ease adoption in heavily regulated sectors, while business support and skills programmes are tailored separately to sector needs.⁶³ For instance, the principal concerns are regulatory uncertainty and liability in FinTech, consumer trust and privacy in retail, and workforce skills and integration costs in manufacturing. Effective policy design therefore requires a targeted rather than uniform approach.

Yet responsibility for these sectors is distributed across government departments. For example, financial services falls within HM Treasury and creative industries within the Department for Culture, Media and Sport (DCMS), while responsibility for emerging technologies cuts across several portfolios. Governance capability consequently involves a coordination challenge as much as a regulatory design one. Sector-specific action must be aligned within a coherent cross-government framework.



Regional ecosystems

Regional intermediaries help build firms' absorptive capacity by strengthening the environment around them. Regional ecosystems mainly support the capability and execution imperatives but also play a role in drawing attention to opportunities for AI adoption. Catapults, manufacturing-extension organisations, growth hubs, chambers of commerce, colleges and universities can all provide neutral advice, shared equipment, training and links to finance that smaller firms cannot assemble alone. Trusted intermediaries can also reduce vendor risk by helping firms test whether systems work as promised and whether benefits justify integration and operating costs.

Greater Manchester illustrates how inherited capability and deliberate institution building can reinforce one another. Its manufacturing base and university assets, together with institutions and initiatives such as PrintCity (a 3D additive and digital manufacturing centre), the Henry Royce Institute and the regional origins of Made Smarter, have supported the adoption of advanced production technologies.⁶⁴ By building on these regional strengths, the aim has been to create a self-reinforcing pathway that enables firms to complete a transition from traditional manufacturing to smart manufacturing.

Yet support often fails to reach firms that are not already technology-oriented. These findings imply that regional policy should invest in outreach and brokerage, simplify access to support and provide intermediaries with sufficiently stable funding to build relationships with firms.

Devolved delivery can help programmes respond to local industrial structures, within a national framework for standards, evaluation and the scaling of successful models. Crucially, regional intermediaries must reach



In the Northwest, still there is the path dependency effect of the history of the region in terms of manufacturing...how factories are still here, and how it might be easy for them to move from traditional manufacturing to smart manufacturing, including 3D printing, but there were also regional capabilities from the public sector.

.. The policies tend to focus on adoption, a kind of simple question. We help you to adopt, yes or no. Once you start to use the technology, it's your own responsibility.

So even if companies have adopted, they know that the technology has much more capacity compared to the ones they are using it. So how do you define successful adoption?

There is still an information asymmetry between the policies and what reaches firms."

Mabel Sanchez Barrioluengo
Senior Lecturer in Science,
Policy and Innovation, AMBS

firms before they have formed an AI use case and continue supporting them after initial adoption, because the evidence identifies both non-consideration among lagging firms and low-intensity use among formal adopters.⁶⁵ By diffusing knowledge across suppliers, customers and adjacent sectors, intermediaries can prevent capability gaps elsewhere in regional value chains from diluting the gains achieved by leading firms.



Frontier innovation and diffusion

A central question in closing the AI ambition gap is whether domestic strength at the AI frontier is a pre-condition for productivity growth.

Frontier strength and downstream diffusion are complements

Relative to the United States, many firms in Europe and the UK face two distinct but connected disadvantages: a smaller AI technology sector, which limits their ability to capture AI's frontier innovation effects, and weaker downstream capabilities, which slow the commercialisation, scaling and productive use of new technologies and therefore cause a delay in reaping the productivity benefits from AI as a breakthrough technology.

