August 2021

Impact review of Innovate UK's AI-related activity

Interim report

Ipsos MORI

Ipsos MORI

Contents

Acknowledgement

This work was produced using statistical data from ONS. The use of the ONS statistical data in this work does not imply the endorsement of the ONS in relation to the interpretation or analysis of the statistical data. This work uses research datasets which may not exactly reproduce National Statistics aggregates.

Executive Summary

Ipsos MORI was commissioned to undertake an impact review of a subset of Innovate UK's grant funding for artificial intelligence (AI) in August 2020. This report sets out the results of the study.

Artificial intelligence in the UK

The adoption of AI in business processes and services has the potential to yield significant economic benefits by improving the speed and accuracy of decision making. The industry is fast growing. Global equity investment in firms seeking to develop applications underpinned by AI grew from £614m to over £36bn between 2010 and 2020. The UK is a leading player in the sector, behind the US and China, and attracted almost £3bn in equity investment in 2020.

The UK AI sector is characterised by a rapidly growing SME base, with the number of firms developing AI products and services increasing from around 400 in the mid-2010s to over 1,000 in 2020. The UK has relative strengths in the application of AI in financial services, cybersecurity, and other industries where it holds a competitive advantage, such as biotechnology and the media. The UK has also attracted significant levels of Foreign Domestic Investment in AI. More than a third of the firms active in the sector are headquartered overseas, and the UK has benefitted from major investments by international technology firms.

Innovate UK support for artificial intelligence

Innovate UK committed at least £323m in support for firms developing technologies underpinned by AI between 2005 and 2020 through its grants for Collaborative R&D, the Investment Partnerships, Knowledge Transfer Partnerships, and the ICURe programme[1]. Its support for the development of commercial applications for the technology expanded rapidly from 2015 onwards, in line with increases in broader market interest. Many of the projects covered by this review were still on-going at the time of writing, with £174m of the £323m committed to AI being spent.

Innovate UK's support has been concentrated on firms whose primary goal was to commercialise novel innovations underpinned by AI, rather than assisting firms with traditional business models to adopt AI as part of their internal processes or products. The technologies under development are expected to have applications across a broad base of the economy, with health, professional services, transport and logistics, ICT, and manufacturing figuring prominently.

Leverage of R&D spending

Innovate UK's support for this technology area led to a temporary expansion in R&D spending, though with on-going effects on the R&D activity of small firms employing 10 to 49 workers. This indicates that support for technology development may be most effective when targeted at earlier stage companies. There are significant uncertainties over the total size of Innovate UK's impact on R&D spending, with a possible range of £47m to £685m. This compared relative to public spending of £174m. At the upper bound, this would imply a leverage ratio of £2.94 per £1 of public spending. However, at the lower bound this would imply that public sector funding has crowded out some private investment in R&D.

[1] A number of funding programmes were excluded from this estimate for various reasons (e.g. those involved in evaluative activity addressed via other evaluations, availability of information and the type of funding model). Those excluded were: Centres, EU funded projects, European Enterprise Network, Knowledge Transfer Network, Launchpad, Procurement, Small Business Research Initiative (SBRI) projects, Industrial Strategy Challenge Fund (ISCF) projects and Vouchers.

Project delivery and technological progress

The findings from the evaluation indicate that projects largely delivered against their objectives and have achieved rapid progression through the intended development pathway. Projects were largely oriented towards refinement of the underlying product (or on making this possible by facilitating access to datasets needed) and on testing the acceptability with end-users. The average Technology Readiness Level (TRL) associated with the innovations under development increased from 3.2 at the point Innovate UK funding was awarded to 5.7 at the end of 2020 (while more than 10 percent had reached TRL9).

The findings also highlighted that few projects were designed to address broader social concerns around ethical issues arising from AI deployment, issues of cultural bias, or data security and privacy. Where these aspects were addressed by the work programme, firms suggested that they were the most dependent on the public funding provided by Innovate UK. These issues were considered important factors in increasing public trust in decisions made, or informed by, AI technologies, and consequently a failure to address these concerns could constrain adoption in the long-term. These findings indicate that private enterprises may not always invest in addressing these concerns unless incentivised to do so by the public sector.

Access to data

Although the UK is a leading nation in terms of opening-up access to datasets, access to high quality datasets to develop and train algorithms was widely reported as a significant constraint by both firms awarded Innovate UK funding and by a broader range of stakeholders in the industry. Almost 40 percent of the projects supported by Innovate UK required access to existing external datasets to enable the project to deliver on its objectives, whilst 20 percent required the generation of new data.

The findings indicate that collaborations with academic institutions and end-users in the public and private sector enabled by CR&D or KTP funding may be important in overcoming these barriers. Almost half of the firms supported by Innovate UK were motivated to collaborate in order to access data, and around 40 percent suggested that this progress could not have taken place without public funding. Innovate UK funding may have produced lasting benefits in this area by strengthening links between firms and data owners, or by creating new useful structures and agreements through which data access issues can be addressed in the future.

Follow-on funding

Around 70 percent of firms awarded funding secured follow-on funding for subsequent development. Firms appear largely dependent on equity investment or public grants for significant sums of follow-on funding. Around 20 percent of lead applicants secured follow-on equity investment, collectively raising over £750m after being awarded funding from Innovate UK. This included several notable deals, including funding rounds of over £40m by Healthy.io, Rigetti, SoftIron, Tessian, and Yoyo.

The support provided by Innovate UK made a significant contribution to these results, increasing the equity investment raised by companies by 5.3 to 16.4 percent. This equates to £212m when aggregated across the project portfolio, or a leverage ratio of £1.21 per £1 of Innovate UK spending. These impacts are not as large as some other portfolios of Innovate UK grants (notably the Biomedical Catalyst). However, this needs to be placed in the context that half of the projects covered by the review were ongoing and hence full impacts will not yet be visible. Nevertheless, insufficient development of underlying business models may be a key factor constraining follow-on investment, with a material share of firms reporting they could not attract funding because the route to market was not clear.

Commercialisation

Firms receiving Innovate UK support have made rapid progress towards commercialisation. Most firms have at least reached the stage of small-scale commercial trials, and 65 percent of firms have begun to earn revenues from the underpinning innovation (albeit generally in small amounts). Innovate UK's support has also enabled rapid scale-up and between 6,200 and 8,000 jobs have been created as a direct result of the funding provided. These effects are substantially larger than the effects on R&D jobs, indicating that Innovate UK funding has enabled firms to progress as far as establishing sales and marketing functions.

Innovate UK's support has not yet had a significant effect on the revenues earned by firms. This this is not unexpected given the low level of maturity of companies at the point funding was awarded, and the broader findings suggest that larger economic impacts can be expected over the next two to three years. However, there were also suggestions that around 20 percent of the firms supported may face constraints because their business model has not been sufficiently matured/refined (for example, almost a quarter of firms reported challenges in finding a model for monetising the technology under development).

Spatial impacts

The AI sector is heavily concentrated in London and around 65 percent of start-ups in the sector since 2000 established their headquarters in the capital. Innovate UK's support for the sector has been more spatially distributed with around 70 percent of its awards going to companies located outside of London. The evidence from the study suggests this has helped to increase firm formation rates outside of London and led to other economic spillovers. However, there was no robust evidence that Innovate UK's support for AI development has had a significant effect in London itself.

Value for money

As many of the projects covered by the review were on-going, it is premature to draw conclusions around the value for money associated with Innovate UK's support for AI. Short-term and partial measures of the economic value of the programme (based on increases in the values of firms awarded grants) suggests the funding provided may deliver £2.12 of economic benefits per £1 of economic cost. While this is likely to significantly understate the long-term impact of the support provided and the benefits of future adoption, this still exceeds the hurdle rate of return normally applied in the economic appraisal of this type of programme.

Lessons

The findings of the study highlight the following lessons for future public support for AI:

- Innovate UK's support for AI has leveraged relatively large amounts of VC investment and may have had significant effects on R&D spending. Comparisons can be drawn with the Biomedical Catalyst which had similarly large impacts and was targeted at a sector sharing characteristics in common with the UK AI technology. These include a strong underpinning academic research base, a healthy investment ecosystem, and long commercialisation cycles. Targeting resources at early stage innovation in sectors with these characteristics appears to lead to significant economic impacts without crowding out private investment (possibly by increasing the number of 'investible' propositions and business models). Indeed, there may be a case for a targeted programme of 'response mode' support for AI development along the lines of the Catalyst programmes.

- Commercialisation outcomes were more frequently constrained by issues relating to the maturity of the underlying business model than technical issues arising from the performance of the technology per se. There may be opportunities to maximise the impacts of Innovate UK support for the sector by pairing traditional funding instruments with commercialisation support aiming to help firms work through the issues relating to how they will monetise their technology, establish a route to market, and demonstrate they can generate scalable revenues.

- Stakeholders underlined the importance of simplifying access to relevant data which may be critical in preserving the UK's competitive advantages in the sector. The Financial Conduct Authority Regulatory Sandbox was highlighted as an example of how real time data could be made available more readily to developers, which allows AI applications to be implemented with real customers in a controlled manner, enabling developers to test their products in small scale trials. There may be opportunities for Innovate UK to consider how it could complement traditional funding instruments with activities of this nature.

- There was some evidence that firms may not always embed consideration of ethical and security issues arising in the development of AI based technologies from the outset, and this could act as a long-run constraint on adoption. There may be benefits in adapting Innovate UK's application and assessment processes to leverage additional consideration of these aspects at early stages of the development pathway, and potentially covering them as part of routine monitoring (at least for projects where these issues could raise possible concerns).

- Innovate UK could potentially consider aspects of spatial strategy in its support for the development of the sector, particularly given the government's current 'levelling-up' priorities. There was evidence that its support has helped to promote the development of AI clusters outside of London, leading to local economic development benefits in lagging regions of the country. The evidence also indicated that grants awarded to firms in London may 'crowd-out' the development of other firms (potentially driven by more intense competition for labour resources and other inputs).

- Few firms supported by Innovate UK have considered the potentially disruptive impact of greater automation on the labour market and reskilling that may be needed to ensure that workers are not displaced by widespread adoption of AI. This can be linked to the nature of the firms that have been supported, which are largely developing products and services that will be adopted by firms with traditional business models (so are unlikely to directly experience the issues that arise). This also means that Innovate UK will have few levers at its disposal to mitigate adverse social consequences arising from adoption if it continues to focus its resources on technology development. There may ways of creating opportunities to influence this important aspect by developing programmes of support for adoption.

1 Introduction

Ipsos MORI were commissioned to undertake an Impact Review of a subset of Innovate UK's Grant Funding for Artificial Intelligence (AI) in August 2020. This report sets out the results of the study.

1.1 Innovate UK's support for Artificial Intelligence

Innovate UK aims to accelerate economic growth by supporting business-led innovation. It does this by providing financial support for research and development (R&D) through grants and loans, supporting knowledge transfer between the academic and commercial sectors, and providing commercialisation support. Its resources are largely allocated through thematically targeted and open competitions.

Between 2005 and 2020, Innovate UK delivered funding for many AI projects through some AI focussed funding competitions and many non-focussed programmes (including response mode funding and sector-specific competitions). Examples of targeted competitions included the 'Harnessing Large and Diverse Sets of Data' CR&D competition.

1.2 Evaluation aims and objectives

This evaluation aims to assess the impact of Innovate UK grant funding for AI related activity in four thematic areas: firm performance (including R&D activity and growth), adoption of AI, skills, and access to data. The Invitation to Tender defined the following specific questions for the review:

- Which interventions have the greatest impact in the growth, skills, data and adoption themes?
- To what extent does grant funding for AI-related activities reduce the risk of innovation and accelerate innovation and innovation-led business performance?
- What impact has Innovate UK intervention had on the commercialisation of AI technologies?
- How effective at stimulating and leveraging longer-term business investment in innovation is Innovate UK funding for AI projects?
- How effective has the support provided by Innovate UK been on promoting further R&D? How effective was it at creating sustainable jobs, investment and growth?
- In what ways has the programme improved UK competitiveness and access to global opportunities e.g. increased exports?
- How has the funding affected regions differently?
- Has the funding had any regional impacts from firms engaged with AI projects? Do firms do better where they are clustered and to what extent has intervention supported clustering?
- Has the funding on AI-related projects had any spill over effects on the adoption and growth of other AI businesses?
- How has the funding in AI-related activity changed overall perceptions of AI technologies?

In addition, the research sought to explore the impacts of Innovate UK intervention on diversity in the AI technology area, adoption of principles relating to the responsible use of AI, skills gaps of relevance to applicant firms and data access barriers. These relate to broader social issues that have arisen from the broader adoption of AI, though it is important to note that Innovate UK grants did not have objectives to address these issues.

1.3 Methodology

The evaluation was based on evidence gathered using the following methodological approach:

- **Evaluation framework:** A framework for the evaluation was developed through a review of the available policy documentation and discussions with the Innovate UK team, setting out the rationale for public support for the development of AI and defining the causal process through which Innovate UK's activities would be expected to lead to their intended outputs, outcomes and impacts.

- **Analysis of monitoring data:** A review of monitoring records associated with the project portfolio was completed to provide evidence on the scale and scope of Innovate UK's support for the technology area.

- **Context review:** A review of the available literature was completed to contextualise the study within the wider evolution of the AI sector and Innovate UK's support for its development. This explored the growth of the sector and factors constraining its development, and social issues that could arising from widespread deployment of AI.

- **Stakeholder consultations:** Consultations were undertaken with a range of stakeholder groups active in the UK AI technology area. These sought to explore the contextual background for AI development and adoption in the UK and issues relating to the responsible use of AI, barriers to adoption, and regulatory issues. In total, 28 interviews were completed with the following groups:

  - Government and regulators (3)
  - Financial market investors (5)
  - Technology developers (5)
  - Large companies integrating AI into operations (4)
  - Overseas investors (3)
  - Interest groups (4)
  - Academic research groups (4)

- **Applicant survey:** An online survey was sent to firms that received financial support from Innovate UK to develop an innovation involving the application of AI since 2005. The survey sought to collect evidence on the on-going development and commercialisation of funded projects and the role of Innovate UK in enabling these outcomes. The sample comprised around 1,000 unique firms and academics that participated in of Collaborative Research and Development (CR&D) projects, Knowledge Transfer Partnership (KTPs), Investment Partnership (IP) and Innovation to Commercialisation of University Research (ICURe) projects[2].

A total of 168 valid responses were received from project leads and collaborators. An adjusted response rate (i.e. excluding invalid contact details) of 26 percent was achieved. The sample was skewed to firms awarded CR&D funding, smaller firms and to more recent projects that were funded since 2015. Ninety-six percent of survey respondents were awarded a CR&D grant compared to 86 percent of the population. Additionally, 66 percent of survey respondents were from micro or small firms compared to 48 percent across the population. Academic institutions were also underrepresented in the sample (12 percent of survey responses, relative to 27 percent across the portfolio).

- **Depth interviews with firms awarded grants:** The evaluation evidence was complemented by six interviews with firms that were awarded grants. These interviews explored the outcomes achieved by firm during the tenure of the grants, post-completion results, and broader issues constraining the commercialisation of underpinning technologies. Firms were sampled to achieve of mix of projects funded across the four funding instruments covered by the review.

- **Data-linking and econometric analysis**: Monitoring records were linked to various secondary data sources including PitchBook data on equity investments and firm valuations, and ONS data sources including the Business Structure Database (BSD), the Business Expenditure on Research and Development (BERD) survey, and the Annual Survey of Hours and Earnings (ASHE). This data was used to complete a series of econometric analysis exploring the effect of Innovate UK grants on the outcomes of interest for the evaluation. Details of the econometric analysis are provided in Annex A.

