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THE DIRECTION OF AI INNOVATION IN THE UK

INSIGHTS FROM A NEW DATABASE AND A ROADMAP FOR REFORM

Carsten Jung and
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SUMMARY

Recent developments in artificial intelligence (AI) could have transformative effects on the economy. With the latest models achieving top scores in scientific and diagnostic reasoning tests, they could usher in a new era of growth. In Jung and Srinivasa Desikan (2024) we estimated that existing models, if widely implemented in the medium term, could help raise growth by 13 per cent. Advanced AI could also help tackle big societal challenges ranging from ill health to environmental degradation.

But realising the benefits of AI requires more than just accelerating deployment. **Policy needs to also provide strategic incentives for aligning AI deployment with the government's missions**. In this paper, we analyse the AI innovation landscape in the UK to determine which type of AI deployment *is and is not* currently taking place. We identify 'AI deployment gaps' and make recommendations for how they can be filled.

To do so, we built a first-of-its-kind (to our knowledge) database of 3,256 AI firms in the UK. It has detailed information on the type of AI applications, sector focus, and specific problem statements that AI applications are solving. From this, we developed measures for the current direction of AI innovation and consider where AI deployment gaps could lie.

Regarding the direction of UK AI innovation, we find the following.

- The UK is seeing rapid and far-reaching AI innovation. We find activity across all sectors of the economy, and across business lines. This shows innovation dynamism in the UK and suggests the first wave of deployment could soon be felt by employees and consumers.
- **15 per cent of AI value propositions focus on solving specific problems in specific sectors, while 85 per cent are focussed on more general process improvements.** This suggests more gradual rather than rapid transformative impacts.
- **70 per cent of AI firms are active in knowledge economy sectors**. In other words, adoption is only slowly reaching beyond knowledge intensive industries – a first sign of potential AI deployment gaps. Only 15 per cent of applications are focussing on product and R&D innovation – ie generating new value propositions – with the remainder focussed on making existing business processes more efficient.
- We find indicative evidence that many businesses often use off-the-shelf models (proprietary and open source, such as those by OpenAI, Anthropic, DeepSeek and Meta) rather than training their own in-house models. **Value add from AI adoption could** therefore, to a large extent, **involve business process innovation** – AI deployment in other words – rather than developing new AI models.

To illustrate what types of problems AI deployment is aimed at – and what the value propositions are – we look more closely at two AI innovation areas: health and transportation. We find the following.

- Public health is a burgeoning field of AI innovation. Health is the second largest sector for AI activity – with most specialised innovation focussed on diagnosis, drug improvement and treatment improvement. However, we highlight that to be more mission-aligned – as is widely recognised in the public health space –

there will need to an increased **focus on prevention**. However, we find that only 12 per cent of value propositions are in the prevention space. More innovation activity in this area could help deliver the government's mission, and policy can help generate it.

- AI innovation in the transport sector has a big focus in autonomous vehicles and operational efficiencies. But for technological innovation to be fully mission-aligned there is a **need to increase access to transport while also reducing carbon emissions**. More innovation would be needed in **transforming the way we travel**, including by personalising the transport offer, increasing on-demand transit and encouraging multi-modal travel. We find that, in the transport sector, only 9 per cent of AI innovations are in this space.

We argue that, to fill these gaps, AI innovation policy needs to be genuinely mission-driven, and closely aligned with the government's various objectives. We make four recommendations.

- First, AI makes it more important for governments to break down their missions into more specific underlying targets and problem areas. AI innovation can best be targeted towards social good if there are clearly identified problems that it can help solve.
- Second, to steer progress, **innovation policy should be explicitly linked to government missions** and specific 'problem areas'. This should be embedded in Innovate UK's grant making and some of the British Business Bank's financial support. It will require coordination with other government departments.
- Third, the government should use **'technology push' policies** – such as R&D tax credits – to align AI innovation policies with its missions. This will mean linking them more explicitly to solving problems related to delivering missions than is currently the case.
- Fourth and crucially, it should also use **'demand pull' policies** – those that establish a market for new innovations where currently none exists. Outcomes-based procurement can be a key tool for this, that gives businesses certainty to invest and innovate. But this will require a significant shift from the current risk averse approach to procurement currently prevalent in government.

While the UK government does already use all the above levers to some extent – via Innovate UK for example – it does so without sufficient strategic direction. We argue that these could be further leveraged, alongside broader procurement, fiscal and regulatory incentives, to steer AI development and deployment.

Table S1 summarises our recommendations and highlights how they connect to the government's *AI Opportunities Action Plan* (Clifford 2025).

TABLE S1

We make four recommendations to accelerate mission-aligned AI deployment

	Recommendation	Connection to *AI Opportunities Action Plan*
1) In-depth tracking of AI deployment and AI impact scenarios, *by new AI tracking unit*	Need to clearly track what type of AI deployment is occurring and where the gaps are. Over time, develop in-depth scenarios for job and business impacts.	Plan calls for technical horizon scanning and market intelligence. Calls for assessment of skills gaps and devising of "sufficient opportunities for workers to reskill."
2) Break missions down into specific problem statements, *as cross-departmental effort, led by mission councils*	Break down the government's missions (such as health) into specific problem areas that need solving.	Calls for AI to be core to delivering the government's missions, both in public service delivery and the economy more widely. "Appointing an AI lead for each mission." Cross-government work to identify use cases and incentivise deployment.
3) Technology push: align innovation policy clearly with missions to create 'technology push', *by Innovate UK and BBB*	Clearly link some of Innovate UK and BBB's funding to solving mission-related problems. Start with areas where problems are clearly established.	Preferential compute and data access for mission-aligned innovators. Mission-focussed national AI tenders. Connect AI policies to new industrial strategy.
4) Demand pull: Use subsidies, procurement and preferential financing for AI adoption and market shaping, *by public procurement by all departments, Innovate UK and BBB*	Gradually increase more outcomes-focussed AI procurement, backed by a central fund. Create BBB funding stream that incentivises AI adoption.	Agile procurement, "two-way partnership with AI vendors and startups". "Drive AI adoption across the whole country" with focus on SMEs.

Source: Authors' analysis

1. INTRODUCTION: AI DEPLOYMENT NEEDS NOT JUST ACCELERATION, BUT DIRECTION

Artificial intelligence (AI) technologies are advancing at a rapid pace, and the UK government has identified AI as a crucial tool for driving economic growth, enhancing public services, and helping it deliver its missions – such as improving public health. This agenda is reflected in the government's *AI Opportunities Action Plan* (Clifford 2025). It focusses on removing barriers to AI adoption across the economy – including fostering widespread adoption by businesses – and it hints at aligning AI innovation with the government's missions.

Generative AI, in particular, has the potential to hugely impact economy and society. In a wide range of cognitive tasks, leading models have achieved undergraduate and PhD level reasoning skills (Jung 2025). In our previous study, we modelled that 59 per cent of tasks in the economy could be impacted by existing generative AI technology, if companies and public sector organisations were to build their processes around it (Jung and Srinivasa Desikan 2024).

We therefore see enormous potential in cutting-edge AI, but steering the direction of its application will be crucial. There is a risk that merely accelerating AI deployment without sufficient direction might fail to improve living standards and deliver the government's missions.

In 2024, AI venture capital (VC) investment in the UK was close to $4 billion. While this is still far behind the US – which saw almost 20 times more VC investment – the UK ranks third, after China (Dealroom.co 2025). The UK is also leading Europe's generative AI patents (though again it is far behind China and the US, and behind some European countries on wider R&D metrics) (CIIP 2024).[1] UK scientist Sir Demis Hassabis won the Nobel Prize in chemistry in 2024 for breakthrough work in AI. The UK ranks highly in generative AI research publications and its renowned computer science university departments also indicate high potential. All this points to the UK's role as an important AI innovation hub.

In this report we argue that, building on these foundations, **the UK could become a global leader in public value creating AI**. The *AI Opportunities Action Plan* (Clifford 2025), together with the new government's broad-ranging vision on mission-based government, could boost growth and deliver public value. This includes priority areas such as improving public health and helping deliver a better transport system.

However, currently much of the policy focus is on 'accelerationism' – meaning making AI better, cheaper and widely deployed. 'AI safety-ism' focusses on avoiding clearly defined risks, no matter how advanced or what type of AI application.

1 See: https://thenextweb.com/news/uk-tops-europe-ai-patents-un-study

We argue that to achieve AI for public value creation, a third strand of policy is needed: 'directionism'. This is the idea that policy can steer the direction of AI deployment actively, using policy incentives – such as targeted funding, public procurement or public infrastructure access – for building products and services that create public value, expressed though government missions (Jung 2025; Blili-Hamelin et al 2025).

TABLE 1.1

Policy should focus more on shaping the direction of AI innovation, as well as acceleration and risk mitigation

	Goal	Policy tools	Examples
Accelerationism	Increase AI deployment by making it better, easier and cheaper to use	Give businesses and people access to capital, digital infrastructure and talent	UK AI Opportunities Plan, investments in public sector supercomputing capabilities (UK Day One 2024)
Safety-ism	Avoid clearly identified risks	Safety testing, privacy safeguards, anti-bias assurance	EU AI Act, AI safety institutes (eg UK, US, Singapore)
Directionism	'Steer' innovation towards solving important societal problems	Provide incentives to build services and research that explicitly solves societal problems	Outline specific missions and milestones eg in preventative health or climate

Source: authors

MEASURING THE DIRECTION OF INNOVATION AND IDENTIFYING 'DEPLOYMENT GAPS'

In this report, we show empirically that there is a case for policy to steer AI deployment more proactively. We highlight that there are innovation areas that could have high social returns but that currently receive relatively little attention. These '**AI deployment gaps'** highlight that policy can play a role in incentivising mission-aligned innovation.