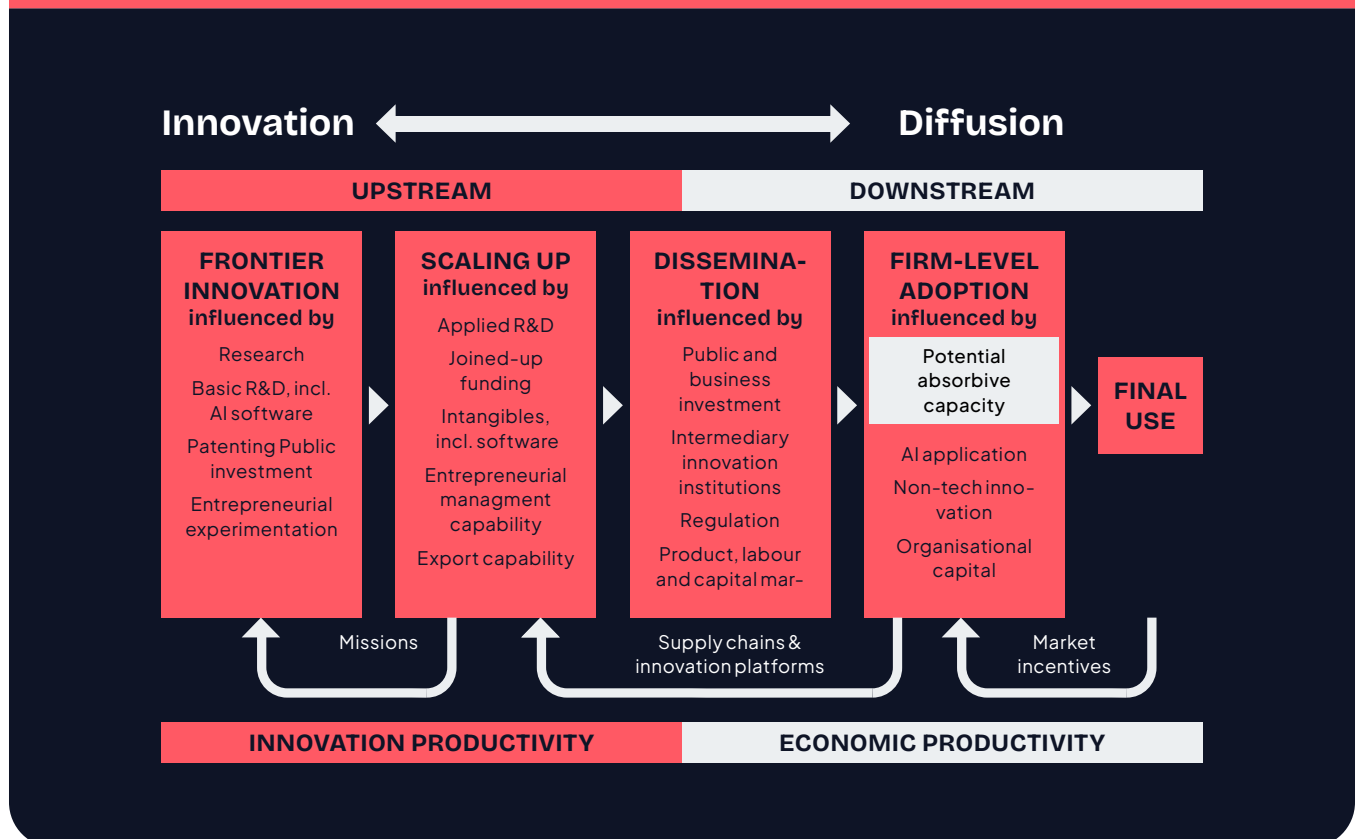
Many firms depend primarily on prior technological capabilities, particularly in communications, computing and large-scale data processing, while knowledge

flows disproportionately towards firms already at the frontier.⁶⁶ Translating research into scalable firms and combining externally available AI with software, data, skills and organisational capital is the key challenge.

Frontier and diffusion capabilities should therefore be treated as complements and cut across all four imperatives. Policy must strengthen selective upstream capacity while improving the institutions and business capabilities that convert external knowledge into productive applications. This requires closing the gap between potential absorptive capacity and realised absorptive capacity (see Figure 2).⁶⁷

Figure 2: The Innovation and Diffusion System

Source: Van Ark, B. (2026), "Rewiring Europe's Productivity Framework: Aligning Investment, Innovation, and Diffusion", Productivity Insights Paper No. 096, The Productivity Institute.





Application-layer innovation as a diffusion opportunity

For the UK and Europe, the most immediate opportunity to bridge the innovation–diffusion–productivity gap lies in the application layers of the AI stack: adapting increasingly commoditised models to sector-specific problems, proprietary data and customer needs in fields where firms already possess domain knowledge, including advanced manufacturing, health, professional services and other knowledge-intensive activities.

This is not passive technology adoption. The application layer is itself a locus of innovation, where firms redesign workflows, establish evaluation and governance systems, and recombine general-purpose AI with firm-specific assets. Realising productivity gains therefore requires complementary investment in skills, data, organisational capital and other intangible assets, rather than frontier R&D alone.