1.4 Limitations

The findings of this report are subject to the following limitations:

- **Identification of Innovate UK projects involving development of technologies using AI:** A text mining exercise was undertaken by Innovate UK to identify the sample of AI related projects, based on project abstracts. This may have captured some projects that had only a passing mention of AI and for which it was not an important aspect of the project. A review of a random sample of 75 projects was carried out to assess the extent of any 'false positives' which identified only two projects that were not connected to the technology area. It is unknown how far the text mining algorithm failed to identify potentially relevant projects that have been excluded from the review.

- **Ability to make comparisons between funding instruments:** It was not possible to make quantitative comparisons between funding instruments because the sample sizes for Investment Partnerships, ICURe and KTP projects were significantly smaller than the sample of CR&D projects.

- **End-users:** Few end-users were engaged as most firms supported by Innovate UK funding were developers of AI products or services. Although end-users were often collaborators, it was not possible to assess the full extent of the impacts from funded innovations on these organisations.

- **Counterfactuals:** It was not possible to apply the text mining algorithm to the applications submitted by firms declined funding, so it was not possible to use declined applicants as a counterfactual group

[2] A number of funding programmes were excluded (e.g. those involved in evaluative activity through other evaluations, availability of information and type of funding model). Those excluded were: Centres, EU funded projects, European Enterprise Network, Knowledge Transfer Network, Launchpad, Procurement, Small Business Research Initiative (SBRI) projects, Industrial Strategy Challenge Fund (ISCF) projects and Vouchers.

to help identify the net impacts of Innovate UK's support (as is typical in these types of evaluation). Alternative approaches were adopted including:

- **Pipeline design:** This involved comparing firms awarded funding in later years to those funded in earlier years. This is motivated by the assumption that firms awarded grants in earlier years will experience the impacts of Innovate UK support at an earlier stage. This approach can be more robust as comparisons are only made between firms that eventually received funding (i.e. mitigating against the risk of biases driven by systematic differences between those that did and did not receive support). However, the validity of the findings rests on the assumption that there are no systematic differences between firms awarded funding in different years that could bias findings. The degree to which this assumption holds is explored in Annex A.

- **AI active non-applicants:** Robustness checks were completed by making comparisons between firms awarded funding to a sample of firms active in the AI sector that were not awarded funding from Innovate UK. This sample was drawn from the PitchBook data platform by selecting firms founded since 2005 active in the 'Artificial Intelligence and Machine Learning' industry vertical[3].

1.5 Structure of this report

The remainder of this report is structured as follows:

- **Section 2** provides an overview of Innovate UK's support for AI since 2005 and its expected impacts on the development and commercialisation of AI products and services (serving as a Theory of Change or analytical framework for the evaluation).

- **Section 3** provides an overview of the broader context for the study.

- **Section 4** provides an overview of the impacts of Innovate UK support in leveraging additional R&D into the development of AI and associated technological impacts.

- **Section 5** provides an assessment of the impacts of Innovate UK support on the performance of firms awarded grants.

- **Section 6** provides an indicative assessment of the value for money associated Innovate UK's support for AI development.

[3] PitchBook defines this vertical as: companies in artificial intelligence (AI) and machine learning develop technologies that enable computers to autonomously learn, deduce, and act through utilization of large data sets. The technology enables development of systems that collect and store massive amounts of data and analyse that content to make decisions based on probability and statistical analysis.

2 Innovate UK grant funding for AI

This section provides an overall framework for the review of the impacts of Innovate UK's grant funding for AI development. This includes an overview of the four funding instruments in the scope of the analysis, and an overview of the key outputs, outcomes and impacts that would be expected from Innovate UK support.

2.1 Innovate UK AI grant funding activities

Innovate UK awarded more than £300m in support for the development of AI applications between 2005 and 2020 through grants for CR&D, Knowledge Transfer Partnerships (KTPs), Investment Partnerships (IP) and the Innovation to Commercialisation of University Research (ICURe) programme. These projects have largely been funded through competitions that were not explicitly targeted at the technology area. These four grant funding instruments are outlined in the table below and were selected for review as they are not covered by other evaluation work, provided similar types of support to projects, and a sufficiently large number of projects were funded (in aggregate) to enable conclusions to be made.

Table 2.1: Overview of grant funding instruments of relevance to review

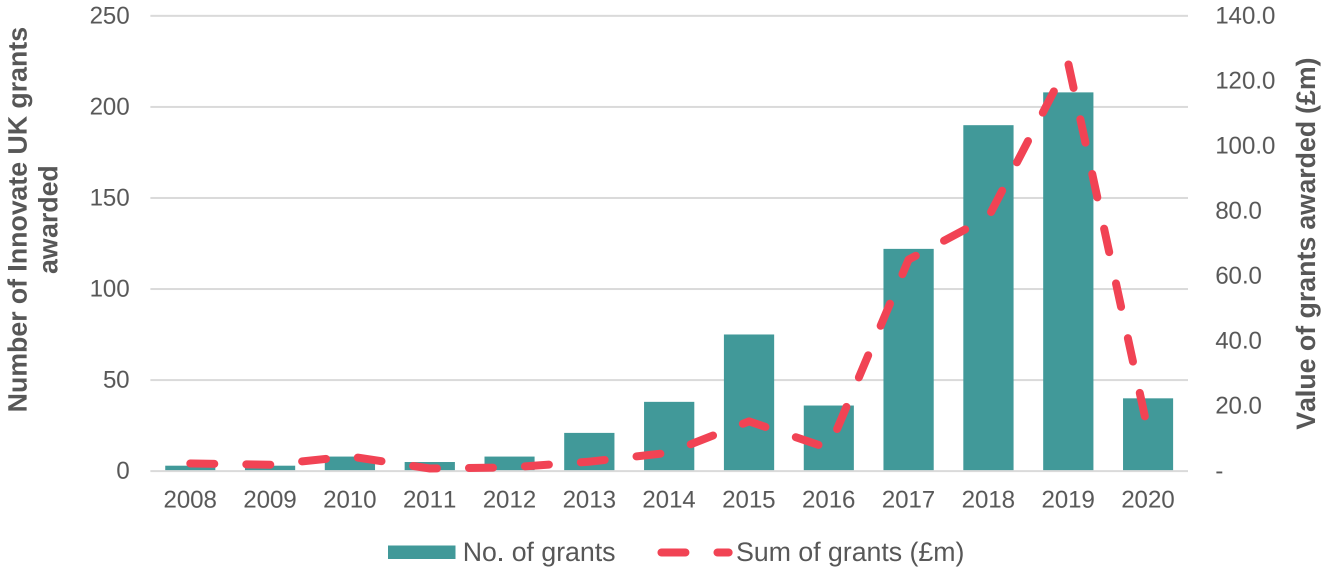
Grant instrument	Description
Collaborative Research and Development (CR&D)	These competitive grant funding programmes seek to fund business-led collaborative R&D projects that include research partners and typically at least one SME. Projects tend to last for one to three years and are intended to demonstrate new and novel technologies, and de-risk them to leverage the private investment required for full commercialisation. Individual competitions have had different areas of focus and seek to focus on large or fast-growing markets, sectors in which the UK has capabilities in research and business to draw on, where the societal benefits are significant, and where government support will make a difference.
Knowledge Transfer Partnerships (KTPs)	The KTP scheme aims to help UK businesses improve their competitiveness and productivity by bringing in new skills and the latest academic thinking. It provides a part-funded grant for a three-way partnership between a UK business, a research organisation, and a graduate 'KTP Associate'. The research organisation supports the recruitment of a graduate to the business need or project, whilst the business contributes the cost of the KTP Associate's salary and a supervisor to oversee the project. KTPs aim to give businesses access to academic expertise that they may not have in house, leading to improved business performance, competitiveness, and productivity.
Investment Partnerships (IP)	The Investment Partnerships programme provides hybrid public-private investment in start-ups that are struggling to access private sector investment. Applications are only successful if they pass a technological assessment (delivered by Innovate UK) and a market feasibility assessment (delivered by venture capital (VC) fund managers). Including the private sector at the assessment stage is expected to ensure that funded projects are viable for follow-on private sector investments. Successful applicants receive full funding for their project, at a grant to equity ratio of 70:30 or 60:40.
Innovation to Commercialisation of University Research (ICURe)	The ICURe programme aims to address barriers that inhibit the commercialisation of academic research. Its purpose is to increase the likelihood of successful commercialisation of academic research and to develop entrepreneurial skills and market knowledge in Early Career Researchers. ICURe provides commercialisation training to teams of university researchers with commercially viable outputs, supporting them to conduct market validation activities. The findings from these activities are presented to a panel of relevant experts that advise on the most appropriate commercialisation strategy. The scheme has also provided grants for some teams that were advised to establish a commercial vehicle (a spin-out) to exploit the underlying intellectual property (providing seed capital to accelerate the growth of the company).

2.1.2 Innovate UK's portfolio of AI projects

Between 2005 and 2020, Innovate UK awarded £323m in grant funding to 757 projects (within the scope of this analysis) seeking to develop technologies underpinned by AI. The value of grants awarded increased substantially from 2015 onwards.

Eighty seven percent of projects in scope were awarded funding in 2017 or the following years (comprising over 550 projects and around £280m in committed funding). Only 49 percent of projects were complete at the time of writing. A further 47 percent were on-going and four percent were on hold or had submitted their final claim. It is important to note that the findings of this review will not capture the full economic impacts of Innovate UK's support, as commercialisation will typically be contingent on firms securing follow-on funding and successfully scaling-up their innovation.

Figure 2.1: Innovate UK funding committed to AI projects, January 2008 to May 2020



Source: IUK MI data 2020. Note that data for 2020 does not capture a full year

The firms benefitting from Innovate UK funding were diverse and could be considered to fit into one of three main groups:

- **AI developers:** Firms whose core business model is the development of AI applications and products (including UK based start-ups and large AI first firms).
- **AI adopters:** Target customers that are not actively developing AI but are interested in using AI in their day to day business activities. These firms were less likely to lead projects funded by Innovate UK but may be involved as collaborators to provide a test bed to allow the performance of the technology to be evaluated.
- **Process and product innovators:** The third group includes firms with traditional business models that are looking to develop AI to enhance their core business functions or expand into new markets.

Hall and Pesenti (2017)[4] provide some background to the types of firms using AI in the UK and finds that "No single company's AI activity is representative. The range of business users is mixed and going to become much more mixed."

2.2 Rationale

The 2017 Industrial Strategy White Paper outlined the Government's aim to make the UK a global centre for artificial intelligence[5], exploiting the potential for the technology to improve performance, reduce costs, and make or suggest more accurate decisions across industry and society. More recently, the publication of the DCMS's 'Our 10 Tech Priorities[6]' reaffirms the focus of central government on the development of AI and includes priorities to "unleash the transformational power of tech and AI". This also announced the development of an upcoming National Artificial Intelligence Strategy.

From an economic viewpoint, AI has the potential to raise productivity substantially, enhance the quality and variety of available products, and create thousands of higher value jobs. PwC (2017) estimated that such benefits could increase the size of the UK economy by 10 percent by 2030. From a social viewpoint, AI provides new ways to solve a wide range of complex problems. For example, the GovTech Catalyst is supporting tech businesses to apply AI solutions to public sector challenges such as cutting traffic congestion, identifying illicit goods at the border, and streamlining business regulation.

The UK is well-placed to become a global leader in AI. It has a strong record in AI research and is regarded as a centre of expertise in the application of AI. Major AI firms, including Deepmind, Swiftkey, and Babylon are based in the UK, as well as leading start-ups such as Ardaga, Amplyfi and Graphcore. Several global AI-intensive firms including Amazon, Beyond Limits and Astroscale have chosen to invest heavily in the UK. Ipsos MORI research for the Office of AI into the AI labour market[7] suggests there may be over 1,000 UK firms whose core business is developing AI-led products or services, and a similar number developing AI internally to improve their products, services or internal processes. TechNation[8] reported in 2020 that the UK was third in the world for the level of AI investment, and the only country of the top five AI nations to have demonstrated consistent positive year-on-year growth for the last five years.

There are, however, several challenges and barriers to innovation in AI, the first two of which are similar to wider issues constraining investment in R&D activity more generally:

- **Imperfections in financial markets:** R&D activity is characterised by high levels of technical risk and uncertainty and the development of intangible assets typified by low levels of (if any) liquidity. These features make them unsuitable for debt finance because intangible assets are difficult to price without specialist expertise and there is little prospect of recovering their value in the event of a loan default. The availability of equity finance through angel investors and venture capital (VC) funds can help mitigate these issues, as the investor shoulders a greater share of the risk in exchange for higher returns. However, information asymmetries may constrain investment as the investee has superior information regarding the likely technical and commercial risks involved[9]. These issues will tend to constrain levels of privately funded R&D investment at socially suboptimal levels.

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[4] Hall, W. and Pesenti, J., 2017. Growing the artificial intelligence industry in the UK. Department for Digital, Culture, Media & Sport and Department for Business, Energy & Industrial Strategy. Part of the Industrial Strategy UK and the Commonwealth.

[5] HM Government (2017) Industrial Strategy: Building a Britain Fit for the Future

[6] Our 10 Tech Priorities. (DCMS). Available at: https://dcms.shorthandstories.com/Our-Ten-Tech-Priorities/index.html

[7] DCMS (2021) Understanding the UK AI labour market

[8] Tech Nation. (2020). UK Tech for a Changing World: Tech Nation Report 2020.

[9] Though against this, some research suggests that investors are attuned to risks and hazards that entrepreneurs are blind to.

- **Spill-over effects:** It is also well established that there are positive externalities associated with investment in innovation, as the benefits of the knowledge created cannot be fully captured by those investing in its production. While some knowledge and invention can be protected in the form of Intellectual Property Rights (IPR), turnover in the labour market allows many forms of tacit knowledge to circulate in the economy and be exploited by other firms. Many forms of innovation cannot be protected, and in some cases, it is possible to circumvent IPR restrictions by imitating the innovations developed by others through alternative means. A recent review found the social rate of return on R&D spending to be 2 to 3 times higher than the private returns,[10] providing a rationale for public subsidies. This may be exacerbated in the case of AI where applications of innovations have the potential to produce widespread productivity gains.

An additional two barriers are particularly relevant for innovation in AI, which provides a strengthened rationale for public investment in AI related projects:

- **Skills gaps and shortages:** Two major reviews of the AI sector and government policy in this area – the Hall and Pesenti (2017) review[11] and a report from the House of Lords Select Committee on AI – strongly emphasised the need to increase the pool of skilled individuals in the AI labour market to achieve the aims of the Industrial Strategy. They highlight that skilled AI developers are difficult for companies to find and command high salaries, particularly for start-ups and smaller firms. In addition, work undertaken as part of this study suggested that there is a gap with respect to non-technical skills such as commercial awareness among otherwise highly qualified AI professionals. Related to this, there is also a perceived lack of understanding of the return on investment from AI systems amongst firms adopting AI solutions, particularly amongst senior stakeholders, that may limit take-up. More recently, the AI Council Roadmap[12] affirms the persistence of skills gaps and outlines a number of recommendations for improving the situation.

- **Access to data:** Hall and Pesenti's review also notes that to continue developing and applying AI, the UK will need to increase the ease of access to data in a wider range of sectors. The UK is second only to Canada on the Open Data Barometer, a measure of how governments are publishing and using open data. However, where data cannot easily be made open, organisations often lack expertise to share it securely introducing barriers to the development of AI applications in these sectors.

2.3 Theory of Change

This section outlines a theory of change for investment in AI projects, building upon the expected outcomes and impacts outlined in the ITT and follow on discussion with Innovate UK:

2.3.1 Inputs

Innovate UK committed £323m in grant funding for the 757 projects within the scope of this evaluation. This was matched by approximately £202m in private funding provided by the firms awarded funding. In the case of the Investment Partnerships, grant funding was matched by equity funding or convertible loans provided by investors. Further resources are consumed by the management of the competition process by Innovate UK and external delivery partners (e.g. SETsquared in the case of ICURe).