We analyse the landscape of 'AI organisations' in the UK – 3,200 organisations that have AI as part of their value proposition. To do so, **we developed a first-of-its-kind database of AI firms operating in the UK, which has detailed information on the type of AI applications, the sector focus, and the specific value propositions of AI firms**. We developed this dataset by building on UKRI data and augmenting it with large scale AI-enabled web scraping (see appendix for our methodology). This is a first step to measure the current direction of UK AI innovation and consider where AI deployment gaps lie.

In the next section, we present our key findings from the analysis of this dataset. We then conduct two deep dives into the health and transportation sectors and show where AI innovation might currently be falling short of helping the government's missions. In our recommendation section, we highlight how UK innovation policy could become more mission aligned.

2.
KEY FINDINGS FROM OUR NEW DATABASE

AI BUSINESSES FOCUS MAINLY ON GENERAL PROCESS IMPROVEMENTS RATHER THAN SPECIFIC PROBLEM SOLVING

In this section, we investigate how narrowly focussed firms' value propositions are. The 'most specific' applications are those that solve a specific problem in a specific sector ("using AI for damp detection in homes", for example). The least specific ones are those that solve a general problem (such as "improving business processes with AI analytics") and market themselves to a wide range of sectors.

We find that 85 per cent of AI firms provide 'general' AI solutions. These are value propositions aimed at general process improvement – like improving analytics, better customer engagement or better product design. On the one hand, this can be a good thing, as AI is a "general purpose technology" that can have a multitude of applications. On the other hand, many of the applications in our dataset describe fairly abstract process improvements, which may not fully realise the transformative potential of AI in solving hitherto intractable problems. Only 15 per cent of organisations develop specific solutions in specific sectors, articulating a narrowly defined value proposition.

With regards to deployment, we hypothesise that such problem-focussed AI applications can have more transformative potential. For instance, DeepMind's AlphaFold is a highly specialised AI application, and is considered to have a transformative potential. They created an AI system that can accurately predict a protein's 3D structure from just its amino acid sequence, solving a 50-year scientific challenge. It could be transformative because being able to predict a protein's structure is crucial for understanding disease and developing new drugs.

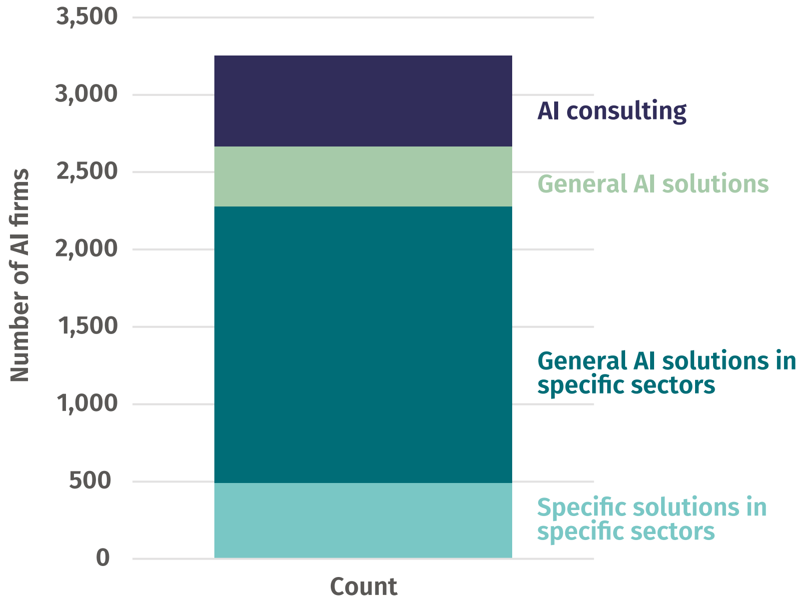
AI applications that are focussed on such 'bottleneck problems' can therefore have high potential to be transformative in the short term. Such a problem solving focus also allows us to more clearly assess what type of progress AI is delivering or, in other words, what the direction of AI innovation is. The direction of AI innovation can be summarised by the problem it is deployed to solve.

However, less narrowly focussed AI applications that lead to gradual process improvements can also have large cumulative impacts over time. For instance, electricity's impact on manufacturing occurred through gradual improvements that ultimately yielded dramatic change. Initially, factories merely substituted electric motors for steam engines with minimal gain. As technology evolved, machines received dedicated motors rather than relying on central power distribution. The real breakthrough came when factories completely redesigned their layouts around workflow rather than power requirements, boosting productivity (David 1990). Such **initial gradual change might begin with the 'AI consulting' companies** – about 18 per cent in our data set – which help businesses adopt AI in their existing processes.

FIGURE 2.1

Eighty-five per cent of firms are working on general applications

Number of firms



Source: IPPR analysis of UKRI (2024) augmented via RAG web scraping

AI ADOPTION IS FOCUSSED ON THE KNOWLEDGE ECONOMY AND PROCESS IMPROVEMENT

We find deployment activity across all sectors of the economy, and across business lines. This suggests there could be wide-reaching application of AI across the economy in the near term. It also shows that there is significant innovation dynamism in the UK and that the adoption phase is clearly under way.

Our findings in figure 2.2 suggest that **70 per cent of AI innovation is concentrated in 'knowledge economy' sectors.** This includes professional services, financial services, and information and communication, as well as health and life sciences. This is in line with our finding from our previous report, where we highlighted that 'back office' knowledge jobs are significantly more likely to be impacted by generative AI than 'front office', customer facing and manual jobs (Jung and Srinivasa Desikan 2024).

Next to the knowledge sectors, wholesale and retail trade also see a significant amount of AI activity. But applications here are not primarily putting AI in brick-and-mortar shops. Instead, activity mainly involves consultancy services such as analysing customer data and providing sales insights.

Looking at applications across business units, we find that software engineering sees the biggest use of AI innovation. In other words, AI is being used as a coding assistant. Product and R&D applications might deliver the most visible short-term transformative changes by improving products – but they see only 15 per cent of activity. This is followed by customer operations, marketing and sales. In sum, this suggests AI innovation is largely focussed on process improvement: **technical**

efficiency (software engineering and the supply chain) and **customer focused efficiency** (marketing and sales, customer operations, and the supply chain).[2]

An example of a company using AI for such efficiency-focussed innovation is Synthesia, based in the UK, which aids companies with text-to-video creation and communication. It is used by many Fortune 100 companies for learning and development, marketing, and sales enablement, among others (Benaich 2024). In our classification, this falls under both 'marketing and sales' and 'customer operations'.

FIGURE 2.2

Nearly 70 per cent of firms are in the knowledge economy and health sectors and only 18 per cent of applications are in "product development and R&D"

Number of firms active in sector and business area (firms can be active in multiple fields)

Market sectors / Business	Marketing and sales	Customer operations	Product and R&D	Software engineering	Supply chain	Risk and legal	Strategy and finance	Corporate IT	Talent and organisation
Professional, scientific and technical activities	718	932	1,248	1,523	159	452	612	264	385
Human health, medicine, pharmaceuticals	402	744	933	1,021	230	355	497	248	251
Financial and insurance activities	458	769	622	894	200	641	712	313	193
Information and communication	592	632	688	857	61	261	712	313	193
Commercial activities, wholesale and retail trade	483	614	367	536	261	230	293	162	77
Government, public administration, social work and compulsory social security	227	405	473	545	75	215	232	152	171
Manufacturing	149	256	336	356	186	87	127	76	78
Education	122	182	329	359	12	55	78	40	154
Transport and storage	105	198	230	282	101	52	90	40	58
Arts, entertainment and recreation	164	150	198	239	13	40	66	27	62
Administrative and support service activities	99	160	68	135	17	45	42	42	71
Electricity, gas, steam and air conditioning supply	43	110	135	161	34	29	62	25	33
Renewable energy, environmental protection and mitigating climate impacts	65	81	126	126	23	26	79	25	56
Accommodation and food services	87	104	56	104	27	15	32	13	16
Agriculture, forestry and fishing	33	59	114	111	35	17	33	9	20
Construction	39	69	84	108	21	24	41	14	25
Real estate activities	54	85	69	102	9	36	46	18	16
Water supply, sewerage, waste management and remediation activities	12	37	43	52	12	6	10	8	7
Mining and quarrying	16	29	41	47	13	7	12	8	9
Defense, policing and arms manufacturing	4	14	45	45	6	4	5	3	2

Colour scale: 200, 400, 600, 800, 1,000, 1,200, 1,400

Source: IPPR analysis of UKRI (2024) augmented via RAG web scraping

2 In Jung and Srinivasa Desikan (2024) we found that the majority of tasks in these jobs could be significantly aided by generative AI. This is therefore an area where further growth might be expected.