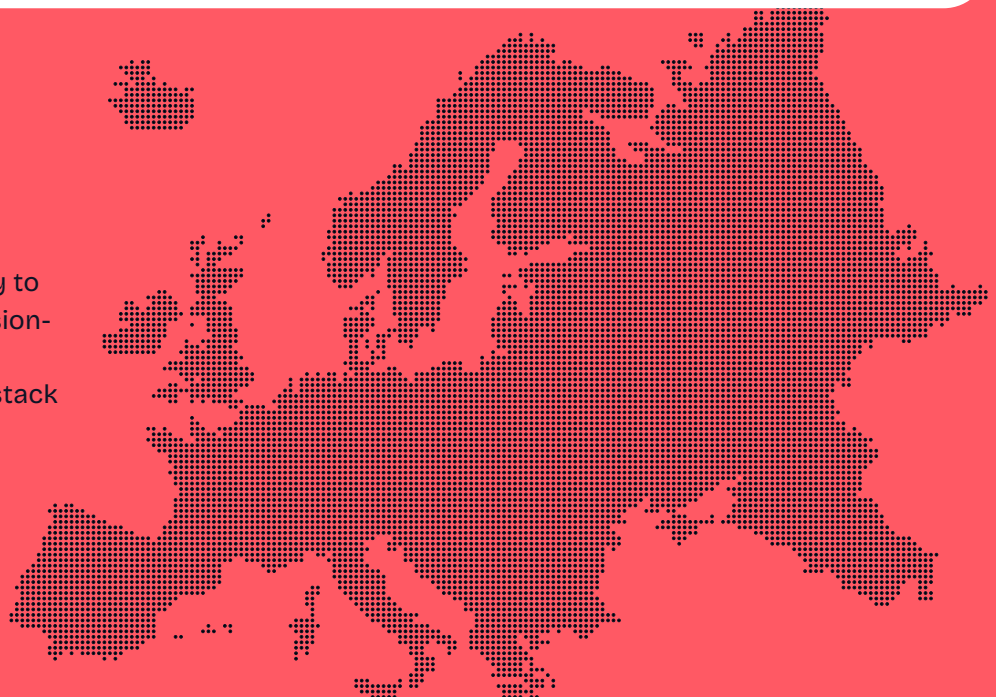
Firms must nevertheless decide where they sit in the AI value chain—frontier developer, integrator or sophisticated adopter—and focus on applications that can create new products, improve core processes or solve previously intractable problems. Secure access to models, compute and data remains necessary, as does selective upstream capability for strategically sensitive uses. The broader productivity opportunity, however, lies in enabling many more firms to commercialise, adapt and scale AI successfully. Innovation policy should therefore connect vertical support for strategic technologies with horizontal measures on scale-up finance, competition, skills, data access, market integration and business capability, so that frontier advances diffuse into productive use across the economy.



Even though you could say... we'll get the software, we'll get the hardware, we'll get the GPUs, and we'll make use of them, and we'll have the benefit, that's true. But I think there is another benefit to having a large technology sector... there's got to be the externalities. The workers who are moving from firm to firm, the knowledge that's being shared, even if casually... without the technology firms, I think there is a disadvantage that's more than the need to acquire the appropriate products or services.

Martin Fleming
Research Scientist, MIT FutureTech

For the UK and Europe, the most immediate opportunity to bridge the innovation–diffusion–productivity gap lies in the application layers of the AI stack





Recommendations.



Closing the AI ambition gap requires coordinated action across actors and levels: business leaders choose and own the use cases, managers and workers turn them into changed work, and policymakers, regulators and regional institutions build the conditions under which productive adoption can diffuse widely.

The final section of this report sets out recommendations for **business leaders**, **people managers** and **policymakers**, followed by reflections on the future trajectories of AI adoption and productivity.

Our review of the evidence and the insights obtained from experts have important implications for organisational strategy and pro-productivity policy aimed at making AI a major driver of productivity

growth. The recommendations that follow should be read through the four imperatives identified in this report: focusing attention on the most relevant AI opportunities; strengthening incentives to act; building the complementary capabilities required for adoption; and executing the organisational changes needed to realise value.



Business leaders: link AI use cases to strategy and performance

For business leaders, technology procurement is only the starting point. Firms need to focus organisational attention on the AI use cases most closely linked to strategy, customer value, operational bottlenecks and measurable performance. This requires senior leaders to set a clear 'North Star': what problems AI is expected to solve, which outcomes it should improve, who owns those outcomes and what level of return is required.

The incentive to act should be strengthened by treating AI not as an IT experiment, but as a core business priority, with clear accountability, resource commitments and explicit links to productivity, quality, revenue or service outcomes. At the same time, firms need to build the managerial, workforce, data and organisational capabilities that make adoption productive. The evidence shows that management quality predicts AI adoption, and returns are to a large extent earned

through the complementary organisational work surrounding the technology - including process redesign, data integration, workforce development and outcome measurement. Additional spending on AI can produce diminishing or even negative returns when complementary capabilities are weak. Business leaders should therefore build absorptive capacity alongside AI investment and execute the workflow redesign needed to convert adoption into sustained performance.