[10] For example, see 'The Rates of Return to Investment in Science and Innovation,' Department for Business, Innovation and Skills (2014), 'Measuring the Returns to R&D,' Hall and Meiresse, Handbook on the Economics of Innovation, 2009, and 'The Intellectual Spoils of War? Defense R&D, Productivity and Spill-overs' Moretti, Steinwender and Van Reenan (2016).
[11] Hall, D. & Pesenti, J. (2017). Growing the artificial intelligence industry in the UK.
[12] AI Council. (2021). UK AI Council AI Roadmap.

2.3.2 Activities

The activities undertaken can be split into two main categories, those undertaken by Innovate UK and those undertaken externally by the funding applicants:

- **Competition administration:** R&D funding across all four funding instruments are allocated through a competitive application process. This process is supported by awareness raising activities and events to stimulate engagement amongst prospective applicants, led by Innovation Leads and external partners (such as the Knowledge Transfer Network or, where applicable, university Technology Transfer Offices). Applications are generally assessed on their commercial, technical and economic merits by independent assessors, with awards made to the highest scoring applications. Post-award, firms may be required to complete a due diligence process or finalise a collaboration agreement. Firms awarded funding are generally assigned a monitoring officer (although the specifics of the monitoring process vary across the four funding instruments).

- **Delivery of R&D activities:** Delivery of project proposals would often, but not always (e.g. ICURe), involve the delivery of a technical work programme of testing and refining the technology under development in increasingly realistic environments. CR&D projects are generally more advanced, involving a one to three-year programme of activity focused on refining prototypes (TRL4 to 7). ICURe funding was granted to support the development of a newly established spin out and whilst this could include further R&D, funds may also be used for other purposes such as establishing a management team and other business functions.

- **Market research:** In addition to technical development work, some projects may involve the delivery of a complementary programme of market research to validate the market for the innovation and develop the optimal business model for exploitation.

2.3.3 Outputs

The competition processes could be expected to deliver the following direct results:

- **Increased R&D spending and employment**: If the independent assessment process is effective in directing resources to projects that would not be taken forward by the private sector anyway, then applicants would be expected to invest greater levels of resources (including R&D workers) in the development of the project forming the focus of their proposal. This effect could be dampened if the funded project diverts attention from other parallel R&D projects. Additionally, if delivery of the project requires the firm to recruit R&D workers with scarce skills, this could place upward pressure on wages, encouraging reductions in R&D spending amongst other firms.

- **Reduced barriers to data sharing:** Projects may also be expected to reduce barriers to data sharing. CR&D projects provide a framework through which organisations can collaborate and could be expected to increase the amount of data accessed, shared, and used. Some projects may strengthen links between data owners and users and facilitate the creation of structures and agreements through which these can be accessed in the future. Projects may also improve the quality of data accessed. Quality data to train and test machine learning algorithms is a core component of AI development and projects may highlight weaknesses in current datasets, identify possible new applications of existing datasets, or fund the collection of new data.

- **Technological progress**: Increased levels of R&D spending would be expected to lead to accelerated progress through the development pathway. A key assumption is that challenges encountered during delivery are overcome, though in some cases the project may result in technologies that are not suitable for further development and commercial exploitation (though this may have benefits such as avoiding abortive R&D efforts or highlighting avenues for further research that may be productive).

- **Establishment of spin outs:** For ICURe specifically, projects may be given a recommendation to establish a spin out with or without Innovate UK grant funding.

2.3.4 Commercialisation outcomes

In turn, these outputs would be expected to deliver a range of commercialisation outcomes, including:

- **Leveraging of follow-on investment:** Commercial and technical de-risking of projects would be expected to enable recipients to leverage additional public or private funding to continue the development of the project. Funding may come from a variety of sources – such as internal resources, equity investment from venture capital or corporate venture funds, licensing the IP developed through the project to other organisations, or by attracting other public sector funds. Equity funding is also a direct input for Investment Partnership projects.

- **Commercialisation and adoption of new AI products and processes:** Providing firms can successfully demonstrate their technologies, this would be expected to eventually lead to the commercialisation of AI products and processes and their adoption by users.

- **Firm expansion (turnover, GVA and employment):** Successful exploitation would be expected to be visible in an expansion of the firm in terms of its turnover (including export sales), output (GVA), and employment. These effects would be particularly significant amongst those launching a new product or service, though process improvements could also lead to similar effects indirectly.

- **Firm productivity:** Successful exploitation may also result in gains in productivity if firms exploiting novel AI products and services are able to serve their customers at lower costs or attain higher prices for their products or services.

- **Knowledge spill-overs and agglomeration effects:** A range of processes, such as learning by imitation and via the circulation of workers in the labour market may enable other firms to 'free-ride' on the investments in made in R&D, resulting in productivity gains and growth beyond the pool of firms receiving funding. These effects are often mediated by proximity, with past studies showing that knowledge spill-overs tend to be more prevalent at the local level as the costs associated with collaboration and knowledge exchange tend to fall with distance. This leads to 'clustering' effects and Innovate UK's support for AI has the potential to facilitate the emergence or growth of clusters (particularly outside the key centres).

2.3.5 Skills outcomes

These outcomes may also be accompanied by a variety of skills development outcomes:

- **Accumulation of skills in AI development & deployment**: The delivery of projects can be also expected to produce several benefits in the form of improving the capacities of participating organisations and staff. The completion of work packages is likely to result in the development of skills and knowledge among R&D staff. In turn, this may lead to the genesis of new ideas and lines of enquiry.

- **Improved understanding of issues of public acceptance**: Market engagement activity or engagement with the public as part of a project may identify issues or concerns with the use of certain AI applications. This increased awareness may help firms find ways to mitigate these issues.

- **Improved awareness of principles of responsible AI deployment:** Some projects may lead to improved awareness of the principles for responsible AI deployment. This may be achieved through market engagement activity or engagement with the general public as part of a project, identifying concerns with AI use and weaknesses in current uses which could be addressed by an innovation.

2.3.6 Other workforce outcomes

Innovate UK's also has the potential to deliver other positive or negative workforce outcomes:

- **Increased diversity in the workforce:** Recent research for DCMS has indicated a lack of diversity in the workforce, particularly within small AI businesses and teams both in terms of gender and ethnic diversity[13]. In terms of gender diversity, a low proportion of women were working in AI development roles, and more than half of the teams interviewed employed no females in AI roles. In addition, a LinkedIn study using machine learning to analyse its members' profiles identified a significant gender gap among AI professionals in the UK. Interviewees also noted a lack of diversity in terms of social background in the AI workforce, and suggested that the lack of vocational routes into the industry may be a contributory factor. Whilst the AI workforce was generally thought by stakeholders to be no less diverse than in other parts of the tech industry, this could carry more significant implications. AI solutions have greater potential to replicate the modes of thinking of their creators, which risks negative social impacts if the AI workforce is dominated by one group whose biases and stereotypes go unchallenged. For example, existing biases in recruitment processes could become embedded in technology that learns from decisions made by humans. On the other hand, there is also a possibility that AI technology could help to correct such bias.

- **Distributional impacts of AI:** Widespread adoption of AI has the potential to lead to negative impacts on some sectors of the economy. In March 2019, an ONS analysis[14] showed that around 1.5 million jobs in England are at high risk of at least partial automation in the future, largely due to forms of AI technology and robotics. Women, those without a degree, and those at the beginning and nearing the end of their working lives are most at risk. Subregions with a higher proportion of the workforce at risk of automation are often those that experienced significant job losses in the last century and have struggled with economic and social deprivation (with implications for the 'levelling up' agenda). Ipsos MORI's research[15] shows that most of the public are not concerned about AI leading to major job losses, and are more likely to say that businesses should continue developing and using AI and robotics to automate work than to think they should cease doing so. However, the technology may face a backlash should it appear to be creating unemployment and exacerbating inequalities.

[13] DCMS. (2021). Understanding the UK AI Labour Market. Available at: https://www.gov.uk/government/publications/understanding-the-uk-ai-labour-market-2020

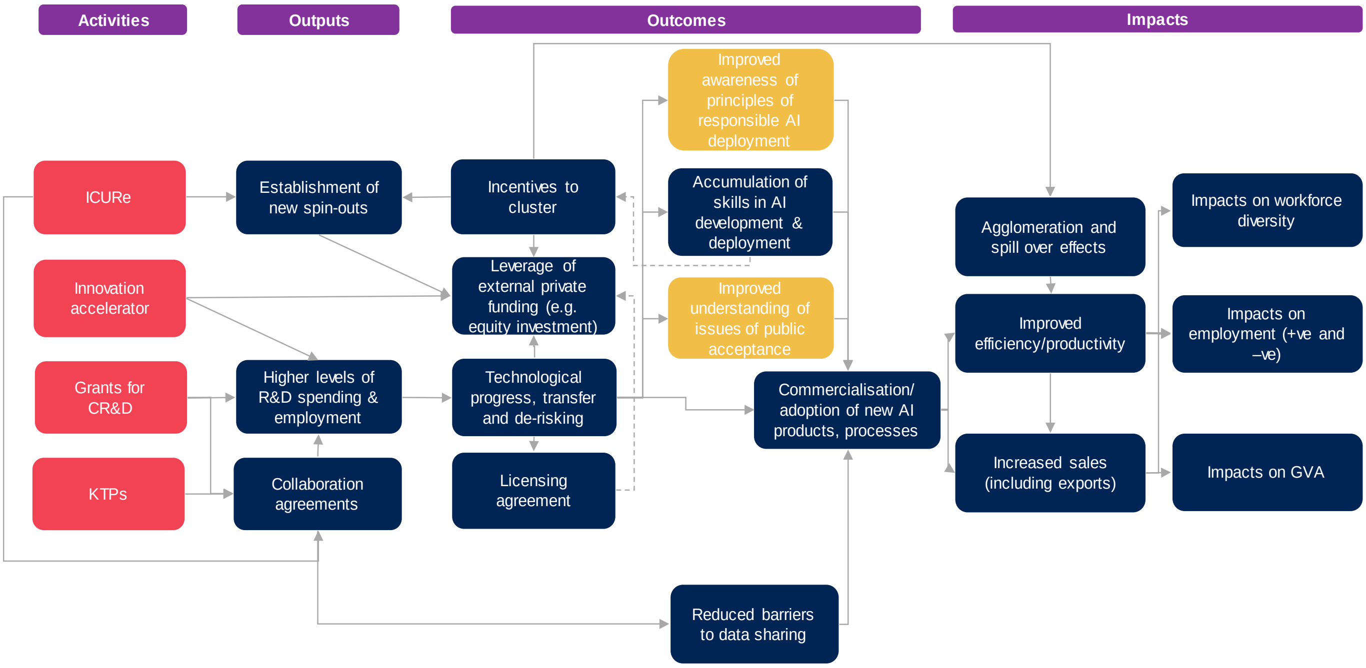
[14] ONS (2019) Which occupations are at the highest risk of being automated? https://www.ons.gov.uk/employmentandlabourmarket/peopleinwork/employmentandemployeetypes/articles/whichoccupationsareathighestriskofbeingautomated/2019-03-25

[15] Ipsos MORI. (2018). AI, Automation, and Corporate. Available at: https://www.ipsos.com/sites/default/files/2019-05/ai_automation_cr_web.pdf

2.4 Logic model

A logic model, summarising these processes, is provided in Figure 2.2. The outcomes in yellow boxes are those not considered to be directly impacted by Innovate UK funding, though funded projects may have had indirect impacts.

Figure 2.2: Logic model – Innovate UK's support for artificial intelligence



Source: Ipsos MORI analysis

3 AI landscape in the UK

This section provides an overview of the broader landscape for AI in the UK. This summarises the findings of a literature review conducted exploring the context for the study and incorporates findings from the stakeholder consultations.

3.1 Artificial intelligence (AI)

For the purposes of the study, Artificial Intelligence (AI) had been used as an umbrella term referring to a set of advanced general-purpose digital technologies that enable machines to do highly complex tasks effectively:

- This includes machine learning systems that change and improve over time in response to previous outputs. Human designers set the initial parameters and the goal that systems are intended to achieve. The system operates by choosing between alternatives in ways that are not programmed in advance, learning iteratively from its environment. This means the system has the potential to develop in unexpected ways.

- Deep learning is a type of machine learning that makes use of a layered structure of algorithms, so that outputs from one layer are used as inputs for the next. This complex structure allows the system to assess and improve its accuracy over time, but also means that the process of arriving at an output is always changing and cannot be described in a way that is understandable to humans.

- Although machine learning has been the focus of much recent interest, not all AI is a type of machine learning. Symbolic AI uses knowledge and rules that have been input by humans and are intelligible to humans. This can be used for applications such as search, reasoning, planning and knowledge representation, or to supplement machine learning to create a hybrid system. EPSRC is looking to encourage research in this area, including areas such as explainable and trustworthy AI[16].

3.2 Classification and use of AI technologies

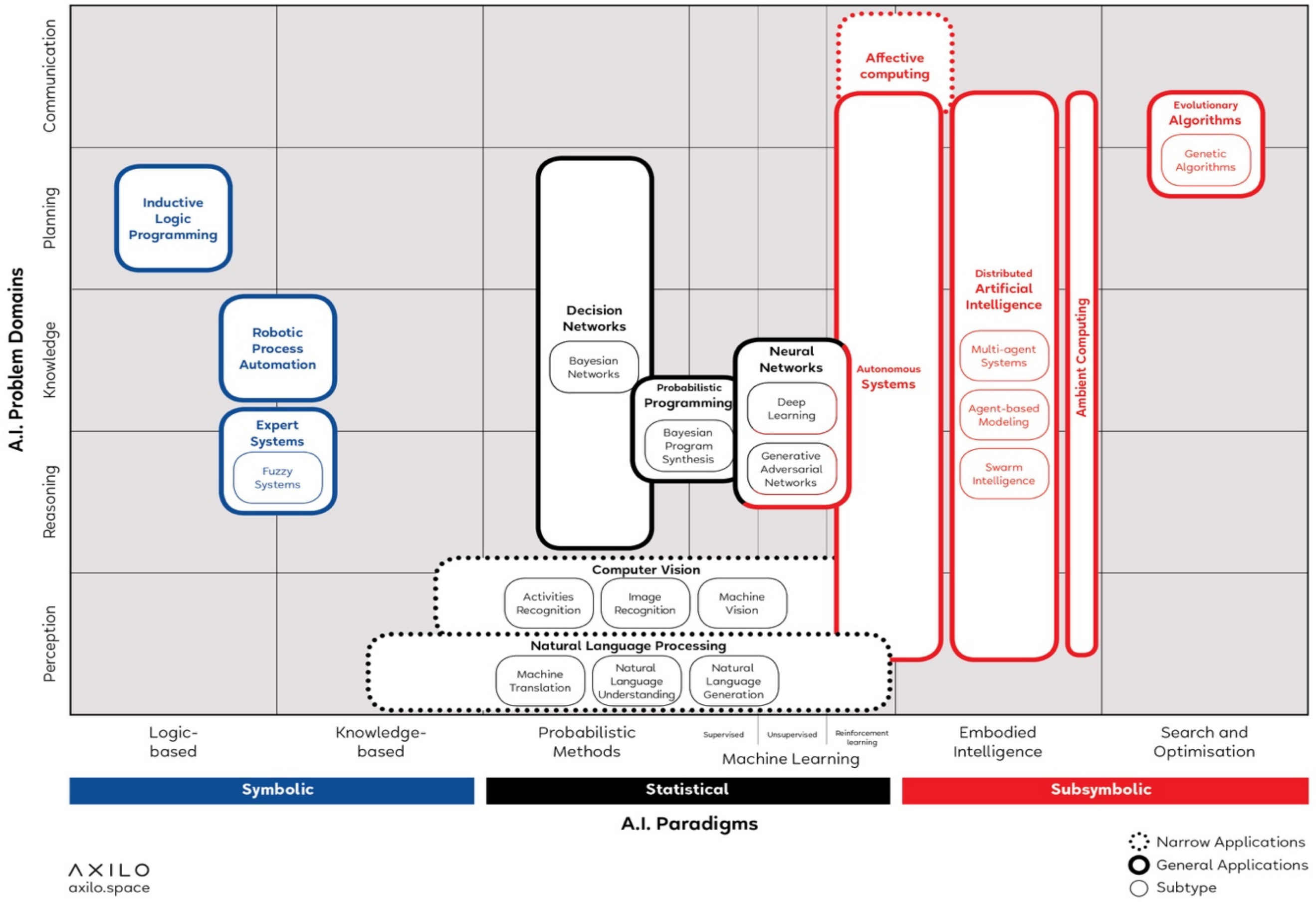
There are multiple ways to classify AI technologies. One maps AI applications and paradigms as presented below[17]. AI paradigms include:

- **Logic-based tools**: tools that are used for knowledge representation and problem-solving
- **Knowledge-based tools**: tools based on ontologies and databases of notions, information, and rules
- **Probabilistic methods**: tools that allow agents to act in incomplete information scenarios
- **Machine learning**: tools that allow computers to learn from data
- **Embodied intelligence**: engineering toolbox, which assumes that a body (or at least a partial set of functions such as movement, perception, interaction, and visualization) is required for higher intelligence
- **Search and optimization**: tools that allow intelligent search with many possible solutions.