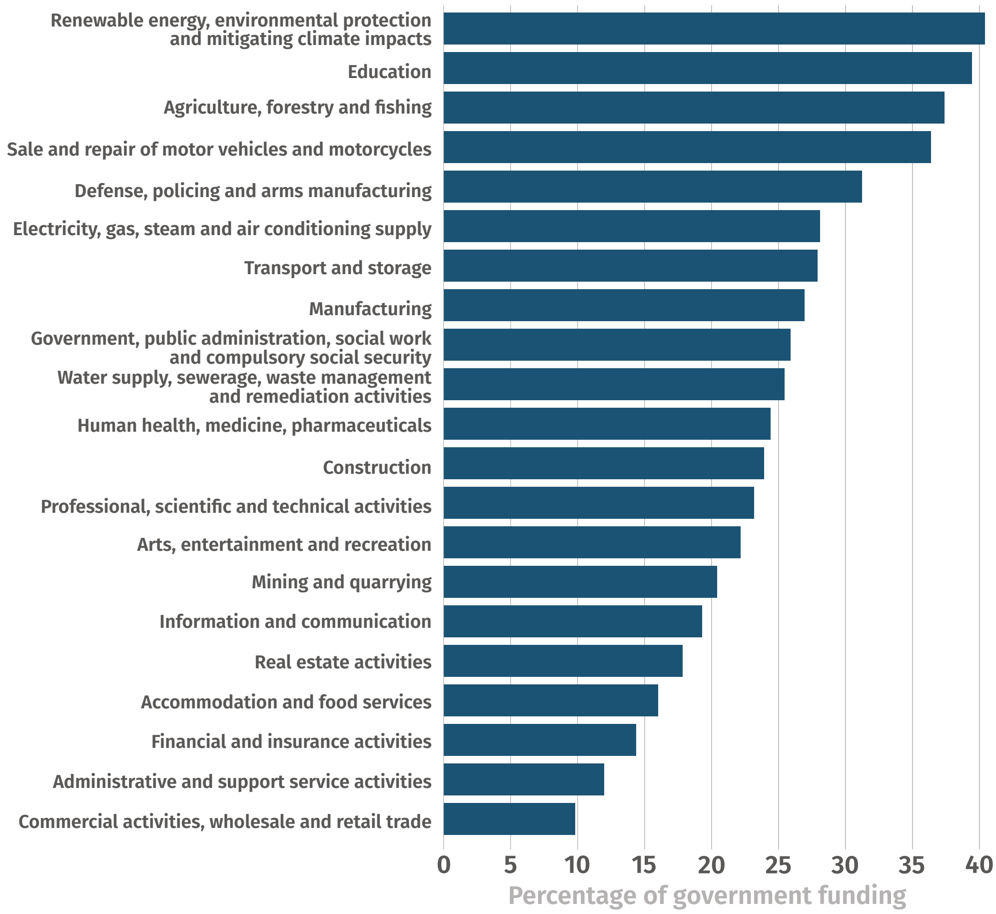
AI firms in our dataset are primarily focussed on **providing services over research** (90 per cent services versus 10 per cent research focus). The healthcare and education sectors have the highest proportion of research-focussed firms. In terms of customers, **most AI firms sell their product to other businesses**: about 59 per cent of firms are targeting businesses, about a quarter are aimed at government customers, and consumer-focussed applications make up about 15 per cent.

In the overall sample, **22 per cent of the firms received some type of public funds**. Encouragingly, AI firms in sectors that have relatively more public policy interest tended to be supported more with public funding – such as climate change and education related businesses. AI firms offering services to the agriculture, forestry and fishing sector had the third highest percentage of public funding. Sources of public funding for agriculture sector, for instance, included Innovate UK funding, EIT Food Accelerator Network[3], Agri-Tech Catalyst programme, the government's Farming Innovation Pathways competition. This shows that the UK has a well established set of innovation funding institutions. But, as we argue below, these could be significantly improved to make innovation more focussed on delivering missions.

FIGURE 2.3

About four in five firms active around climate and education received public some public funding

Share of firms in a given sector that received some type of public funding



Source: IPPR analysis of UKRI (2024) augmented via RAG web scraping

3 The programme is open to companies established in EU member states or Horizon Europe-associated countries, which includes the UK.

The public funding also tended to go to more specialised companies. Using our categories from figure 2.1, about a quarter of firms with a focus on a specific sector (either with specific solutions or general methods) received some type of public funding, while only 8 per cent of firms that had a very broad sector focus had received funding.

THE USE OF OFF-THE-SHELF MODELS: AI ADOPTION IN THE UK COULD TO A LARGE EXTENT INVOLVE BUSINESS PROCESS INNOVATION RATHER THAN AI SOFTWARE INNOVATION PER SE

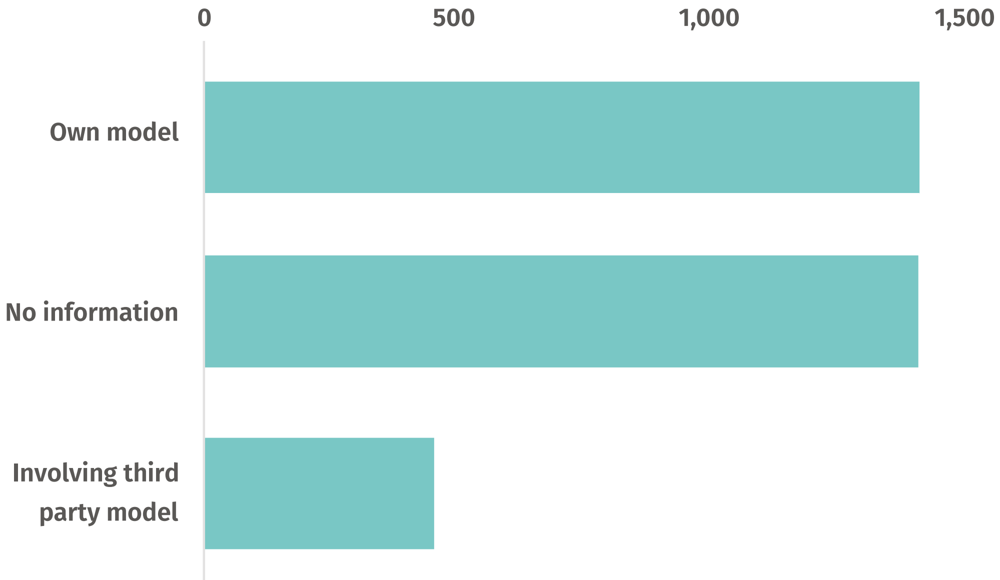
Given the likely advantage of frontier AI model providers (due to the high infrastructure costs of training core AI models), most smaller AI businesses can be expected to work with leading AI models rather than develop their own foundation models.

Our dataset provides indicative evidence of this: **less than half of firms state that they are working on their own proprietary AI models** (figure 2.4), with about the same amount providing no information as to what models they use. Given there is an incentive for advertising proprietary technology, this suggests that a majority of firms might be building their offering on top of third party foundational AI models. In those cases, the main value add would be the additional software 'on top of' the core models or adopting third party models to specific use cases.

FIGURE 2.4

Four out of 10 firms do not explicitly state whether they are building a proprietary model or using a third party one

Number of firms



Source: IPPR analysis of UKRI (2024) augmented via RAG web scraping

This would not be surprising. There are strong grounds to believe that, for purely economic reasons, many firms will use leading off-the-self models (such as those by OpenAI, Anthropic, Google, DeepSeek, Mistral or Meta) rather than develop their own AI models. As well as being cheaper than developing a custom model, these off-the-shelf models have been found to outperform domain-specific ones – even those that have been trained on domain-specific proprietary data (Mollick 2024). As Mollick writes:

> ***"Bloomberg created BloombergGPT to leverage its vast financial data resources and potentially gain an edge in financial analysis and forecasting. This was a specialised AI whose dataset had large amounts of Bloomberg's high-quality data, and which was trained on 200 ZetaFLOPs [4] (that is 2 x 10^23) of computing power. It was pretty good at doing things like figuring out the sentiment of financial documents… but it was generally beaten by GPT-4, which was not trained for finance at all. GPT-4 was just a bigger model (the estimates are 100 times bigger, 20 YottaFLOPs, around 2 x 10^25) and so it is generally better than small models at everything."***

In early 2022, a DCMS study found that, of AI-adopting firms, about 60 per cent did not develop it in house (DCMS 2022). Since the cost of training cutting-edge models has risen by a factor of 44 times since 2020, firms are less likely than ever to be able to develop their own in-house models.[5]

However, if a large number of UK-based AI firms chose to build products on top of a small number of AI foundational models, this could give significant market power to the few providers of such models. As the UK's CMA (2023, 2024) points out, such market concentration could 1) distort choice and increase prices, and 2) limit competition in the deployment of AI foundation models.

That said, recent improvements in open source models (such as DeepSeek's R1, Meta's Llama 3.3, and Mistral Small 3) have come close to closing the gap with commercial alternatives (though continuous improvements make this a dynamic picture). There is also some evidence that AI deployment firms rely more on open source models.

In either case, the potential for AI models to become widely and cheaply available points to an interesting dynamic: much of AI innovation going forward might in fact not lie in developing cutting edge models. Instead, value add might come from innovative ways of building software on top of these models, and building the digital and physical tools for organisations to adopt third party models. Much value add for UK businesses might indeed come from solving 'deployment problems' rather than fundamental AI research. Box 2.1 highlights some of these examples.