People managers: redesign work and build worker capabilities

For people managers, AI adoption should be treated as a work redesign and capability-building agenda, not simply a training agenda. Workers are often closest to the processes where practical use cases, risks and unintended consequences emerge, so they should be involved early in identifying where AI can create value. People managers can strengthen incentives for adoption by building trust as employees need to understand how AI will affect tasks, jobs, skills, performance expectations and the distribution of productivity gains. Training should therefore be embedded in real work rather than delivered as generic AI literacy alone.

Because task-level productivity gains are often largest among less experienced workers, training design influences how these benefits are distributed and whether they develop into durable expertise rather than dependence on the tool. Workers need domain knowledge, data literacy, judgement, verification skills and confidence to experiment responsibly. Worker voice is also central to execution. Firms with representative structures are more likely to combine AI adoption with consultation, training provision and improved working conditions, while transparent decision-making and clear data protections can convert informal experimentation into governed organisational learning.

Expectations nevertheless diverge. Executives anticipate modest medium-term productivity gains alongside employment reductions, whereas employees expect some job creation, implying different assumptions about whether AI will augment workers or reorganise work around fewer employees.⁶⁸ Organisational investment can help narrow this gap by linking skills development, worker voice and job redesign to transparent decisions about deployment, performance and the distribution of gains.



Policymakers: widen access and strengthen diffusion conditions

For policymakers, the priority is to widen access to AI by strengthening the conditions under which firms notice, trust, adopt and productively use it. In particular, SMEs and other firms outside the technology frontier can be helped to identify relevant AI opportunities through trusted intermediaries, sector-specific guidance, regional brokerage institutions and practical business support.

Policymakers also need to reduce adoption risks and uncertainty by improving regulatory confidence, lowering transition costs and helping firms navigate existing and emerging frameworks, including through initiatives such as the AI Growth Lab in the UK. International evidence on the productivity J-curve suggests that delayed productivity gains from AI have been more evident in the United States than in Europe and Japan, reflecting greater investment by US firms in the organisational capital needed to complement new technologies. Slower productivity growth outside the US should therefore not be attributed simply to productivity J-curve effects, but to lower investment in process redesign, skills, data and managerial capability.⁶⁹

For the UK and Europe, comparative advantage may lie particularly in the application layers of the AI stack, where increasingly commoditised models can be combined with existing domain knowledge in advanced manufacturing, health, professional services and other knowledge-intensive activities. Technology and innovation policy should support this recombination

while maintaining selective upstream capability. AI-as-a-service can lower fixed costs and technical barriers more rapidly than many firms could achieve independently, but access depends on competitive markets, interoperable infrastructure and safeguards against excessive dependence on a small number of providers.

Competition policy is therefore a key enabling policy. It helps ensure that shared AI infrastructure remains accessible, contestable and usable as a platform for wider diffusion and business capability building. Finally, policymakers should strengthen the data infrastructure for adoption policy. UK participation in Eurostat's harmonised AI survey series would create a common benchmark for assessing progress, identifying gaps and evaluating interventions, while still allowing complementary UK surveys to explore sectoral, regional and organisational detail.





AI productivity as a shared societal responsibility

AI's productivity gains are likely to be unevenly distributed across firms, at least initially.

The benefits of developing and implementing AI may accrue disproportionately to market leaders and early adopters, thereby widening productivity gaps between firms.

AI's productivity effects must therefore be assessed in terms of opportunity, risk and uncertainty together. The same exposure that creates scope for productivity gains may also generate displacement risks, while the eventual scale and distribution of both effects remain uncertain.

Ultimately, closing the AI ambition gap depends not on the pace of technological advance alone, but on whether complementary enablers develop quickly and broadly enough to convert that advance into productive

and safe use. Aligning technology with management, worker skills, organisational redesign, regional institutions and adaptive governance is therefore the central challenge.

If these enablers remain uneven, AI will reinforce existing productivity divides and may, despite massive benefits in terms of consumer surplus, deliver little more than a temporary increase in the level of productivity as applications diffuse. If they are built together, diffusion can generate broad-based productivity gains, better work and shared prosperity, while AI's role in accelerating research and innovation may also raise the underlying rate of productivity growth more permanently.

Aligning technology with management, worker skills, organisational redesign, regional institutions and adaptive governance is therefore the central challenge.



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