[16] 'Artificial intelligence technologies' portfolio area, accessed on EPSRC website on 29th September: https://epsrc.ukri.org/research/ourportfolio/researchareas/ait/

[17] Corea, F., 2019. AI Knowledge Map: how to classify AI technologies. In An Introduction to Data (pp. 25-29). Springer, Cham. Accessed at https://www.forbes.com/sites/cognitiveworld/2018/08/22/ai-knowledge-map-how-to-classify-ai-technologies/ on 29th September 2020

Figure 3.1: The AI Knowledge Map



Source: Axilo & Francesco Corea

The literature review and interviews with stakeholders identified a range of practical implementations across industry sectors for AI and related technologies (summarised in the table below).

Table 3.1: Examples of AI applications in industry

Sector	Examples of AI implementations
Manufacturing	Optimised predictive maintenance of machines Greater ability to detect and respond to changing consumer demands Managing supply chains
Healthcare	Analysis of data from fitness trackers to improve management of chronic conditions as well as predicting and preventing acute episodes of illness. Assessing medical images to detect, characterize and monitor diseases
Retail	Finding patterns in consumer behaviour and making recommendations Sorting and packaging products in warehouses
Finance	Processing loan applications Recommending insurance policies Detecting fraudulent transactions
Journalism	Drafting articles and writing sport reports
Law	Sifting court documents and legal records for relevant information
Cybersecurity	Detecting unusual patterns of behaviour in a network

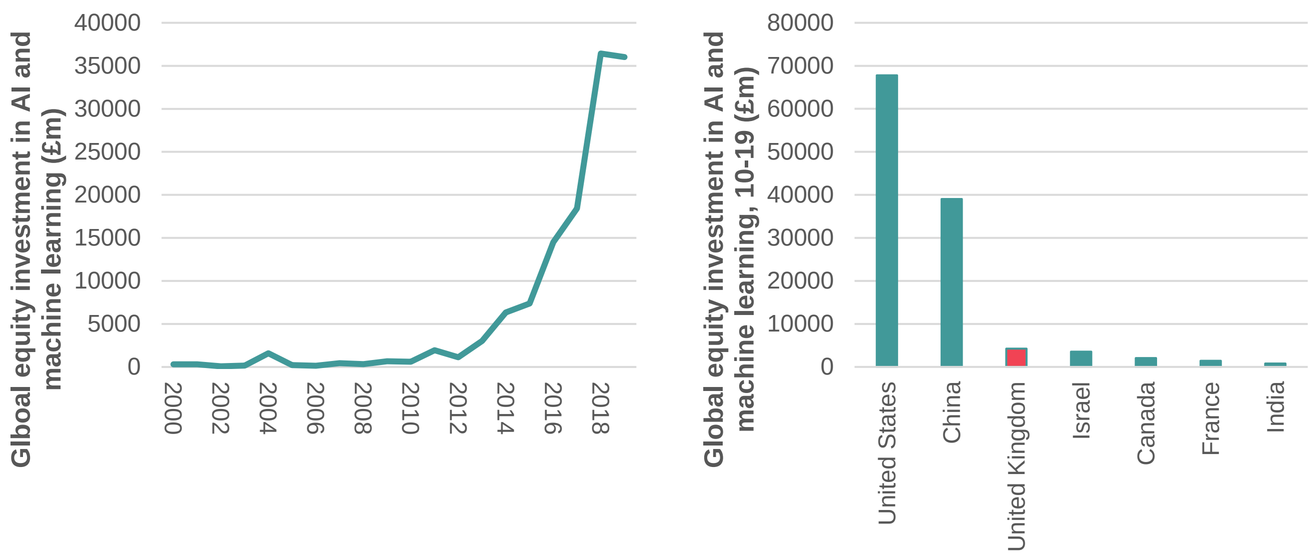
Source: Ipsos MORI

3.3 AI industry in the UK

The AI industry in the UK includes global tech firms operating in the UK, small and medium-sized firms whose core business is to develop AI, firms with traditional business models that are developing AI in-house, and firms with traditional business models that could adopt an externally developed AI solution. Many major US tech firms operate in the UK and have acquired specialist UK AI companies (e.g. DeepMind's acquisition by Alphabet/Google). The operations of these acquired companies have largely remained in the UK, though ensuring this investment remains in the UK is a key policy goal[18].

Investor interest in AI expanded rapidly in the 2010s. Global equity investment (including private investments placed by angels and venture capital (VC) funds, and investment raised on public equity markets) in firms active in the AI and machine learning 'industry vertical' rose by a factor of 58 between 2010 and 2019 (from £614m to £36bn). Global investment has been highly concentrated in a small number of countries - only seven nations accounted for more than one percent of equity investment since 2010. The US and China were clear global leaders, together claiming 84 percent of investment in the technology area. The UK leads the remaining nations with an apparent specialism in the technology area, which included Israel, Canada, France and India. It claimed 4.4 percent of global equity investment in 2019, broadly in line with its share of global equity investment across all sectors (4.7 percent).

Figure 3.2: Global equity investment in AI and machine learning, 2000 to 2019



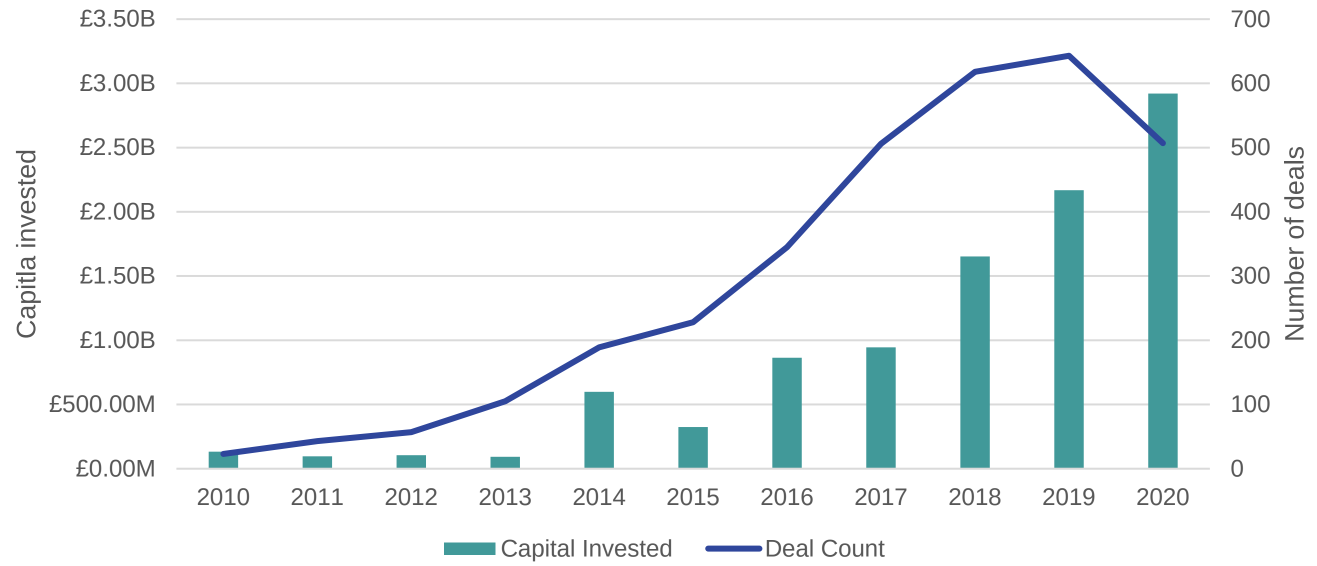
Source: PitchBook, based on Ipsos MORI user-defined queries. Comparisons to countries claiming at least one percent of global equity investment.

Investment in UK headquartered companies working in the AI and machine learning industry vertical has risen broadly in line with global trends (to almost £3bn by 2020). Data from PitchBook indicated that 1,435 companies active in the AI and machine learning 'industry vertical' had a presence in the UK. UK headquartered firms that raised significant levels[19] of external investment included Babylon Health (a firm seeking to develop an AI based system for triaging patients in primary care), Graphcore (processing units for machine intelligence), Darktrace (a platform to detect and respond to internal and external cyber threats), and Onfido (automation of identity verification).

[18]Hall, W. and Pesenti, J., 2017. Growing the artificial intelligence industry in the UK. Department for Digital, Culture, Media & Sport and Department for Business, Energy & Industrial Strategy. Part of the Industrial Strategy UK and the Commonwealth.
[19] More than £200m.

A substantial share of firms with a UK presence (516 of 1,435) were also headquartered overseas, indicating it has been successful in attracting Foreign Direct Investment (FDI) relative to other large economies in Europe. For example, PitchBook data indicated that 164 of 780 AI and machine learning firms in France were headquartered outside of the country, whilst Germany had 965 firms in the AI vertical with 297 headquartered in other countries. The UK AI sector also appears to have outperformed the UK overall in terms of FDI (with France securing greater levels of overseas investment projects than the UK in both 2019 and 2020[20]).

Figure 3.3: Investment in AI firms headquartered in the UK between 2010 and 2020



Source: PitchBook, based on Ipsos MORI user-defined queries.

The figure overleaf provides UK and global shares of equity investment in AI and machine learning broken down by industry sector. Comparisons between the two can help reveal areas of specialism and comparative disadvantage:

- **Areas of strength:** The UK attracts a disproportionately high share of equity investment in the software sector (54 percent vs 44 percent globally). Many of these companies are active in the cybersecurity industry, reflecting the UKs comparative strength in this area. Other areas of strength include media, commercial services, computer hardware and pharmaceuticals and biotechnology. Stakeholders confirmed these areas of relative strength and noted the UK's relatively well-developed academic base in these areas. Finance was also sector that was frequently noted as a key strength of the UK in terms of the development and adoption of AI technology (again, linked to the depth of the broader industry in the UK).

- **Areas of competitive disadvantage:** The UK has fallen behind with respect to investment in start-ups focused on the application of AI to transportation systems. Globally, firms developing AI in this sector have accounted for 17 percent of investment. This share falls to less than one percent in the UK.

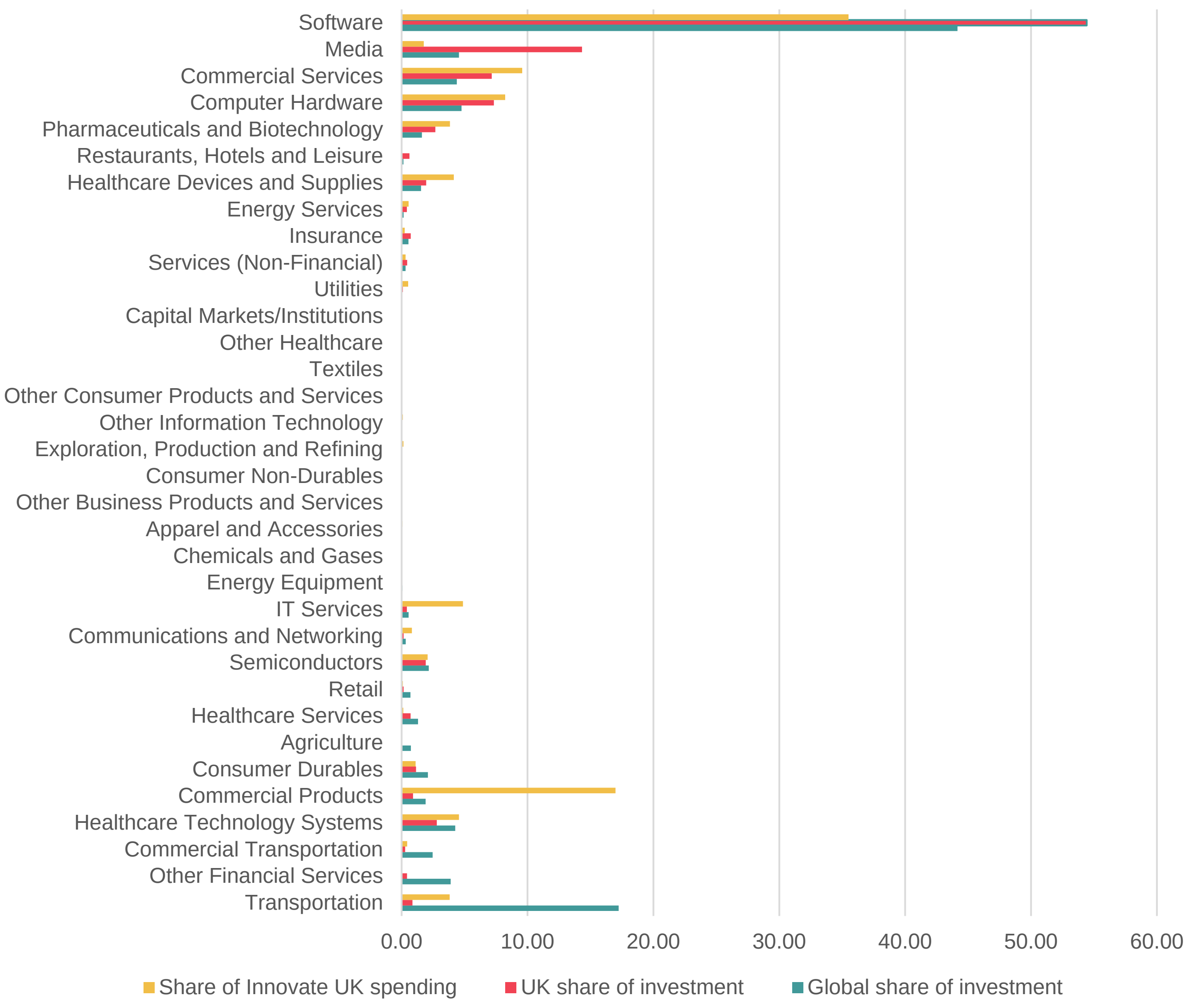
[20] EY (2021) FDI Attractiveness Survey. Available at: https://www.ey.com/en_uk/news/2021/06/uk-exceeds-investor-expecations-with-resilient-foreign-direct-investment-performance-in-2020-new-ey-report-reveals

Innovate UK grant funding for AI has broadly mirrored patterns of global and domestic private investment with some key exceptions (note the breakdown of grant funding by sector is based on those tracked by PitchBook to allow comparability, an only covers 54 percent of the relevant firms):

- **Commercial products:** A substantially higher share of funding has reached companies operating in the commercial products sector. These companies tended to be manufacturers in traditional industries (e.g Tata Steel/Corus, BAE Systems) and in industries more directly related to artificial intelligence (e.g. L3 ASV – a manufacturer of unmanned marine vehicles for civil and defence applications). This could indicate that Innovate UK funding is supporting development and adoption of AI in sectors where private investment is negligible. However, it should be noted that these types of companies are typically less dependent on VC investment and their internal investments in AI R&D would not be visible in the data compiled by PitchBook.