4 ZetaFLOPS is a measure of how fast a supercomputer can perform floating-point operations per second.

5 See: https://www.edge-ai-vision.com/2024/09/ai-model-training-cost-have-skyrocketed-by-more-than-4300-since-2020

BOX 2.1: EXAMPLES OF BUSINESSES USING THIRD PARTY MODELS FOR AI DEPLOYMENT

This box provides examples of what AI innovation based on third party models can look like.

PwC UK has partnered with OpenAI to integrate advanced AI capabilities into its services. A key initiative includes the launch of a UK tax AI assistant, developed in collaboration with OpenAI and Harvey (PWC 2023).

Octopus Energy, a UK-based energy supplier, has incorporated ChatGPT into its customer service operations. The AI system handles 44 per cent of customer inquiries, effectively performing the work of 250 human agents while achieving higher customer satisfaction ratings than human representatives (Marr 2023).

Firms in our database that are explicit about the third party models they use include:

- Bubblo, a discovery platform for users to find and engage with bars, clubs and restaurants. It offers recommendation for venues based on a constant flow of user-generated data from various digital and social media sources. The AI-powered platform uses IBM Watson's AI to rank venues.
- CUBE, a UK-based firm, that is leveraging AI to provide comprehensive regulatory intelligence solutions to the financial services industry. As part of this it uses large language models like GPT to condense and compress large regulatory documents into brief summaries.

3.
DEEP DIVES: WHAT ARE THE VALUE PROPOSITIONS OF AI COMPANIES AND WHERE ARE THE GAPS?

In this chapter, we conduct two sector deep dives to illustrate in more detail the value propositions of AI firms and, therefore, the direction of AI innovation. We use AI tools to break this down, **distilling the detailed information we have about each firm into a succinct value proposition** (see appendix for the methodology). Next, we categorise them into value proposition categories. This is an innovative new approach towards approximating the 'direction of innovation'. It helps us to analyse whether firms' business models are geared towards solving missions and helps create public value.

CASE STUDY 1: SIGNIFICANTLY IMPROVING PUBLIC HEALTH WILL REQUIRE MORE FOCUS ON PREVENTION

> ***"Improve healthy life expectancy for all and halve the gap in healthy life expectancy between different regions of England"***
> Labour Party (2023a) 'Build an NHS fit for the future'

Improving public health is an objective of the government – it is both crucial for improving people's living standards and an economic imperative since it is linked to better economic outcomes (IPPR 2024). Using cutting-edge AI models could be key for improving population health. As we showed above, AI in health – after professional services – is the second largest AI innovation area.[6]

Table 3.1 summarises the value propositions of AI in health, zooming in on those that provide specific and general solutions focussed on the health sector.[7] It shows that about **two thirds of AI applications are focussed on better diagnostics, better drugs and better treatment**. In other words, AI innovation is focussed on the core clinical functions. For example, Kheiron Medical Technologies' AI-driven 'Mia' suite significantly improves breast cancer detection rates by analysing mammograms with deep learning algorithms. With regards to drug discovery, Isomorphic Laboratories uses advanced AI technologies like AlphaFold to accelerate drug design by predicting molecular structures and interactions. Within treatment optimisation, Pear Bio is improving cancer treatment by employing AI and computational biology to personalise therapy, based on each patient's unique tumour microenvironment.

6 Note that many offers are of a general kind that advertise to the health sector but are not necessarily exclusively focussed on it.

7 If a wider list of companies were included, including those providing general solutions sold to multiple sectors (including health), then 'operational efficiency' would be the most frequent category.

TABLE 3.1

Of the specialised healthcare applications, only about 12 per cent of AI innovations are in the preventive space

Value proposition category	Count	Share of total	Description
Diagnostic enhancement	48	24%	Companies using AI to improve accuracy, speed and efficiency of diagnosing conditions
Drug discovery and development	32	16%	Accelerating pharmaceutical research and drug design
Treatment optimisation	24	12%	Tailoring and improving healthcare interventions for existing conditions
Operational efficiency	24	12%	Streamlining healthcare workflows and administrative processes
Preventive healthcare	24	12%	Predicting and preventing health conditions before they develop, including diet, exercise and mental wellbeing approaches
Remote monitoring and health tracking	18	9%	Real-time tracking of patient health metrics
Surgical and procedural enhancement	12	6%	Improving precision and outcomes of medical procedures
Mental health treatment	10	5%	AI applications for managing diagnosed mental health conditions
Patient engagement and empowerment	6	3%	Tools to involve patients actively in their healthcare
Accessibility and inclusive care	2	1%	Making healthcare more accessible to underserved groups
Integrated community health systems	0	0	Connecting diverse stakeholders to collectively promote health at the community level through cross-sector data sharing and coordinated interventions

Source: IPPR analysis of UKRI (2024) augmented via RAG web scraping

Prevention is crucial for improving population health – but it sees little innovation activity

However, there is evidence that there are still some areas that receive insufficient investment. Some of the largest potential gains in public health lie not in the detection and treatment of disease, but in its **prevention**. The Labour government stated that they agree with this: "We know that with a relentless government focus on prevention, people could live healthier and happier lives, economic growth could improve, and there would be less pressure on the NHS" (Labour Party 2023a). IPPR (2024) has argued that the UK needs to shift from a reactive "sickness model", where health is considered a personal responsibility until acute illness, to a proactive "health creation system" that would focus on preventing illness across society through workplaces, communities, schools, and other spaces where people actually spend their time.

In table 4.1, we highlight in green the types of value propositions that might help build a health creation system. **Currently, such potentially high impact innovations make up only about 13 per cent of the total.** And, in our dataset, we found no business models at all that sought to address the important area of delivering health interventions on a community level. This suggests an important deployment gap that policy incentives could help fill (see box 3.1).

BOX 3.1: IDEAS FOR MISSION-ALIGNED AI DEPLOYMENT IN PREVENTIVE HEALTH

As IPPR (2024) highlights, building better community health could be achieved by establishing neighbourhood-level systems that bring together diverse stakeholders to 'create health'. While the NHS treats patients for a few weeks or months in hospitals, people spend 90,000 hours at work, 14,000 hours at school, and most of their time in homes and communities. A 'health creation system' would work through these everyday settings, empowering employers, communities, local authorities and businesses to contribute to population health. Technology can help with this.

This approach would mirror the success of local initiatives like Leeds' approach to obesity or Greater Manchester's work on homelessness, where innovative community partnerships have delivered improved outcomes. With appropriate powers, funding and infrastructure – assisted by technology – local areas could designate "health and prosperity improvement zones" where poor health and economic outcomes cluster. This could be supported by long-term investment and community co-design. It would address the health inequalities that currently lock people out of opportunity – and that the government is clear it wants to address – while ensuring communities have genuine ownership of the assets and spaces that support their wellbeing.

While current AI solutions predominantly focus on clinical applications, future ones could aid such 'community health creation'. They could be used to creating **digital health networks centred around community health hubs**, coordinating resources across sectors. To take an example from our database, Health Navigator's approach to predicting hospitalisations could be expanded to connect with workplace wellness programmes, school health initiatives, and community resources, creating a seamless preventative health network, in a privacy-preserving way.

There are other promising applications in the preventive health space. For instance, the company 'EatingAI' founded in 2019 at University College London (UCL) integrates AI with nutrition science to offer tailored food recommendations, calorie tracking, and insights into eating habits. AI applications such as this can work with voice recognition for meal logging and BMR-based calorie tracking to make it easier for users to monitor their nutrition without manual effort. But such approaches still overly focus on personal action and do not yet sufficiently link with community initiatives and local services.

Moreover, future tools should help address the underlying causes of crucial issues such as childhood obesity. IPPR (2024) emphasises the importance of changing the food environment rather than merely addressing individual choices. Unhealthy foods are currently still among the most enticing and affordable options – including many marketed at children[8] – with stores and advertisements in effect promoting health-harming products. Really turning the dial on better nutrition will involve addressing this, and technological innovation should work towards that goal too.

8 See: https://www.biteback2030.com/our-activists/stories/new-report-the-rise-of-fast-food-on-our-high-streets

CASE STUDY 2: TRANSPORT AI INNOVATION HAS A BIG FOCUS ON AUTONOMOUS VEHICLES AND LOGISTICS BUT NOT ON IMPROVING ACCESS

> *"To deliver net zero, it is essential to decarbonise transport. Labour will secure an efficient, integrated and affordable transport system that reduces carbon emissions and drives economic growth across our country."*
>
> Labour Party (2023b) 'Make Britain a clean energy superpower'

Our second case study investigates AI firms active in the transport sector. Table 3.2 summarises the 211 AI companies that are offering value propositions in the transport space. The areas with the highest activity are autonomous driving, operational efficiency and transport related data management. Other important areas are supply chain improvements, and safety.

Many of these will likely be key for improving growth and customer experience. Indeed, the focus on autonomous driving – together with trials around the world – points towards driverless mobility as a real possibility in the medium to long term.