- **IT services:** Another divergence relates to IT services – most of the companies benefitting from Innovate UK support in this sector were providing cybersecurity services. Only one large IT services company – Capgemini – benefitted from Innovate UK grants.

Figure 3.4: Investment in AI by industry sector, UK and global (% of total investment, 2010 to 2019)

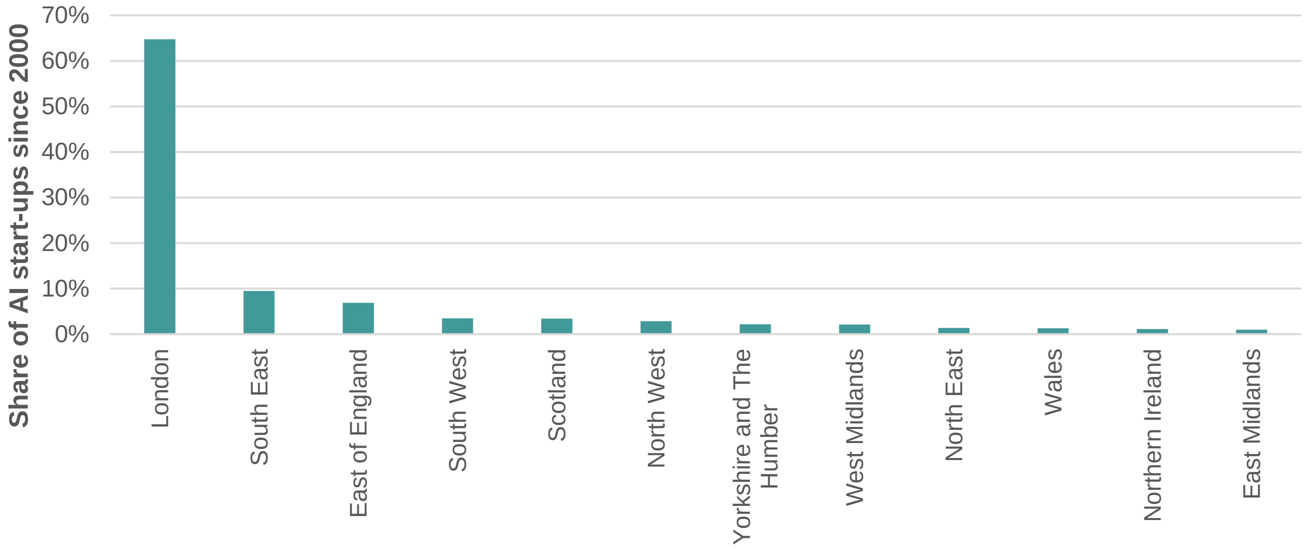


Source: PitchBook; Ipsos MORI analysis

3.3.2 Regional distribution of AI start-ups

AI start-ups are heavily concentrated in London. PitchBook records suggest that London accounted for 65 percent of UK start-ups in the technology area since 2000, with the industry predominantly clustered in the central boroughs of Westminster, City of London, Islington, Camden, and Hackney. There are few notable clusters outside of London (although some notable firms had adopted locations outside of the capital). Just three local authorities outside London saw more than 20 start-ups in the sector since 2000: Cambridge, Oxford, and Edinburgh. For comparison, 139 AI firms were established in Westminster over the same period.

Figure 3.5: Regional distribution of AI start-ups



Source: PitchBook

3.4 Barriers to AI research and development

3.4.1 Access to data

Machine learning systems require large datasets for the system to be trained. The availability, size and quality of these underlying datasets is crucial to their performance and the accuracy and legitimacy of their outputs. However, access to datasets can be challenging in terms of both quality and availability. They also require regular updating and maintenance. Many systems currently “publishing” data have been designed for a different purpose and cannot provide data at a sufficient level of accuracy (e.g. geolocation) and/or in real time. For supervised learning, datasets also need to be labelled, a task which is repetitive and time-consuming. As a result, access to data can be a significant barrier for new AI developers and stakeholders highlighted the significant time and resource needed to negotiate access to and/or creating datasets for use in testing and development.

On the other hand, many organisations have potentially valuable data which is not curated or understood within the organisation, and are not able to make good use of the data they have, let alone make it available to others. There is also a risk that large companies which have control over vast quantities of data could become overly powerful. While the UK is second only to Canada on the Open Data Barometer, a measure of how governments are publishing and using open data, not all data can or should be made open and organisations need expertise, as well as new mechanisms and frameworks (such as data portability and data trusts) to access such data securely and ethically.

Stakeholders consistently suggested that more work needs to be done to simplify access to relevant data. Particular issues were highlighted in the healthcare and transport and infrastructure sectors. The Financial Conduct Authority Regulatory Sandbox was highlighted by many as an example of how real time data could be made available more readily to developers in a regulated context and in a way that would not impact markets. The Sandbox allows AI applications to be implemented with real customers in a controlled manner following approval, enabling developers to test their products in small scale trials. In addition, it was suggested that standardised and repeatable terms should be utilised more widely.

3.4.2 Access to skills

Two major reviews of the AI sector and government policy – the Hall and Pesenti (2017) review and a report from the House of Lords Select Committee on AI – strongly emphasised the need to increase the pool of skilled individuals in the AI labour market to achieve the aims of the Industrial Strategy. Similar issues were also highlighted by recent research into the AI labour market for DCMS[21].

Skilled AI developers are scarce, with one 2019 report estimating that there are only around 36,500 expert researchers in the world capable of working in AI research and applications (although this had increased from 22,000 the previous year)[22]. These individuals currently command salaries that can be prohibitively high for smaller firms[23]. While a shortage of talent is a challenge for many technology fields, it is especially acute in AI because it requires skills from multiple supply-constrained fields: software engineering, computer science, data science, statistics, and mathematics[24].

Stakeholders observed that there is high demand for individuals who are able to understand both AI technology and business needs, and some were of the view that a university education provides insufficient preparation for working in a business environment and the skills this requires. Related to this, there is also a perceived lack of understanding of the return on investment from AI systems amongst firms adopting AI solutions (particularly amongst senior stakeholders), which may limit take-up.

3.4.3 Access to capital

Access to finance for UK AI start-ups was not considered to be a major barrier by most stakeholders, and a consistent view was put forward that the UK was a good place for 'deep tech' venture capitalists and investors to operate in. However, there was a perception amongst some stakeholders that investors and funds not traditionally investing in AI and 'deep-tech' were less likely to understand the longer-term nature of AI development and the need for constant refinement in models and applications. Compared to traditional software firms, AI developers typically face longer timescales to market and greater uncertainty as to how accurate their model is at any point in time (linked to the data changing constantly).

3.4.4 Regulation

Uncertainty with regards to legal liability was highlighted by stakeholders and in the broader literature as a barrier to the wider adoption of AI products and services. As described above, AI applications and models are constantly evolving, and it may not be straightforward to identify where something went wrong. When this happens, it is not always clear who, if anyone, should be held responsible (e.g. the developer, adopter, or user). This problem is considered to be greater where a decision is made autonomously or by a human using the data generated by the model. An explainable application of AI may make it easier to identify

[21] DCMS (2020) Understanding the AI labour market. Accessed at: https://www.gov.uk/government/publications/understanding-the-uk-ai-labour-market-2020

[22] Global AI Talent Report 2019, accessed at https://jfgagne.ai/talent-2019/

[23] https://www.nytimes.com/2017/10/22/technology/artificial-intelligence-experts-salaries.html

[24] Hall, W. and Pesenti, J., 2017. Growing the artificial intelligence industry in the UK. Department for Digital, Culture, Media & Sport and Department for Business, Energy & Industrial Strategy. Part of the Industrial Strategy UK and the Commonwealth.

where the error occurred, though this may not be possible in some applications. There is therefore a need for robust and detailed governance mechanisms on the use of AI to help businesses adopting AI.

3.5 Societal considerations for AI development and adoption

The use of artificial intelligence has potential to create adverse consequences and pose moral dilemmas. It raises significant social and ethical questions that will need to be answered to ensure that AI technology is able to realise its potential to benefit society whilst avoiding harm as much as possible. Widespread investment and use of AI will not take place without a certain degree of both predictability and trust in the technology.

3.5.1 Biases

The process by which machine learning systems develop through learning from existing data poses a risk that social biases will be transferred to these systems. For example, software used to assist decisions around recruitment or university admissions that is trained on previous recruitment or admissions data may reflect the biases of the previous system. Research has identified several instances of algorithmic bias, such as the COMPAS system used to predict reoffending in some US states[25] showing bias against Black people, and a study showing that Google's online advertising system showed ads for high-paying jobs to women less often than to men[26]. Algorithmic bias may not only perpetuate inequalities but worsen them by creating "feedback loops"; for example, if data shows a high number of arrests in a particular area, an algorithm may assign more police patrols to that area, which could lead to more arrests.

AI has significant potential to identify and reduce bias in decision-making. However, for this to happen the AI developers must be aware of the potential for bias and be committed to avoiding it. One obstacle to this may be the noted lack of diversity in the AI workforce[27], a view corroborated by stakeholders interviewed as part of the Office for AI research referenced above. Lack of diversity was predominantly discussed in terms of gender, with a low proportion of women working in AI. For example, a LinkedIn study using machine learning to analyse its members' profiles identified a significant gender gap among AI professionals in the UK. Interviewees also noted a lack of diversity in social backgrounds in the AI workforce, and suggested that a lack of vocational routes into the industry may be a contributing factor.

Whilst the diversity of the AI workforce was generally thought by stakeholders to be no worse than in other parts of the tech workforce, the implications were considered more serious. AI solutions have greater potential to replicate the modes of thinking of their creators, which risks a negative impact on society if the AI workforce is dominated by one group of people whose particular biases and stereotypes go unchallenged. Hall and Pesenti[28] note "*Currently, the workforce is not representative of the wider population. In the past, gender and ethnic exclusion have been shown to affect the equitability of results from technology processes. If UK AI cannot improve the diversity of its workforce, the capability and credibility of the sector will be undermined."*

It is possible to mitigate some of the risks related to bias when developing AI through identifying potential bias in data, assessing the potential impact of this, and applying corrections to the underlying data or algorithmic process. Having a diverse and representative workforce, educated on the issues surrounding

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[25] Angwin, J., Larson, J., Mattu, S. and Kirchner, L., 2016. Machine bias. ProPublica. Accessed at https://www. propublica. org/article/machine-bias-risk-assessments-in-criminal-sentencing on 29th September 2020.
[26] Datta, A., Tschantz, M.C. and Datta, A., 2015. Automated experiments on ad privacy settings: A tale of opacity, choice, and discrimination. *Proceedings on privacy enhancing technologies*, *2015*(1), pp.92-112.
[27] Hall, W. and Pesenti, J., 2017. Growing the artificial intelligence industry in the UK. Department for Digital, Culture, Media & Sport and Department for Business, Energy & Industrial Strategy. Part of the Industrial Strategy UK and the Commonwealth.
[28] Ibid.

bias, was also an important factor in the eyes of many stakeholders. Stakeholders were also keen to highlight that the best way to address this issue was to be aware of potential issues at an early stage of development and to have a process to regularly review these issues over time.

3.5.2 Data protection, privacy and surveillance

AI systems create data protection challenges since, by combining data sets and identifying patterns in new ways, they can make it possible to infer information about individuals that the individual has not consented to reveal publicly, including highly sensitive information. Legal frameworks, such as GDPR, exist to govern the use of citizens' data by government analysts, protecting rights to privacy, ensuring equal treatment for all, and safeguarding personal identity. These are an essential ingredient in maintaining public trust in government's ability to manage data safely, a view emphasised by stakeholders.

Teams making use of artificial learning approaches need to understand how these existing legal frameworks and general legislation apply in this context. Many stakeholders pointed out the potential for wider reputational damage (for AI uses more widely, not just for the firms directly involved) should these not be adhered to, in addition to the punitive fines likely to be imposed. As the volume of publicly available data increases and more powerful AI techniques are developed, this possibility may become more likely and existing legislation and codes of practice may need to be revisited. For many stakeholders, particularly those involved in the development of AI applications and those in policy circles, public policy should play a role in providing an environment in which the many contentious issues could be discussed early. A proactive approach to consulting on potential changes policy was preferred over a reactive one. Uncertainty with respect to the future legal framework for some applications such as autonomous vehicles was reported to be a likely roadblock for progress.

3.5.3 Automation and redundancy

Widespread adoption of AI is expected to have profound implications for the economy, labour markets, and society more widely. While this technology is expected to improve productivity and boost growth, these labour market changes may also result in job losses. The scale of these job losses is the subject of much debate and uncertainty. One study from Deloitte in 2014 found that 35 percent of UK jobs will be affected by automation over the next 10 to 20 years, while a 2016 report from the OECD suggested that only 10 percent are at risk.

Job losses due to automation could exacerbate existing inequalities. Andrew Haldane, Chief Economist at the Bank of England, reported in 2015 that those "most at risk from automation tend, on average, to have the lowest wage". In March 2019, ONS analysis showed that around 1.5 million jobs in England are at high risk of some of their duties being automated in future, largely through AI technology and robotics. Women, those without a degree, and those at the beginning and nearing the end of their working lives are most at risk. Differences in local labour markets mean that some areas have a higher proportion of their workforce whose jobs are at risk of automation. These are often areas which experienced significant job losses in the last century and struggle with economic and social deprivation (and the concentration of the AI sector in the London and South East regions risks exacerbating these subregional disparities).

The pace and nature of job losses due to automation will depend on the speed at which technology is developed, the speed at which businesses take up this technology, and the extent to which existing roles can be adapted (for example, to focus on more creative and less on routine tasks) rather than eliminated. As with previous periods of technological development, it is widely predicted that new industries and job roles will emerge as others disappear. New roles are likely to require different skill-sets to the jobs they replace, either making use of skills that complement technology or involving skills that are more difficult to automate such as creativity, social skills, or complex manipulation. Given rapid technological development there is also likely to be a need for people to learn new skills over the course of their career, develop transferable skills such as flexibility and problem solving, and cultivate an ability to adapt to different contexts. Government, businesses, and society will need to respond to these changes to ensure that people are well-placed to adapt to them and the benefits of AI are fairly shared.

3.5.4 Public perceptions of AI

Widespread adoption of AI will not be possible without public confidence and trust in the technology. Previous research shows that the public sit somewhere between indifference and suspicion of artificial intelligence technology[29].

Many people may not yet know enough about the technology to form a view. In 2017, research into public views of machine learning found that most participants knew very little about the technology before taking part. A more recent poll conducted in 2019[30] however, suggested that 63 percent knew something about AI while 12 percent reported 'knowing a lot'. Their reactions to learning more about machine learning included recognising that it was an important technology which could have an impact on their lives, rejection of the notion that machines could ever really replace human workers, and overall suspicion. In other polling, a majority (53 percent) of the public would not feel comfortable with AI making decisions which affect them. These attitudes may create barriers to the diffusion and adoption of AI. This risk was acknowledged by stakeholders consulted in the study. There was a broadly consistent view that this issue may (in the short term) require public intervention for example through retraining. In the long term, however, AI developers, investors and most other stakeholders highlighted the wider social benefits that AI could bring about and a shift to higher productivity work for workers across the economy.