However, while beneficial for growth, **91 per cent of business models do not seem to be directly relevant for delivering Labour's goal (above) to deliver a transport system that is – in aggregate – efficient, integrated and affordable.**

TABLE 3.2

Only 9 per cent of transport AI activity seems to be clearly mission aligned

	Firm count	Examples
Autonomous vehicle technology	32	Autonomous driving safety, advanced 3D perception, battery management optimisation
Operational efficiency	29	Process optimisation, operational efficiency enhancement, manufacturing optimisation, fuel efficiency optimisation
Data management and analytics	27	Geospatial data analysis, vehicle data optimisation, complex data challenges
Security and compliance	26	Enhanced security intelligence, privacy compliance, threat detection
Logistics and supply chain optimisation	25	Supply chain optimisation, inventory optimisation, delivery logistics
Customer experience	18	Passenger experience optimisation, enhanced user interaction, travel experience optimisation
Safety and risk management	18	Driving risk management, collision prevention, workplace safety enhancement
Traffic management	12	Public transport optimisation, (urban) traffic management
Aviation and aerospace solutions	8	Flight route optimisation, airport management, airline efficiency
Maritime and shipping solutions	6	Maritime data analysis, port optimisation, seaborne trade optimisation
Land use and infrastructure planning	5	Urban sustainability, land use and infrastructure planning
Infrastructure maintenance	3	Road and infrastructure inspection, road and infrastructure maintenance
Multi-modal transport integration	2	Simplified trip planning, seamless travel solutions, transport network optimisation
Demand-responsive planning	0	Public transport or pooled ride hailing, personalised travel optimisation

Source: IPPR analysis of UKRI (2024) augmented via RAG web scraping

What seems to be missing is more applications aiding the transformation of the way we travel

However, there are few applications addressing the more complex, systemic challenges needed to deliver net zero transport that better serves the country's needs. **The problem at the heart of transport innovation is the need to expand access to transport – especially for people currently under-served by it – while lowering emissions.** The current system often requires car ownership, especially for people in rural areas, families and elderly people. Without a car, people become locked out of a lot of things such as jobs, and access to nature. For AI applications to have a positive transformative impact, they would have to address this problem too.

Autonomous vehicles – relying on AI systems – can help with this. But the risk is that without careful policy interventions, autonomous vehicle deployment might increase carbon emissions and environmental degradation. This is because automated travel could increase the number of miles travelled, and lead to longer commute times and urban sprawl – all of which can indirectly increase carbon emissions (Connected Places Catapult 2020). It might also lock out those on lower incomes.

A vision for transforming the transport system, with innovation

IPPR has outlined six pillars for delivering a transport system for the future that serves the mobility needs of the country, while aligning with net zero goals (Frost 2024, Frost and Singer Hobbs 2024). Some businesses model adoptions that could foster such mission-aligned changes are: 1) demand-responsive transit; 2) multimodal transport; and 3) dynamic planning of transport infrastructure and land use (described in box 3.2). **However, business models in this space make up only 9 per cent of the overall AI activity in the transport space.**

BOX 4.2: THREE IDEAS FOR WHAT MISSION-ALIGNED AI IN THE TRANSPORT SPACE COULD LOOK LIKE

- The need for **demand-responsive transit**. One way transport access could be increased is via on-demand transport. While distances between hubs will still be best served via public transport, distributed on-demand systems could be best for getting passengers *from* non-hub areas and *to* non-hub areas (for example, locations in rural areas). To do this, AI could help make transport delivery in rural systems more efficient – via an 'Uber for public transport', for example. In public engagement work, such proposals garner more public support than a focus on applying AI deployment on private vehicles. AI could also help with better route modelling and traffic regulation.[9] Sadly, in our analysis we find few AI activities in this space.
- The need for **multimodal transport**. Multimodal transport can be climate aligned and improve access by integrating various travel options into cohesive networks, reducing car dependency while providing alternatives for all residents. This approach cuts carbon emissions and ensures that those without cars – often the elderly, disabled, or economically disadvantaged – can reach essential services. In practice, this means transport hubs where buses meet trains with bike parking and pedestrian connections, all navigable through a single platform. AI could enhance these systems by predicting demand, optimising connections between modes, personalising journeys based on accessibility needs, and enabling smart pricing that automatically offers discounts to disadvantaged users.
- The need for **dynamic planning of transport infrastructure and land use**. Transport and planning are inextricably intertwined. Long-term land use, including where new housing is built, needs to be done intelligently. Better modelling – via digital twins[10] for example – can help improve this (DfT 2024). Similarly, the implications of transport investments for the future transport network are highly complex and require better modelling which AI might be well placed to provide. Data analytics could help identify the most effective ways to boost ridership, or where weak points in the system are.

9 At some point, we'll make the shift from fuel duty to a new way of road pricing. There is a much more sophisticated and dynamic approach that takes into account pollution levels and the business of roads on the day. This would perfectly account for all the externalities of transport. Traditionally, balancing simplicity and efficiency would be key. But advanced data processing could potentially involve novel solutions.

10 A digital twin in transport policy refers to a virtual replica or simulation of a transportation system that mirrors the physical infrastructure, vehicles, and traffic patterns in real time. This technology integrates data from various sources to create a dynamic, living model that can be used to test scenarios and inform policy decisions.

4.
POLICY RECOMMENDATIONS FOR MISSION-DRIVEN AI INNOVATION

Our recommendations build on and deepen the government's *AI Opportunities Action Plan* (Clifford 2025). In particular, we stress the need for breaking the government's missions down into more detailed targets, wherever possible. The government's innovation policies should then be used to incentivise innovation to help deliver them. This can be via two routes: 'technology push' and 'demand pull' (figure 4.1). The former boosts mission-aligned innovation, the latter helps bring it to market. In our below recommendations, we outline how this can be done.

FIGURE 4.1
Strategic innovation policy should both boost technology supply and demand-side adoption

TECHNOLOGY PUSH

- R&D grants, supporting risky innovation
- Financial support of innovating companies, decreasing the cost of innovation
- Innovation ecosystem support (eg infrastructure and skills)

DEMAND PULL

- Procurement, creating a market
- Deployment subsidies, accelerating cost decrease
- Financing for adoption, scaling

$\underbrace{\hspace{6em}}$

Where possible, make these outcome and mission focussed

Source: Authors' analysis

While the UK government does already use all the above levers to some extent – for example, via UK Research and Innovation (UKRI), its subsidiary Innovate UK, and the British Business Bank (BBB) – it does so without sufficient strategic direction. We argue that these agencies could be further leveraged, alongside broader procurement, fiscal and regulatory incentives, to steer AI development and deployment. Table 4.1 summarises our recommendation and highlights how they connect to the government's *AI Opportunities Action Plan* (Clifford 2025).

TABLE 4.1

We make four recommendations to accelerate mission-aligned AI deployment

	Recommendation	Connection to *AI Opportunities Action Plan*
1) In-depth tracking of AI deployment and AI impact scenarios, *by new AI tracking unit*	Need to clearly track what type of AI deployment is occurring and where the gaps are. Over time, develop in-depth scenarios for job and business impacts.	Plan calls for technical horizon scanning and market intelligence. Calls for assessment of skills gaps and devising of "sufficient opportunities for workers to reskill."
2) Break missions down into specific problem statements, *as cross-departmental effort, led by mission councils*	Break down the government's missions (such as health) into specific problem areas that need solving.	Calls for AI to be core to delivering the government's missions, both in public service delivery and the economy more widely. "Appointing an AI lead for each mission." Cross-government work to identify use cases and incentivise deployment.
3) Technology push: align innovation policy clearly with missions to create 'technology push', *by Innovate UK and BBB*	Clearly link some of Innovate UK and BBB's funding to solving mission-related problems. Start with areas where problems are clearly established.	Preferential compute and data access for mission-aligned innovators. Mission-focussed national AI tenders. Connect AI policies to new industrial strategy.
4) Demand pull: Use subsidies, procurement and preferential financing for AI adoption and market shaping, *by public procurement by all departments, Innovate UK and BBB*	Gradually increase more outcomes-focussed AI procurement, backed by a central fund. Create BBB funding stream that incentivises AI adoption.	Agile procurement, "two-way partnership with AI vendors and startups". "Drive AI adoption across the whole country" with focus on SMEs.

Source: authors

RECOMMENDATION 1: THE GOVERNMENT NEEDS TO BETTER TRACK AI DEPLOYMENT TO INFORM POLICY

In order to steer AI adoption reliably, the government needs a better evidence base. It should **set up a new AI tracking unit** that conducts in-depth monitoring and reporting of how AI is being deployed. Currently, there is some survey-based information and industry datasets, but they are high level and entirely unspecific about the type of applications that are being deployed. For example, the Department for Science, Innovation & Technology (DSIT 2023) survey looks at sectors and technologies, but not at what the technology is actually *deployed for*. While such data outlines that AI is being deployed for 'health and wellness', there is little information on what kind of applications are most prevalent, or what problems are being solved. It is therefore hard to judge whether AI's positive potential is actually being realised or whether there are deployment gaps, or even concerning developments. We have tried to begin filling this gap with the dataset in in this paper. But much more could be done to keep citizens up to date on how AI is used in the economy and to inform policy making.

The AI tracking unit would, over time, also develop scenarios for how the labour market and various sectors of the economy could be impacted by emerging AI trends. Ultimately, this could help the government make forward looking, rather than purely reactive, policies. This unit should be situated across DSIT, HMT, Go-Science and DBT and inform mission councils with scenarios. It could also play an important role in the feedback loop needed to assess the efficacy of the policies put in place to steer innovation.