Research also shows that a majority of the public are not concerned about AI leading to major job losses, and are more likely to say that businesses should continue developing and using AI and robotics to automate work than to think they should cease doing so. However, the technology may face a backlash in future should it appear to be creating unemployment and exacerbating existing inequalities. Many support regulation to restrict the automation of work: 44 percent support an 'automation tax', and 50 percent support 'human quotas', minimum proportions of people which every company would need to employ. This could limit the ability of the technology to drive productivity and reduce costs.

To increase public acceptance of AI, the industry will need to:

- Demonstrate fairness in the use of AI, trustworthiness and reliability of the technology, and effective oversight.
- Address negative public perceptions, for example by working with Non-Government Organisations (NGOs) and science agencies to produce creative public engagement and education campaigns about the benefits of AI.
- Participate in dialogue which gives a central position to the views of the public, acknowledges, and addresses legitimate concerns and arrive at a sophisticated and balanced view of the risks and

[29] Ipsos MORI. (2018). AI, Automation, and Corporate. Available at: https://www.ipsos.com/sites/default/files/2019-05/ai_automation_cr_web.pdf
[30] BEIS (2019 AI PR Survey. Available at: https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/802548/BEIS_AI_PR_Survey_40309009_Topline_summary_V1__1_.pdf

benefits. The approach taken by the Warnock review leading to the establishment of the Human Fertilisation and Embryology Authority is frequently cited as an example to follow in this context.

Whilst a certain level of public trust in the technology will be required for its widespread deployment, some stakeholders also warned against simplistically attempting to build trust in AI, given its potential to be used to mislead or deceive users. Rather, citizens and consumers will need to develop the skills to decide whether to trust it for themselves. Some stakeholders stated that the explainability of some AI applications may make this more challenging.

3.6 Responsible AI development

Several organisations have begun developing standards for responsible AI development[31] to ensure the development of AI is consistent with ethical principles. Various definitions have been put forward, many of which contain the same core principles. Responsible AI is thought to be AI technology which:[32]

- is socially beneficial;
- operates and is applied in a way that reflects human and societal values;
- operates as intended, avoiding unwanted or unpredictable behaviours;
- is reliable, secure from attack, and appropriately cautious in its approach to risk;
- is accountable to people and subject to human direction and control, with clear liability when systems make mistakes;
- is transparent and operates in a way that can be understood and investigated if it fails;
- does not create or reinforce unfair or irrational bias; and,
- has privacy safeguards and provides appropriate transparency and control over the use of personal data.

Some definitions also state that responsible AI should:

- be able to be used by users with differing levels of skill and technical knowledge; and
- be developed with the diverse nature of societal needs in mind.

In practice, developing responsible AI involves: establishing processes and governance structures to ensure these principles are adhered to; designing AI systems that comply with these principles from the outset; auditing the performance of AI against these principles; and disseminating AI skills and understanding (through training and otherwise) to democratize the technology[33].

[31] For example: https://ai.google/static/documents/responsible-development-of-ai.pdf; https://www.microsoft.com/en-us/ai/responsible-ai;
[32] https://ethicsinaction.ieee.org/; https://futureoflife.org/ai-principles/; https://www.partnershiponai.org/about/
[33] https://www.accenture.com/_acnmedia/PDF-92/Accenture-AFS-Responsible-AI.pdf

The Government Digital Service and Office for AI have developed guidance on understanding artificial intelligence ethics and safety[34] and using these in public-sector projects[35]. This guidance sets out a framework for the responsible delivery of AI projects which involves:

- Reflecting on the ethical purposes and objectives of the project, and its impact on individuals and communities, using the values of respect, connection, care, and protection;
- Acting at every step of the project in a way that reflects principles of fairness, accountability, sustainability and transparency; and,
- Implementing a process-based governance framework to ensure these values and principles are integrated throughout the project.

However, as with similar frameworks, interpreting ethical principles requires weighty, complex and sensitive decisions to be made: most obviously, determining how human and societal values and social benefits are to be defined. There is also potential for some of the principles listed above to conflict with one another. For example, making AI technology accessible to as many people as possible may afford less control over the purposes it is used for. Because of this, commitments to responsible AI also focus on developing a better understanding of these issues and the implications of AI use, so that ethical decisions can be made by a wider group of stakeholders. There are a number of existing initiatives working to develop and discuss ethical codes for AI by bringing together academia, the private sector, the public sector and the general public, including the Alan Turing Institute, the Leverhulme Centre for the Future of Intelligence, the World Economic Forum Centre for the Fourth Industrial Revolution, work being done by the Royal Society, the Partnership on Artificial Intelligence to Benefit People and Society and the Digital Catapult through their Machine Intelligence Garage Ethics Committee.

[34] https://www.gov.uk/guidance/understanding-artificial-intelligence-ethics-and-safety
[35] Leslie, D., 2019. Understanding artificial intelligence ethics and safety. arXiv preprint arXiv:1906.05684. Accessed at https://www.turing.ac.uk/sites/default/files/2019-06/understanding_artificial_intelligence_ethics_and_safety.pdf on 29th September 2020

4 Project outcomes

This section explores the extent to which Innovate UK's support for AI R&D has accelerated the development of AI technologies. This section outlines the nature of the projects that were funded and explores the effects of Innovate UK support in enabling collaboration, technological progress, and the acquisition of skills and knowledge. This section draws on a survey of firms supported by Innovate UK, depth interviews and econometric analysis exploring how far the support provided has leveraged additional investment in R&D related to AI technologies (detailed results are provided in Annex A).

4.1 Characteristics of AI projects

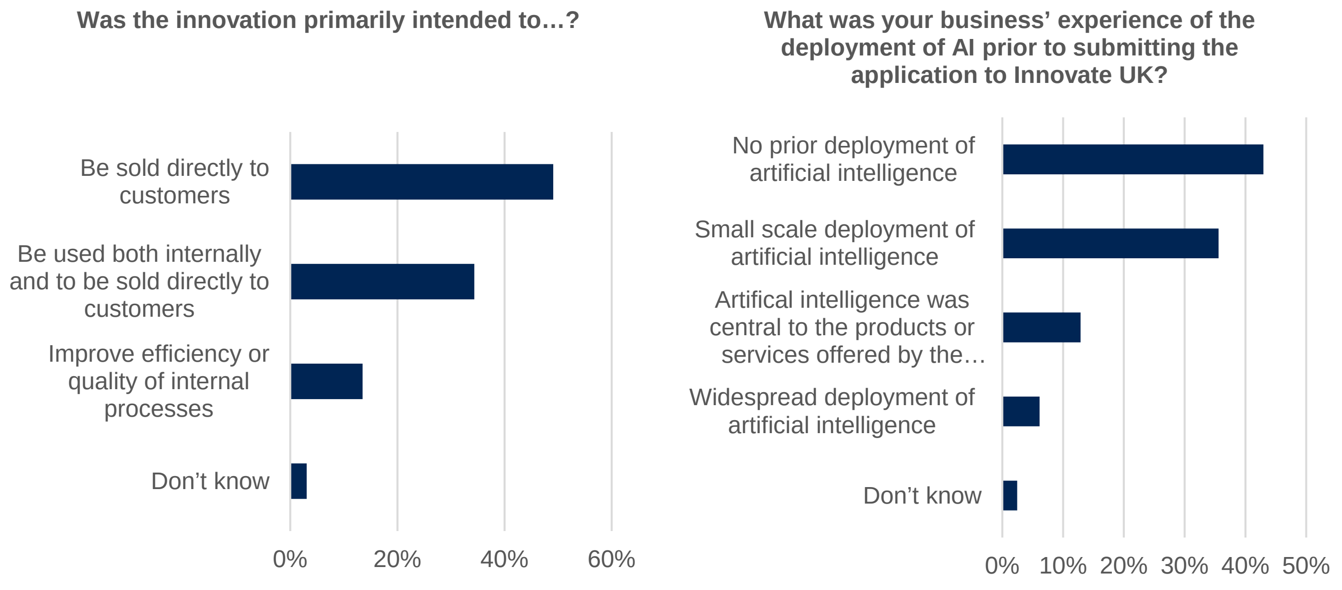
The survey of firms supported by Innovate UK indicated that AI or related technologies were in most cases central to the innovation underpinning the project (130 out of 168)[36]. AI was not a central focus in 38 cases. Here, the application of AI was secondary with examples including the development of data analytics software that incorporated AI in part, autonomous technologies such as wind farm inspection where the development of AI driven analytics was not the project focus, and augmented reality applications.

4.1.1 Objectives of the project

Over 80 percent of projects involved the development of a product intended to be sold directly to customers (or both used internally and sold to customers). This implies that most firms supported by Innovate UK funding over the period were AI developers.

In addition, 79 percent of respondents had little to no prior business' experience of the deployment of artificial intelligence in business processes before their application. This evidence suggests that Innovate UK funding has largely supported new and small-scale start-ups developing potentially disruptive products, but less in the way of support to firms looking to exploit AI potential to drive internal productivity gains and potentially less towards AI-first scale-up firms.

Figure 4.1: Primary intent for innovation and experience with AI deployment

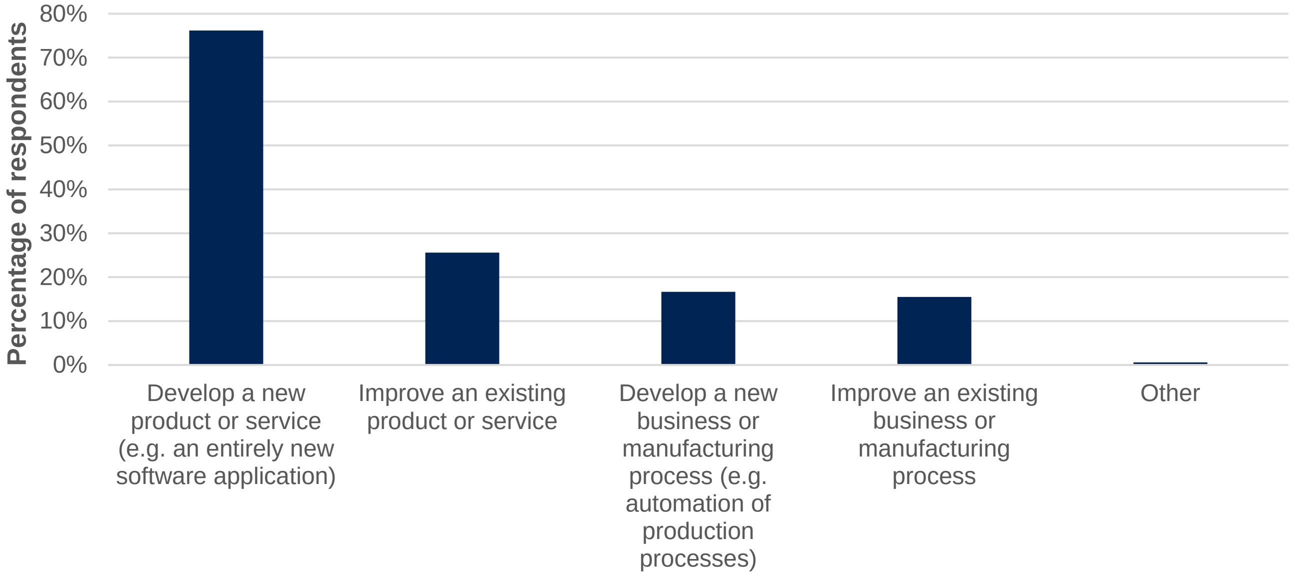


Source: Ipsos MORI (2021)

[36] Of the 168 respondents to the survey, 96 percent were CR&D applicant firms. CR&D, KTP and IP respondents have been grouped together for this reason.

Most applicants aimed to develop a novel product or service. There were fewer examples of firms exploring AI to make incremental improvements to existing products or services or introduce new or enhance business or manufacturing processes.

Figure 4.2: Commercial objective of deploying AI in the project



Source: Ipsos MORI (2021)

The most frequently reported sector of intended application was human health and social work, indicating Innovate UK has provided the most significant levels of support for digital health technologies (which may be linked to schemes such as the Digital Health Technology Catalyst). However, the range of applications were diverse, with products intended for the professional, scientific, and technical activities, and sectors such as transport and infrastructure, IT, and manufacturing all receiving significant levels of support. The range of sectors covered by projects is likely linked to the wide applicability of AI technologies and the top five in the list below map relatively well to those most prominently discussed in the literature with some exceptions:

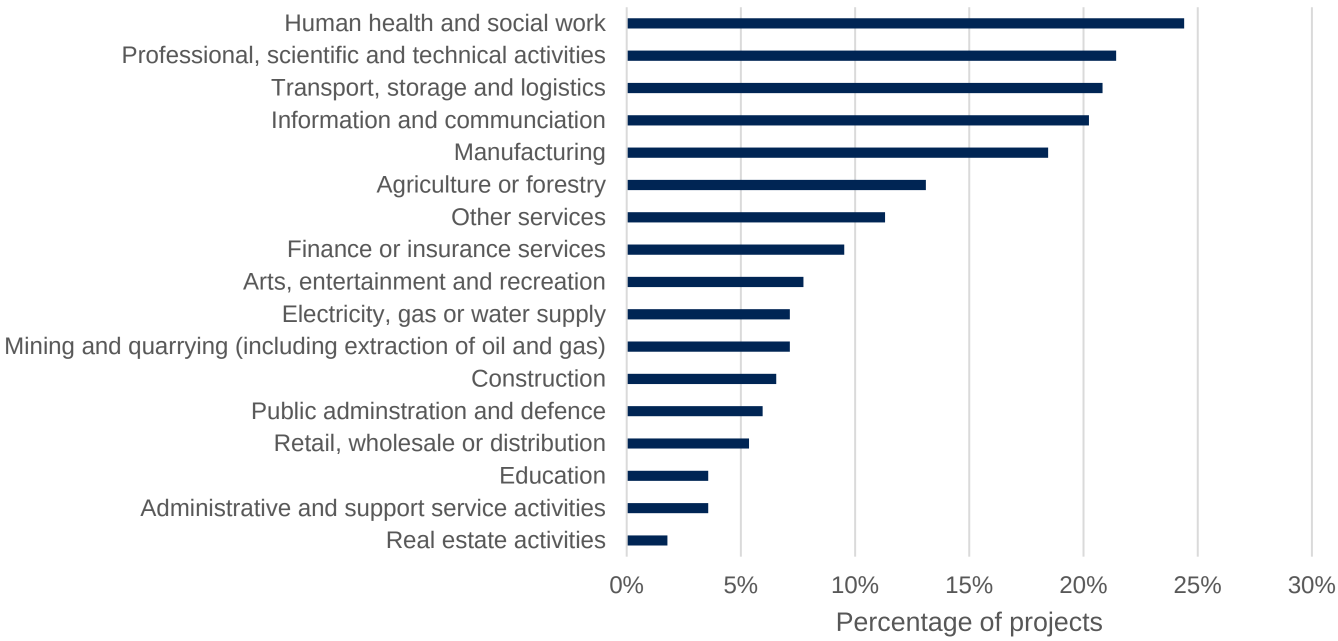
- **Financial services:** Innovations intended for the financial and insurance services sector were ranked eighth most common, which contrasts with the UK economy's relative strength in this industry. Projects funded through the Next Generation Services ISCF, focused on AI in accountancy, legal services, and insurance subsectors of professional services, were not included in this review and this finding may stem from the exclusion of ISCF projects in the review.[37] It may also reflect the sector focus of Innovate UK funding towards those prominent in the Industrial Strategy and where university research and academic links may have strong impacts on commercialisation. Stakeholder consultations and the literature also suggested that this sector was one of the leading adopters of AI and may require less support in early-stage technical development given the lower volumes of applications received by Innovate UK.

- **Electricity, gas or water supply:** Innovations related to energy supply were also relatively less frequent (potentially surprising given the potential for innovations in this space to help support a reduction in emissions using the data generated by smart meters and other smart systems). Again,

[37] Although the Digital Health Technology Catalyst was funded under the Medicines Manufacturing ISCF programme, it was conceived prior to the introduction of ISCF and projects funded through the programme were considered in-scope.

projects funded through the Prospering from the Energy Revolution (PFER) ISCF were not included, many of which are AI related (leading to a potential understatement of Innovate UK's support for applications in this industry)[38].

Figure 4.3: Industrial sector(s) that the innovation was intended to be applied by the end-user



Source: Ipsos MORI (2021)

4.2 Project design

As might be expected, projects funded by Innovate UK were predominantly oriented to refining the products or services under development, activities that enabled this to happen (access to data), or work that would support downstream commercialisation (e.g. testing acceptability for end-users or validation of the route of the market).

However, the findings also showed that projects were generally not designed to explore, or find solutions for, some of the adverse social impacts that could arise from the exploitation of AI:

- **Data security:** Activities to ensure user privacy, protect user data, or secure the technology from cyber-attack were not widely reported by firms leading these projects. This may raise concerns if a lack of development work in these areas threatens future user acceptance and/or adoption. These aspects were noted in stakeholder consultations as important things to consider throughout the development process, though more research is needed to understand the point at which this activity becomes critical (as product development may take precedence at early stages). Case study interviews also highlighted that uncertainty (and, possibly, lack of comfort) with regulations around data security are a potential barrier to project development:

  "I think that one of the main problems that we have is the GDPR stuff. I mean, I am actually quite comfortable, but there are people in my team which are a bit scared all the time. 'We cannot do this,

[38] It was noted that since the population of projects in the scope of this review was defined, more projects focused on financial services have come forward through Innovate UK's response mode funding mechanisms, and there may be value in revisiting the portfolio in the future.

we cannot do that.' And the lack of knowledge of what is possible, what is not possible." AI developer, CR&D funding

- **Workforce implications:** Only a small share of firms had used the project to explore workforce implications and/or any reskilling that may be required. This could be linked to the nature of firms being supported by Innovate UK, many of which were developing AI driven products and services that would be adopted by other parties. These firms are unlikely to directly experience (or have any control over) issues that could arise from workforce disruption and there may be little in the way of levers at Innovate UK's direct disposal (via its funding and associated conditions) to mitigate against these risks. Depth interviews with firms highlighted a view that adoption of AI would often increase efficiency (stimulating job creation) rather than lead to the destruction of jobs:

  "Again, this, kind of, goes a little bit back to the ethics side of it where, you know, people [think] putting these AI systems in place will basically get rid of people's jobs, but that, in my experience, it's nothing really like that. It's about efficiency, you know? So, actually, implementing it in one way means that the business is far more efficient, which means they have more money, and actually, they probably employ more people. So … there's that side of it that needs to be tackled, that perception of it that somehow it's bad thing, because it means you won't be able to get a job.", AI developer, KTPs

- **Ethical issues and bias:** Relatively few firms reported that they had used the project to explore ethical issues arising from the deployment of AI or to address possible cultural biases that may arise in AI driven decision making. Again, these were aspects that stakeholders cited as issues for consideration throughout the development cycle, but it likely that firms prioritised product development. One interviewee highlighted that AI trials and deployment do not just raise ethical issues, but also potential safety concerns (for example, when used to automate robotic platforms or vehicles). There was also a view put forward by some that there was insufficient regulation of some forms of trials:

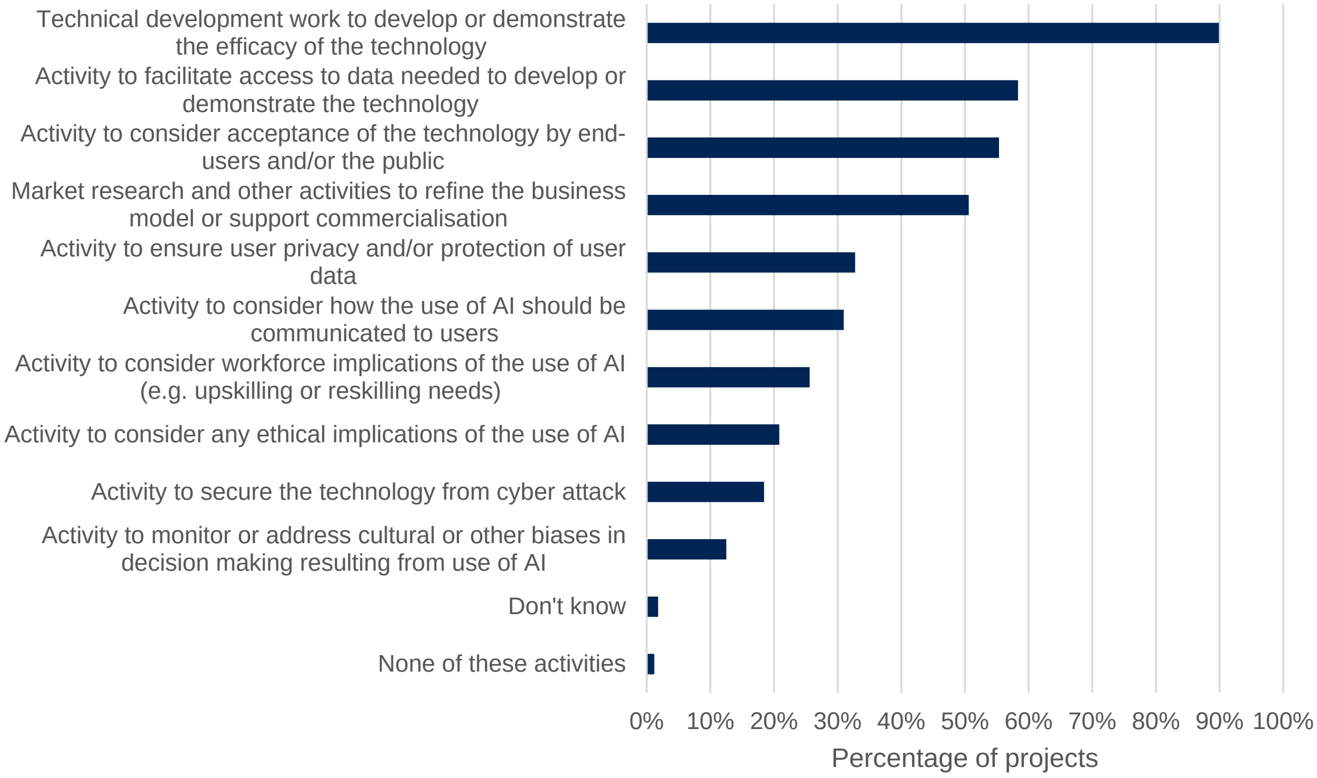
  'There should be more barriers in there to make sure things are run properly ... At the moment, pretty much anyone can do whatever they want,' Hardware developer, CR&D

  Nevertheless, some developers did not consider some aspects such as the 'explainability' of products as a significant issue. For example, in one case, a view was put forward that customers had no need to understand how a product worked, they were just interested in the benefits it provided:

  "I am a user. So, I am the user of our own product, right? I don't need to understand how AI works, I just want to experience the impact. And as a user, I don't need to understand it. I just need to experience it, that this is actually doing something useful for me. So, the less that the user knows, the better I think in this respect," AI developer, CR&D

  Stakeholders more broadly suggested a lack of consideration of these factors was thought to risk the image of AI more generally, and potential adopters may be unwilling to use a product/service provided by a developer that had not considered these in fear of the potential reputational repercussions. Consequently, Innovate UK could consider requiring AI related applications to be supported by a plan to explore the ethical considerations, potential for bias and the adequacy of data security.

Figure 4.4: Activities that the Innovate UK funded project involved



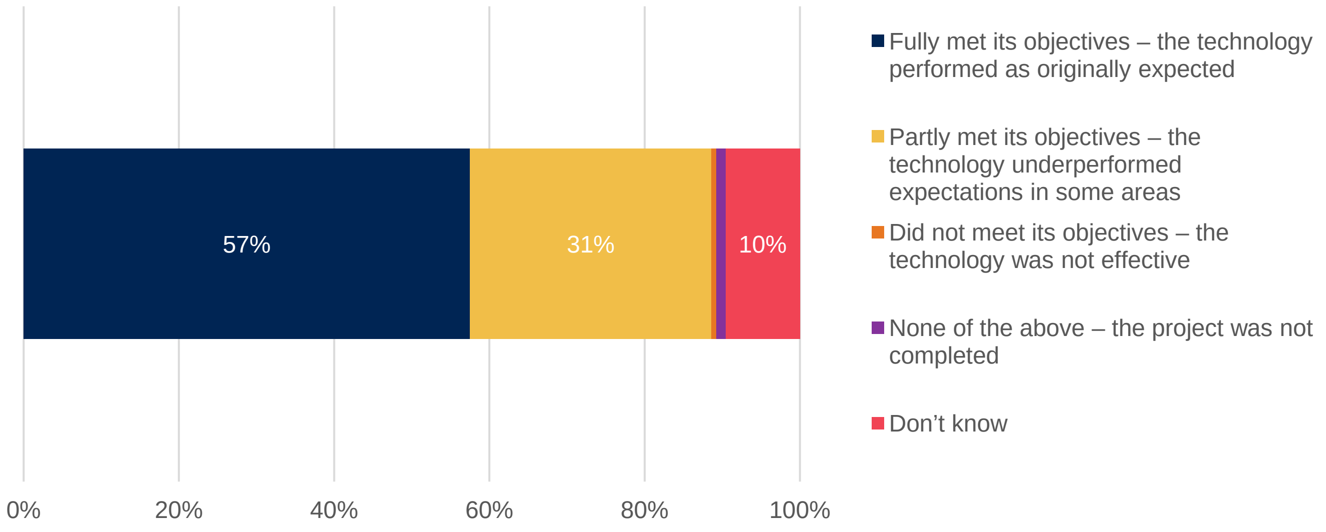
Source: Ipsos MORI (2021)

4.3 Project delivery

4.3.1 Achievement of technical objectives

Firms awarded grants were largely positive regarding the success of the projects funded by Innovate UK. Respondents largely reported that the project had fully (96) met or partly (52) met its technical objectives with none stating it had not met any of its objectives. Overall, this meant that 88 percent of projects had met objectives to at least some extent. This compares to 95 percent reported by firms benefitting from CR&D funding between 2012 and 2016. This could suggest that AI projects funded were slightly riskier relative to Innovate UK's overall project portfolio, but not significantly so.

Figure 4.5: Extent to which funded projects met objectives



Source: Ipsos MORI (2021)

4.3.2 Challenges encountered in project delivery

The challenges reported by firms securing grants from Innovate UK broadly aligned with those outlined in Section 3:

- **Access to data** was the most widely reported barrier by firms awarded grants. Eighty-eight percent of projects were reliant on access to data or the generation of new data. In addition to this, 32 percent of those projects required access to external data with a further 37 percent requiring generation of entirely new data through the project. Of the sectors for which more than 10 observations were available, projects in the manufacturing, transport, storage and logistics, and professional, scientific and technical activities sectors were more dependent on the generation of new data through the project (with 50 percent, 50 percent and 52 percent of projects respectively).

  Depth interviews underlined the importance of data to the successful delivery of projects:

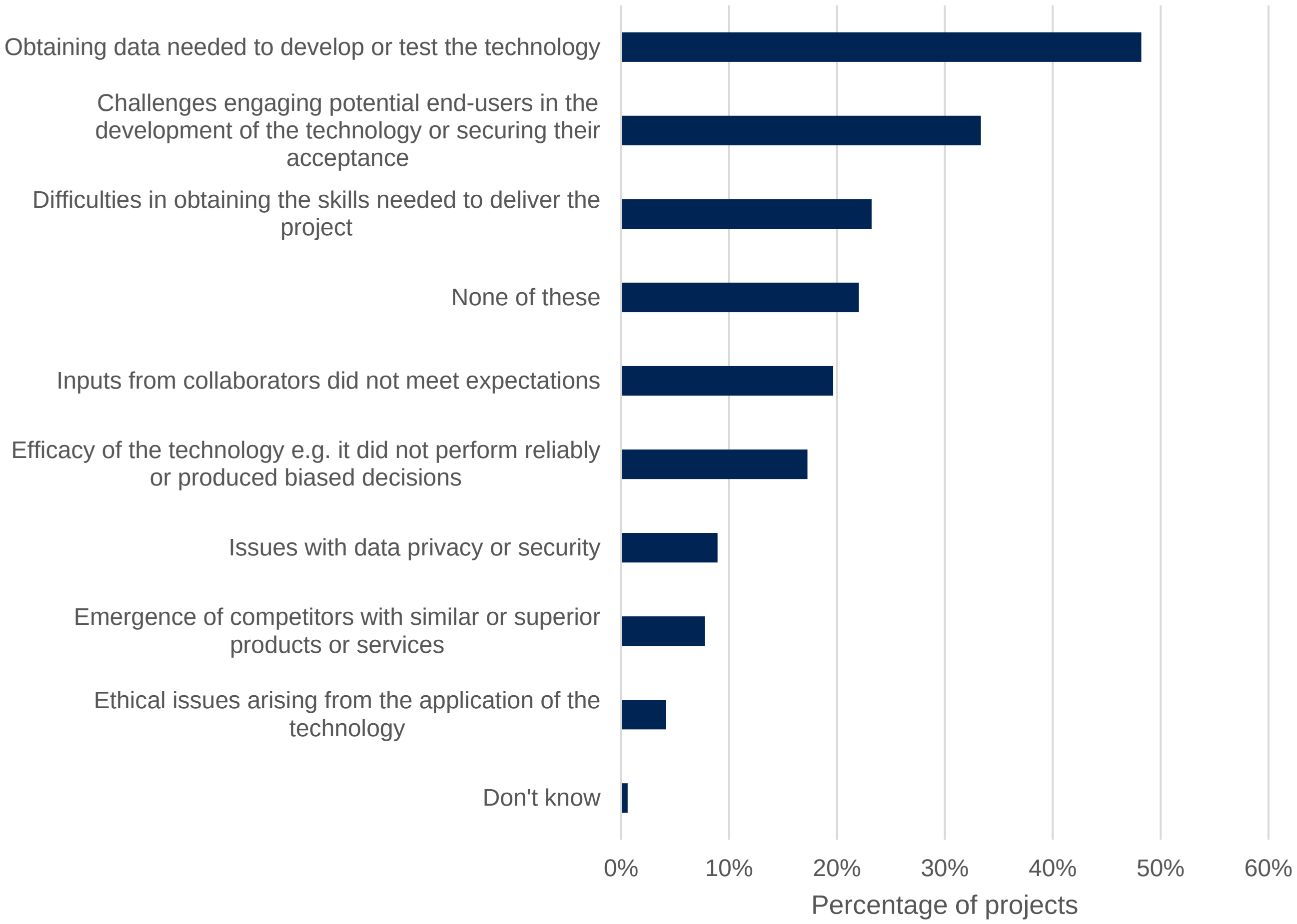
  "I think there's a tendency in, sort of, AI research to throw as much computational power at your problems as possible, and just assume that it's going to work out, whereas the reality is, it's more about the data." AI developer, CR&D programme

  The degree to which data access was problematic appeared highly dependent on the nature of the technology being developed. For example, while one firm developing image recognition software to identify weeds was readily able to access an image dataset of sufficient size for the project, others encountered more substantial difficulties. One firm seeking to develop speech and language therapy software had access to around 100 hours of speech recordings, requiring them to generate additional audio recordings (raising additional issues around obtaining appropriate consents). Quality issues were frequently highlighted, with one respondent reporting trialling a large number of training datasets before finding one that allowed the system to produce satisfactory results. Firms relying on external datasets also highlighted issues with their stability that were outside of their control – such as changes made to the way that data was processed (meaning algorithms may need to be adapted on an on-going basis to changes in the external environment, increasing development costs).