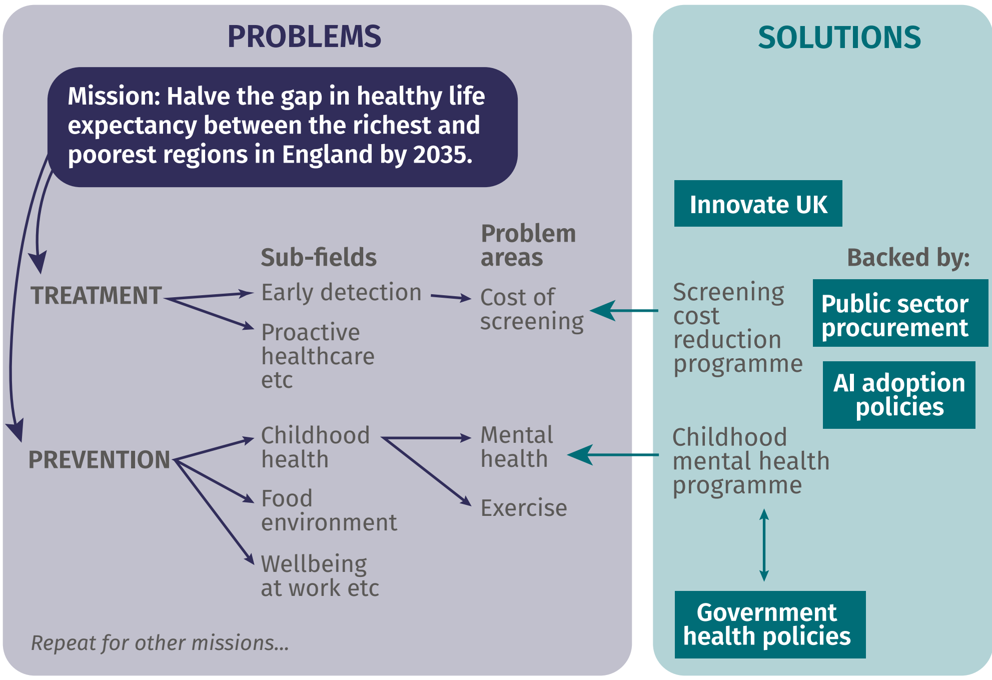
RECOMMENDATION 2: BREAK MISSIONS DOWN TO SPECIFIC PROBLEM STATEMENTS

The UK government has set out five missions to guide its policy making. In order to tangibly drive innovation policy, the next step will be to break them down further into 'problem areas' and specific problems that need solving. In other words, only if the government sets clear targets can it put in place policy incentives that clearly guide AI adoption towards delivering those targets.

As we showed above, for the case of prevention in public health, next to high-level targets (such as improving healthy life expectancy by a certain amount), the government will have to be clear about the sub-fields involved in delivering the overall target (for example, childhood health) (figure 4.2). This will have to be further broken down into 'problem areas', such as the need to improve the food environment for young people in order to reduce obesity. It is important that such problem statements are formulated in a way that allows business and innovating organisations to target their efforts towards resolving them. Australia's CSIRO provides an example of how this could be done (box 4.1).

FIGURE 4.2

Missions need to be broken down into problem areas that AI innovation can help tackle



Source: Authors' analysis

In our forthcoming work, we will develop concrete ways these missions can be broken down into problem areas to be tackled.

BOX 4.1: AUSTRALIA'S MISSION APPROACH TO BREAKING DOWN MISSIONS

Australia provides an example of this approach of breaking down high-level missions into specific problem areas. In its CSIRO Missions Program, it has a high-level mission on increasing drought resilience: reducing drought impact by 30 per cent by 2030. This is broken down into specific actionable problem statements across farm innovation, regional resilience, and risk management tools, enabling targeted innovation efforts. CSIRO's model combines setting such targets with fostering collaborations between government, research institutions and industry to deliver products that tackle them (OECD 2021).

RECOMMENDATION 3: ALIGN INNOVATION POLICY CLEARLY WITH MISSIONS TO CREATE 'TECHNOLOGY PUSH'

UK innovation agencies – especially UKRI and its subsidiary Innovate UK – have evolved significantly over the last few years, taking a more proactive approach to shaping innovation and technology deployment. This is for good reason: cross-country evaluations suggest that targeted grants aimed at specific technologies or challenges led to more radical innovations, whereas broad based SME grant schemes are effective for wider diffusion of existing innovations (Testa and Szkuta 2018). The UK's R&D tax credit scheme – in place since the 2000s – has supported tens of thousands of companies annually and is credited with boosting business R&D expenditure and innovation across sectors (Dechezleprêtre et al 2023).

But a number of improvements could make UK innovation policy more effective and more aimed at delivering clearly defined outcomes while avoiding the mistakes of past overhauls of the innovation system (see box 4.1).

First, **innovation policy should be more mission oriented, linking funding to tackling specific problem areas.** For instance, while Innovate UK has overall strategic themes – "net zero, healthy living and agriculture, and digital and technologies" (Innovate UK 2022) – its competitions could form part of a more cohesive plan towards delivering outcomes. The scoping of grants is often very open ended, unspecific and not connected to the wider government policy agenda in a particular sector.

Similarly, the British Business Bank (BBB) plays a crucial role in supporting UK growth via financing small enterprises. It is the largest domestic investor in UK venture and venture growth capital.[11] Like Innovate UK, it is broadly mission aligned: its aim is to boost GDP growth, tackle regional inequalities and provide ecosystem funding – for example for R&D intensive firms (Future Fund) and life science firms (Life Sciences Investment Programme).[12] But it is largely sector and application agnostic, and in many of these it remains somewhat neutral as to the outcomes of the innovation process.

As a result, as McLaren and Kattel (2025) and Coyle and Muhtar (2021) point out, **UK innovation institutions are largely not mission or outcome oriented**. Moreover, they argue that UKRI focussed mostly on 'frontier' innovation but less on the

11 Over the past decade, it has supported 11 per cent of all UK equity deals and accounted for 15 per cent of total equity investment (BBB 2025).

12 Delivered through British Patient Capital (BPC).

crucial intersection of deployment of frontier technologies across the economy.[13] As we outlined above, process innovation to allow deployment is crucial for realising the gains from technologies. Below therefore, we recommend more ‘demand pull’ deployment incentives.

Second, UK innovation policy **needs a step change in cross-department coordination in order to deliver on missions** (ibid). For instance, while Innovate UK supports a wide array of initiatives in health, these are mostly not implicitly or explicitly linked to initiatives in other government departments – for example the Department of Health and Social Care. Strikingly, Innovate UK itself does not have a holistic account of how its funding relates to wider governmental objectives. In other words, there is a huge opportunity for improving both the understanding of the kind of innovation being funded, and aligning it better with government missions.

Missions and their sub-targets from the previous section can play a key coordination role. The government has already established mission boards. But these are currently not meaningfully used to affect policies across departments, nor innovation agencies. The coordination that does take place is more *ad hoc* rather than routine. While there were some nascent coordination efforts in the (now defunct) Industrial Strategy Challenge Fund (ISCF), there is no senior coordination mechanism between innovation agencies and government departments (ibid). And while the UK’s Advanced Research and Invention Agency (ARIA) aims to drive “paradigm shifts in science and technology, addressing critical challenges such as climate change, artificial intelligence, and healthcare innovation”, it should trial adding funding calls that are more clearly aligned with big challenges relating to the government’s missions and their underlying targets.

BOX 4.2: GOOD PRACTICE WHEN REFORMING INNOVATION FUNDING – BE BOLD, KEEP WHAT WORKS AND ENSURE INSTITUTIONAL LEARNING

While we recommend significant improvements to the UK’s innovation ecosystem, it is important to learn from past attempts and build on its existing foundations.

Ensure continuity. There are a number of other areas where innovation policy should be improved by making it more outcomes focussed and mission aligned. That said, Coyle and Muhtar (2021) highlight the need for continuity where possible for programmes to run their course – to ensure investment certainty, retain talent and allow reform to be built on solid foundations.

Put in place feedback mechanisms. Coyle and Muhtar (2021) also highlight the need for allowing existing programmes to run until completion, in order to then conduct a thorough assessment of their effectiveness. They highlight that there is “a failure to learn or to build on successes.” Rigorous and routine assessment of programmes is essential for iterate improvement of innovation policy over time.

Start incrementally. Making policy coordination work across departments is hard. Therefore, the government should commit large-scale funding to new mission-based innovation funds in areas where mission alignment is more clearly established (for example, health) or urgent, while prototyping other areas first.

13 UKRI is the UK’s largest public funder of research and innovation, directing research funding and shaping the UK’s research and innovation ecosystem. Its main aim is to simulate growth by helping research that ultimately finds useful application in the economy.

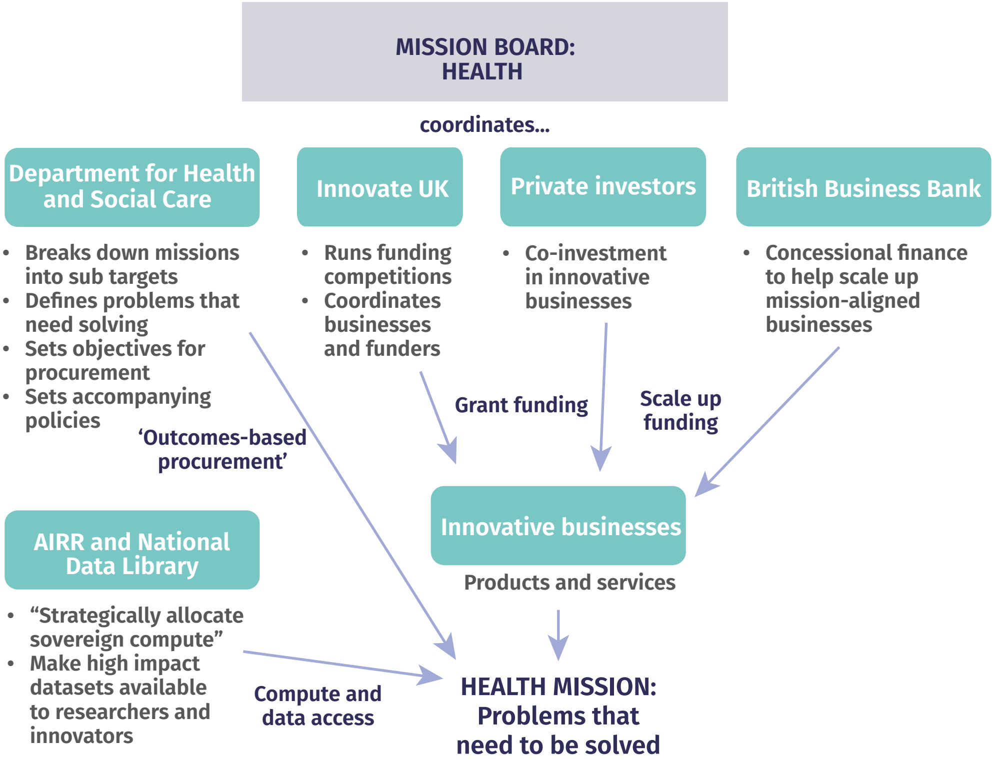
To operationalise this mission-oriented approach, Innovate UK would need to start to restructure their operations around mission councils, rather than traditional sectoral or thematic funding (while avoiding pitfalls of the past – see box 4.2). The government should:

- boost the power and remit of mission boards to **coordinate across departments**. They should have specific decision-making powers that help all departments that are affected by them **prioritise between their policy decisions.** Their decision making should be informed by cross-departmental taskforces that coordinate work on specific problem areas and develop proposals for coordination (see the Japanese SIP as a useful prototype of this, box 4.3)
- **embed core mission metrics** (for example, problem areas regarding healthy life expectancy) into governance and funding decisions of innovation institutions, such as Innovate UK
- redesign internal review processes and application criteria so that funding calls and project assessments **explicitly address mission-related milestones**, sub goals and problem areas
- put in place **capacity building programmes** that help stakeholders understand and embrace the new mission-oriented framework. This could include dedicated training for programme managers, clearer guidance for grant applicants, and transparent reporting on how funding decisions reflect evolving mission priorities
- undertake **regular stocktakes** and reviews at mission board level to evaluate progress, recalibrate objectives, and shift resources as needed. Feedback loops from funded projects, community stakeholders, and independent evaluators should continuously refine how Innovate UK and the British Business Bank invest and manage their portfolios.

This is all while noting that **not all innovation funding needs to be linked to missions**. This is because, firstly, the missions are insufficiently comprehensive to cover all areas of importance, and secondly, there are many areas of innovation that are foundational and so sit above clear mission alignment.

FIGURE 4.3

Mission boards should coordinate activities across departments to help solve mission-related problems



Source: Authors' analysis

BOX 4.3: JAPAN'S APPROACH TO CROSS-DEPARTMENTAL COORDINATION

Japan's Strategic Innovation Promotion Programme (SIP) provides a good example of cross-departmental coordination. Japan leverages a combination of policy levers beyond direct funding to support mission-aligned businesses (OECD 2021). It integrates coordination across government departments to align diverse government efforts, fostering a coordinated approach to addressing societal challenges. It has successfully delivered innovation in areas such disaster resilience, sustainable energy, and cybersecurity. SIP employs regulatory reforms and public procurement policies to create favourable market conditions for innovation, while also establishing public-private partnerships to drive collaboration across sectors. Furthermore, it supports the commercialisation of research through targeted roadmaps, and ensures accountability through monitoring and evaluation mechanisms – all designed to maximise societal impact and economic sustainability.

RECOMMENDATION 4: USE SUBSIDIES, PROCUREMENT AND PREFERENTIAL FINANCING FOR AI ADOPTION AND MARKET SHAPING, CREATING 'DEMAND PULL'

Coyle and Muhtar (2021) point out that UK innovation institutions focus mostly on 'frontier' innovation but less on the crucial intersection of deployment of frontier technologies across the economy.[14] There are four economic reasons why financial support for deployment can be advantageous (Alfaro-Serrano et al 2021).

- **Innovation often lies in implementation**. As highlighted above, process innovation in adopting businesses is often a crucial prerequisite for deployment. Especially with general purpose technologies such as electricity, computers or AI it is insufficient to merely spur the development of the core technology. Innovation at the *implementation stage* is equally important.
- **Public goods and external benefits:** New technologies in areas like clean energy and public health often provide broad societal benefits (reduced pollution, disease prevention, etc) that might not be reflected in market prices.
- **Learning-by-doing and cost reduction:** As firms produce and deploy more units of a technology, they often improve manufacturing efficiency and drive down costs. Subsidising adoption can therefore help reduce costs in the future.
- **Network externalities and initial market inertia:** Many technologies become more valuable as more people use them, so subsidising early adopters can be a natural solution.

Financial support for deployment can therefore serve as **'demand pull' or a deployment cost reduction instrument** in the innovation system, complementing R&D incentives and funding ('technology push'). Deployment support can help form new markets, encourage producers to scale up manufacturing, and bend down the cost curve over time.

Gradually increase procurement for innovation

Procurement is an important tool to boost innovation, with high public returns but insufficient private returns. By committing to purchase a specific innovation, the public sector can create a guaranteed demand that reduces investor risk and ensures the product is developed to meet specified performance *or* outcome criteria.

Our example from preventative health innovations above could fall into this category: preventing people from falling ill can deliver big savings for health services but these cannot be captured by private investors alone. The state can therefore act as a purchaser of prevention-focussed services, while making future health care cost savings.

Public procurement can serve as a powerful catalyst for AI innovation, by making a market which ensures investments in successful innovations that solve specific problems pay off. Procurement could link to missions and innovative solutions that tackle problems which need solving. The *AI Opportunities Action Plan* (Clifford 2025) acknowledges this, by highlighting that government should set quality and performance criteria in its procurement, as well as ensuring that it "support[s] the domestic start up and innovation ecosystem". The plan suggests that procurement should be agile, iterative, and linked to missions.

A more mission-oriented approach to procurement could emphasise outcomes over specific requirements, giving suppliers freedom to innovate in how they meet those outcomes. This would involve some risk taking.

14 Innovate UK is the UK's largest public funder of research and innovation, directing research funding and shaping the UK's research and innovation ecosystem. Its main aim is to simulate growth by helping research that ultimately finds useful application in the economy.

This would be a radical shift in how procurement works. Traditional procurement typically focusses on detailed specifications of what to buy. There is a rich literature criticising this approach and arguing for **using procurement as a strategic element of innovation policy** (Edler and Georghiou 2007; Edler et al 2016; Mazzucatto 2013). Similarly, the National Audit Office (NAO) observed that departments frequently go to market with "poorly defined requirement[s] and an over-emphasis on minimising cost", which prevents them from taking full advantage of suppliers' innovative ideas (NAO 2025). It argues that public servants have been "inhibited from developing innovations… by risk-averse attitudes", with rigid targets and budgets leaving little space to experiment (ibid). A Cabinet Office (2023) report also summarises that UK procurement is marked by a "relatively low appetite for risk and experimentation".

The Procurement Act (2023), which came into force in February 2025, opens the door for changing this. While not explicitly recommending outcomes-based procurement, it is permissive and supportive of it. This represents a significant shift from the previous requirements-based approach.

Other countries have already gained significant experience with a more outcomes-based approach. For instance, Finland has incorporated innovation into its procurement strategy by establishing clear outcome targets in key innovation areas. Building on these, the creation of the Competence Centre for Innovative and Sustainable Procurement (KEINO) provides essential guidance to public purchasers throughout the country. Finland therefore shifted from strict technical specifications to outcome-based tenders that define desired results rather than prescribing solutions. A success story is the procurement of low-carbon public buildings – rather than tendering a conventional design, municipalities specified strict energy performance outcomes. Suppliers innovated with new materials and smart systems to meet the goals, and KEINO helped share these practices nationally.

Another illustration of the power of outcomes-based procurement is the vaccine procurement by governments during the Covid-19 pandemic. Here, governments provided pre-deployment funding (technology push) combined with outcomes-based procurement policy, via advance purchase agreements (demand pull). The latter provided the certainty needed for a rapid development.[15] In 2020, the US government's Operation Warp Speed used such contracts (a form of procurement promise) as well as direct funding to speed vaccine scale-up.

The government could take three initial steps to take advantage of the freedoms delivered by the Procurement Act (2023) and increasingly experiment with the demand-pull lever for mission-aligned innovation.

- **Outcome-based pilots for AI procurement**: Require a few major procurements each year to specify desired outcomes rather than fixed solutions, allowing suppliers to propose innovative approaches. Government could issue model templates for outcome-based tenders. This could even be done within traditional tenders (NAO 2025). This will be a key way of making procurement policy more mission aligned. The government is clear, in its National Procurement Policy Statement (Cabinet Office 2025), that it wants procurement to support the delivery of its missions. But it will be insufficient if the risk-averse approach from the past is not gradually overhauled.
- **Devise a central 'procurement for innovation' fund**: Create a small central pot that co-funds early-stage public procurement pilots, or challenge competitions that are outcomes focussed. A central fund could help reduce budget risks for departments. It could build on successful examples of pre-commercial deployment funding, such as the UK SBRIs, which fund companies to develop solutions for specific problems and, if successful, provide further funding to

15 For example, purchase commitments were conditional on vaccines meeting minimum efficacy requirements (typically around 50 per cent) and receiving FDA authorisation.

develop them. If it is developed to a standard that addresses the problem, this might ultimately result in the public sector purchasing the product.
- **Strengthen skills, guidance and early engagement**: Offer procurement teams short, practical training modules on innovation-friendly methods, plus template documents and case studies. Build on the powers from the Procurement Act (2023), which allows for and encourages early market consultations to better understand promising ideas reflected in procurement tenders (NAO 2025).

Longer-term improvements of procurement would involve developing a "national procurement for innovation strategy" which could build on insights from our above recommended deployments. Ultimately, this could see more outcomes-based procurement measures implemented in standard procurement practices.

Deployment subsidies

While procurement can be essential for making a market for new products, deployment subsidies can help reduce the cost of deployment. They are generally best used when the policy goal is to stimulate widespread uptake across many private buyers, particularly if success depends on reaching a critical mass (for example, to exploit network effects or learning-by-doing). They can take the form of outright subsidies, grants, tax credits or price guarantees.

One example where subsidies encouraged adoption and brought down cost is offshore wind. This technology was not cost-competitive in 2008 – it was aided by guaranteed-price contracts in Europe. Costs fell over 60 per cent between 2010 and 2021, resulting in a thriving industry – to the point that recent UK offshore wind auctions saw bids with minimal subsidy. Offshore wind is now considered fully cost-competitive with fossil fuels in many countries, including the UK. Another prominent example is incentives for electric vehicle (EV) adoption in the United States and Europe. The US federal government's EV tax credit (up to $7,500 per vehicle) significantly increased EV purchases, with research estimating that EV sales would have been about 29 per cent lower without these subsidies (Xing et al 2019).

These successes highlight that **deployment subsidies can be temporary catalysts**: they need not be permanent if they achieve cost parity, at which point they can be withdrawn.

The concept of using temporary subsidies to kickstart markets is not entirely new in the UK, as evidenced by the approaches in offshore wind or the Plug-in Van Grant (for low emission vehicles). R&D tax credits – which the UK makes wide use of – are also a form of deployment subsidy (though often they are required to have some technical uncertainties, rather than merely applying an existing technology in practice). Systematically applying such mechanisms to a new technology, such as AI, would represent an extension.

DSIT and HMT should therefore devise and trial specific deployment subsidies with regards to specific mission-aligned AI applications.

Concessional finance linked to deployment

Preferential finance too can help accelerate technology deployment. In the UK, this could be done by building on existing processes to deliver finance to small businesses by the British Business Bank (BBB). The BBB provides financial assistance, including debt and equity commitments, to UK small- and medium-sized enterprises (SMEs). Notably, 92 per cent of British Patient Capital (BPC)-backed firms have utilised equity investment for research and development

(BBB 2024),[16] but the BBB does not currently link this to technology adoption and the majority of its financing is on commercial terms.

But linking preferential finance to technology deployment can play an important role in advancing mission-aligned AI. It can complement deployment subsidies – where financial market failures, credit constraints and the high upfront costs of technology adoption inhibit firms from adopting technologies with high future returns.

The BBB could therefore start a pilot programme of AI deployment linked to concessional finance. How the incentive is structured matters greatly. Well-designed programmes from other countries successfully combine targeted support with performance targets. For instance, Germany's KfW (a public development bank, similar to the BBB) converts portions of loans into grants when specific energy performance standards are met. This has led to outcomes-focussed technology deployment which has achieved significant reduction in carbon emissions.

In particular, the BBB could link such a programme clearly to technology AI deployment that is marked as mission aligned, for example as a result of participation in Innovate UK mission-focussed programmes. This could serve as the final stage of support, following earlier Innovate UK seed funding. It could complete the process, outlined in figure 4.1, of making a market through procurement, bending the cost curve through deployment subsidies, and scaling adoption via concessional finance.

16 Assessments of the BBB show that it has improved access to finance for SMEs. By 2019, it had supported nearly 90,000 businesses and increased the supply of SME finance by about £13.9 billion, far exceeding its initial five-year target of £10 billion (NAO 2020). Crucially, the BBB catalyses private capital – attracting roughly £5.60 of private investment for every £1 it invests (ibid).

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APPENDIX: METHODOLOGY

FIRM SELECTION

We build on the UKRI WAIfinder dataset that collects the names and some basic information about all UK-based AI organisations. We use an LLM with RAG (see below) to augment the dataset.

The original WAIfinder dataset is aggregated from an internal UKRI database, Glass.ai, and Crunchbase, and the original dataset is sparse, with primarily a brief description and locational data. It adopts a broad view of AI informed by diverse topic tags—such as Image & Vision Computing, Robotics & Autonomy, Artificial Intelligence, Augmented Reality, and Autonomous Vehicles. In practice, this means we group together organisations that explicitly position themselves under these terms (for instance, by describing AI-related activities in their project, product, or service descriptions), as well as those flagged by data sources like Gateway to Research, Crunchbase, and Glass.ai.

By integrating multiple streams, ranging from research institute data to company information scraped from websites, the WAIfinder approach inherently captures a wide spectrum of AI and machine learning-related endeavours, though we acknowledge that other datasets may define AI-related firms differently.

Building on this underlying definition, we identified additional AI organisations active in key sectors – such as climate, manufacturing, health, retail, agriculture, and education. This meant adding 63 firms, including Palantir, Alibaba Cloud, Google Health, and IBM. By doing so, we attempted to close potential gaps in the WAIfinder dataset. This expanded search allowed us to find firms that self-identify as AI or data-focussed yet may not have been indexed in the WAIfinder sources.

However, because many companies employ AI or machine learning internally without prominently advertising it, and because not all organisations maintain a clear digital footprint, our dataset may exclude those who do not publicly declare AI involvement. Therefore, while our definition strives to be comprehensive – capturing both explicit AI labels and related keywords – it remains subject to the limitations of self-reporting and data availability. Out of the 3,334 entities, we find that 3,150 entities are still a going concern and focus our analysis on these. This dataset only includes firms that have an office in the UK.

What this provides is an illustrative overview of the AI innovation space. It covers firms that have AI at their core, that are developing certain specialised solutions. But it does not cover the use of generalised AI with existing businesses.

TERMINOLOGY

LLM (large language model) is a type of artificial intelligence model designed to understand and generate human-like text by processing vast amounts of data. Examples include OpenAI's GPT4 and Anthropic's Claude models, which are capable of tasks such as answering questions, summarising text, and language translation.

RAG (retrieval-augmented generation) is a technique in AI that combines information retrieval and text generation. It uses external knowledge sources to retrieve relevant information and integrates this with a generative model to produce more accurate and contextually relevant responses. It is commonly applied in systems requiring up-to-date or domain-specific knowledge. We use the Perplexity API for this.

AUGMENTING FIRM INFORMATION WITH LLM AND RAG

Next, we used RAGs to collect up-to-date information on firms, and LLMs to organise the collected information into categories that would be helpful for analysis. We see this as an innovative, experimental approach. It is akin to 'web scraping', collecting data about firms from multiple websites and summarising them using AI. Our dataset collects these sources and allows for cross-checking the LLM's summaries.

We have conducted this for 50 firms and found the sources used are the same ones that a human researcher would use via a regular web search, and we found the summaries accurate. This does not constitute a full robustness check. As the AI and data science literature evolves, quantitative methods for this should become available. In the absence of this, **we consider our findings as indicative and experimental, rather than conclusive.** However, the approach suggests a highly innovative way of analysis for government and business researchers, in the absence of more traditionally constructed datasets (for example, via ONS surveys).

Our final dataset contains the following information:

- name of firm
- RAG information
- LLM extracted information
- research versus services
- augmenting versus automating score
- end user category
- business unit category
- sectors based in
- government funding received
- technologies used
- operational category
- financial information
- going concern status.

SPECIFICITY OF FIRMS' VALUE PROPOSITION

We used GPT-4 to specify the type of value proposition an AI organisation is making, based on the table below.

TABLE A1

We used this matrix for classifying the specifics of AI applications

	General sector applicability	Single-sector applicability
General application	*Least specific type of AI application*	
Specific application (solving a narrowly defined problem)		*Most specific type of AI application*

IDENTIFYING FIRMS' VALUE PROPOSITIONS

For distilling the value proposition for the firms, we use an LLM to summarise each firm's information into one simple problem statement and value proposition. We do this via the prompt, 'Summarise the business model in one sentence, highlighting what problem they are trying to solve, and what is special about their solution? Keep strictly to one sentence'. We then use further clustering techniques with some manual adjustment to group these into value proposition categories.

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