- **Engagement from end-users -** the second most reported challenge was securing engagement from end users and/or securing their acceptance. For commercialisation, this is an important challenge to overcome but it may not always be clear to potential customers what the additional value of using AI could be. Some stakeholders cited potential uncertainty amongst adopters as to the effectiveness of using AI in applications and potential concerns around liability. Depth interviews also suggested that user testing was critical in understanding whether technologies would be used for unintended applications and whether adjustments to the design would be needed (one case involved a robotics platform intended for use in farm applications being repurposed by farmers to tow a dead cow that could not be accessed by tractor, creating unexpected stresses on the system).

- **Skills and recruitment -** obtaining the skills required to develop the project was the third most widely reported barrier, reflecting the labour market challenges highlighted in the preceding section. Depth interviews highlighted some specific skills deficits in the AI workforce. One issue highlighted was that of relatively weak templates or processes for product development (i.e. systematic processes for building, testing, and validating products) leading to inefficiencies in the R&D process. As companies were often small firms, some had also never experienced hiring employees and did not have networks from which they could draw to generate candidates. Interviewees also made it clear that successful development of AI required the pairing of domain expertise with technical skills – i.e. to define what data was needed to train algorithms in an effective manner. Subcontracting was often used as a way of addressing these issues.

Figure 4.6: Challenges or barriers faced in delivery of project



Source: Ipsos MORI (2021)

4.3.3 Skills shortages

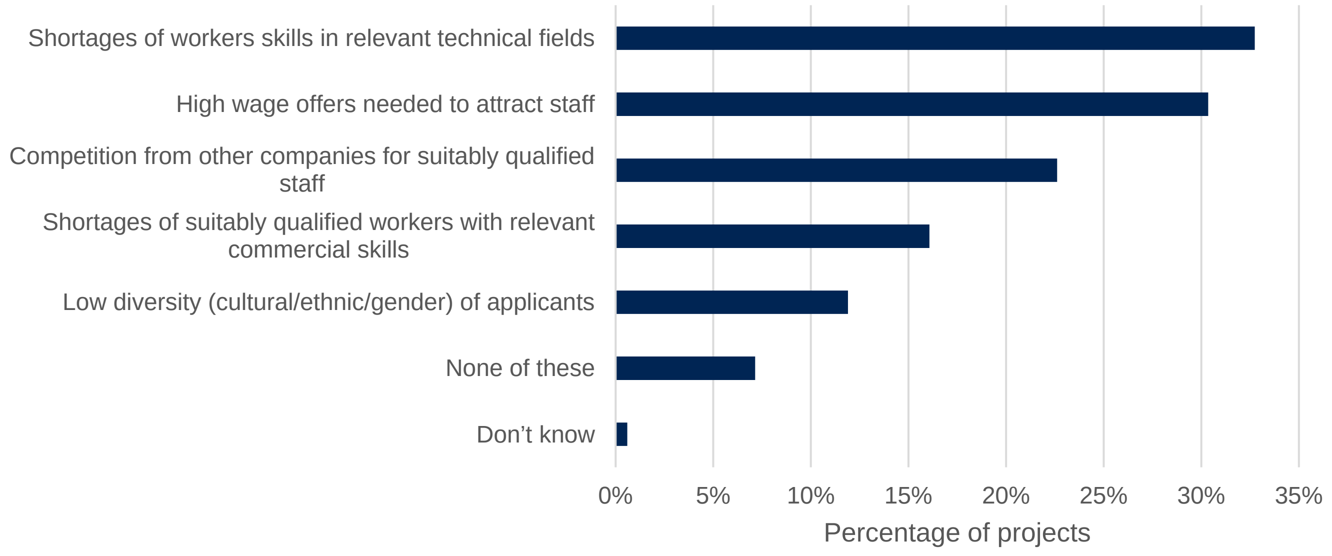
As highlighted in Section 3, stakeholders in the AI landscape indicated that AI development requires a wide range of technical skills from as AI application programming interfaces and deep neural networks through to user experience (UX) and data science. The skills required for more managerial roles also include data literacy, governance, and ethics.

The survey of firms receiving Innovate UK support indicated that labour market constraints were most acute for technical skills, requiring firms to make high wage offers to attract talent (aligning with the views of stakeholders consulted). This was reinforced by the depth interviews, which suggested that while there was a certain supply of individuals with the required skills, small companies were typically in competition with large, highly profitable, firms able to make substantially larger wage offers. Deficits in commercialisation skills were less widely reported (though as flagged above, depth interviews indicated that specific skillsets as well as an absence of standardised processes led to some inefficiencies).

Interviews also stressed the potential benefits of the KTP model in helping to address skills issues via the placement of graduate students with the firms:

> *"Yes, so, he worked there for two years, yes, and you know, it's great to see, because I think the KTPs are particularly good for the student, because of the amount of money that is given to training. You know, it really changed him from this just graduated, a little bit shy, a little bit scared to speak up, into somebody who is a senior developer now and is a really valuable asset",* AI developer, KTP programme

Figure 4.7: Labour market challenges



Source: Ipsos MORI (2021)

Diversity of applicants for roles was also considered less of a challenge (though as noted above, risks of bias driven by lack of cultural diversity did not appear to be a significant concern for the firms awarded funding). Depth interviews with firms did not highlight concerns regarding the diversity of the workforce. Whilst respondents recognised gender biases in the composition of their workforces, they did not consider this to be a significant issue and drew parallels with the broader engineering workforce. However, it is important to note that most of the specific applications of the technologies being developed by this project sample (e.g. search engine optimisation, weed identification) did not highlight any clear risks of discriminatory decision making.

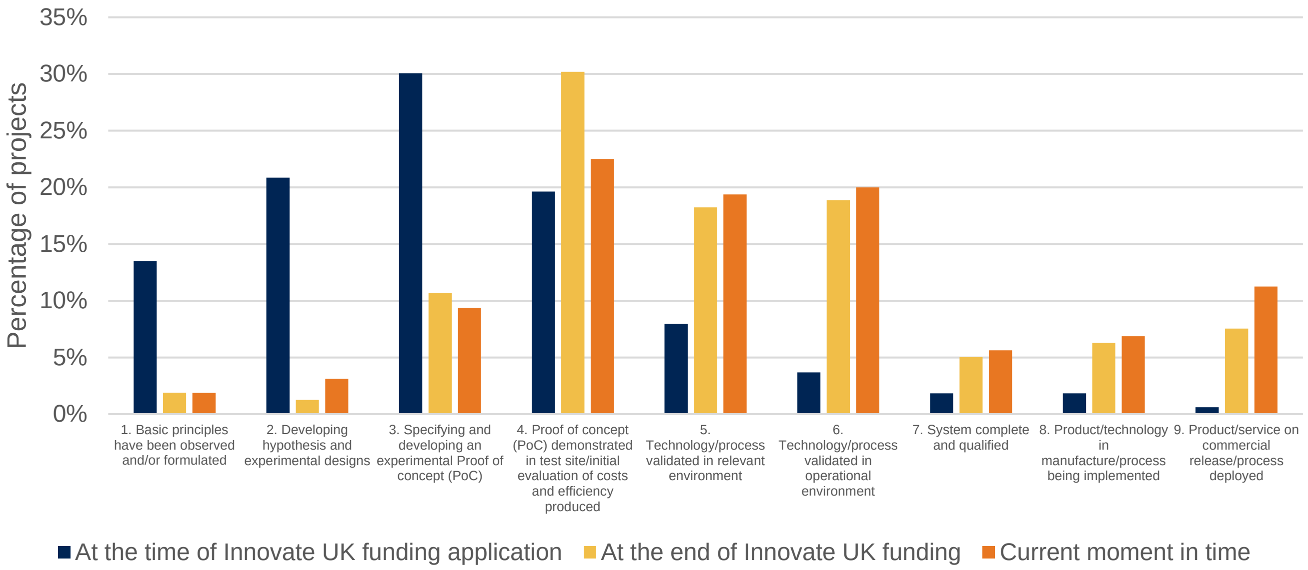
4.4 Technological progress

The figure below illustrates that firms have made significant progress in developing their technologies since being awarded grants. On average, firms progressed from an average TRL of 3.1 to 5.2 by the end of the Innovate UK project. Significant progress was also made following the completion of the project, with the average TRL associated with the portfolio rising to 5.7 by the end of 2020.

Following completion of the Innovate UK funded project, a total of 12 innovations had reached TRL9 and were being deployed commercially (more than 10 percent). These included the RODIO: Railway Optical Detection of Intrusions and Obstacles project which was being deployed by Network Rail as a scalable and cost-efficient solution for detecting obstructions and intrusions for rail infrastructure. It can be used to detect any obstacles on the tracks that might interfere with train journeys and cause delays. Another project reaching TRL9 used AI techniques to automatically extract insights from satellite video, together with complementary satellite and terrestrial data sets, for risk monitoring of complex construction project progress and critical global supply chain assets, by providing ongoing proactive change detection and analysis.

Protection of intellectual property was not a significant issue for firms supported and most firms had not made filings for IP rights following the grant award. Depth interviews did not highlight that IP was a particularly significant factor in determining the commercialisation outcomes of projects.

Figure 4.8: Technology readiness level over time

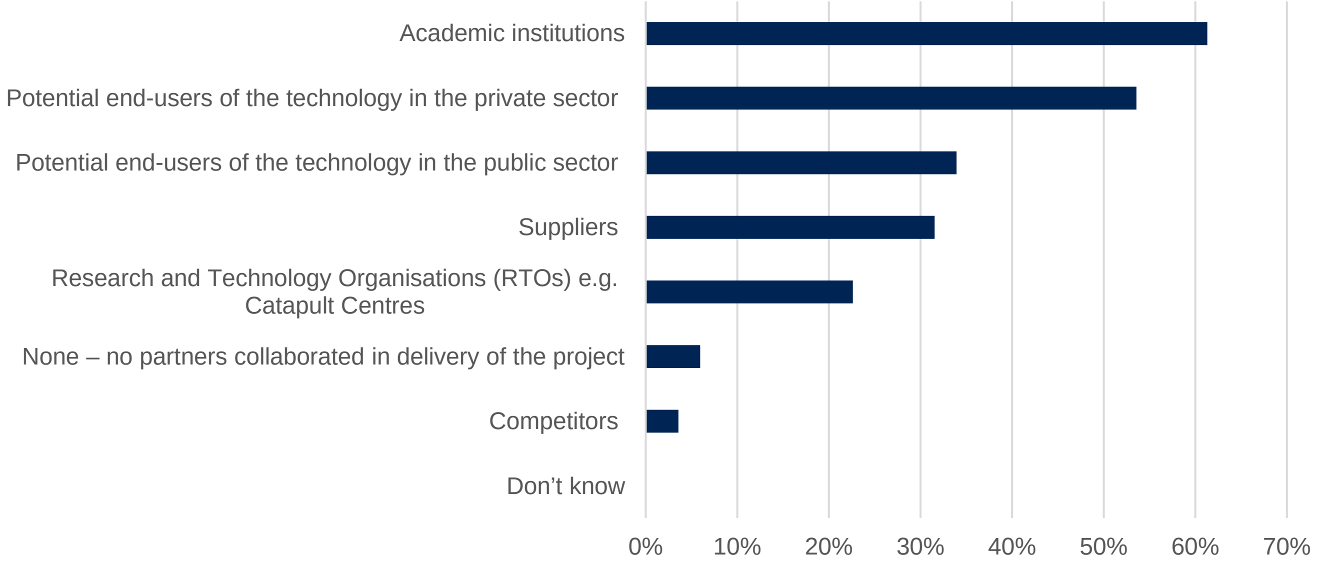


Source: Ipsos MORI (2021)

4.5 Collaboration

Collaboration was widely used by firms to both draw in expertise and knowledge not available internally and to provide a test-bed for the commercialisation of the technology (with many end-users in the private and public sectors involved in the delivery of projects). The survey showed that supported firms were most likely to engage with academics, followed by customers (in both the public and private sectors) and suppliers. Respondents reported they were least likely to collaborate with competitors.

Figure 4.9: Types of partners involved in Innovate UK funded projects

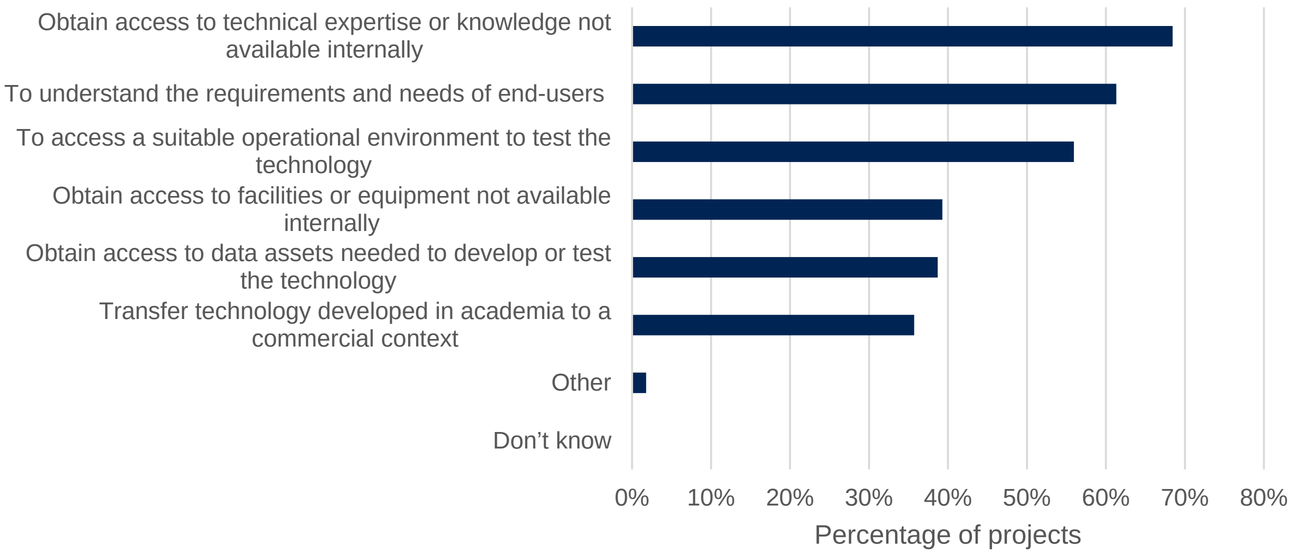


Source: Ipsos MORI (2021)

The most common reason provided by lead applicants for forming collaborations was to acquire access to specific technical skills and or expertise, as shown in the figure below. End-users were largely engaged as collaborators to understand their needs (the second most common reason for collaboration). However, depth-interviews highlighted issues on the adoption side where some firms had unrealistic expectations of what could be achieved, particularly where the staff involved were from non-technical backgrounds:

> *"You know, they were non-technical, it was a start-up, they were just two people, and they wanted this product, and we developed a proposal with them, and we started doing the work, and over the periods of the project, which was about eighteen months, we became very quickly aware that they didn't understand the, kind of, difference between fact and fiction around what AI can actually do and what it can't do",* AI developer, KTP programme.

Figure 4.10: Motivations for forming collaborations



Source: Ipsos MORI (2021)

While the focus of the study was on the commercial benefits associated with Innovate UK's support for artificial intelligence, depth-interviews also highlighted benefits from collaboration for academic institutions. For example, one interview suggested that their participation in the KTP programme both enabled them to produce publications that added to their knowledge and credibility as well as leading to £700,000 in research income.

4.6 Impact on R&D spending

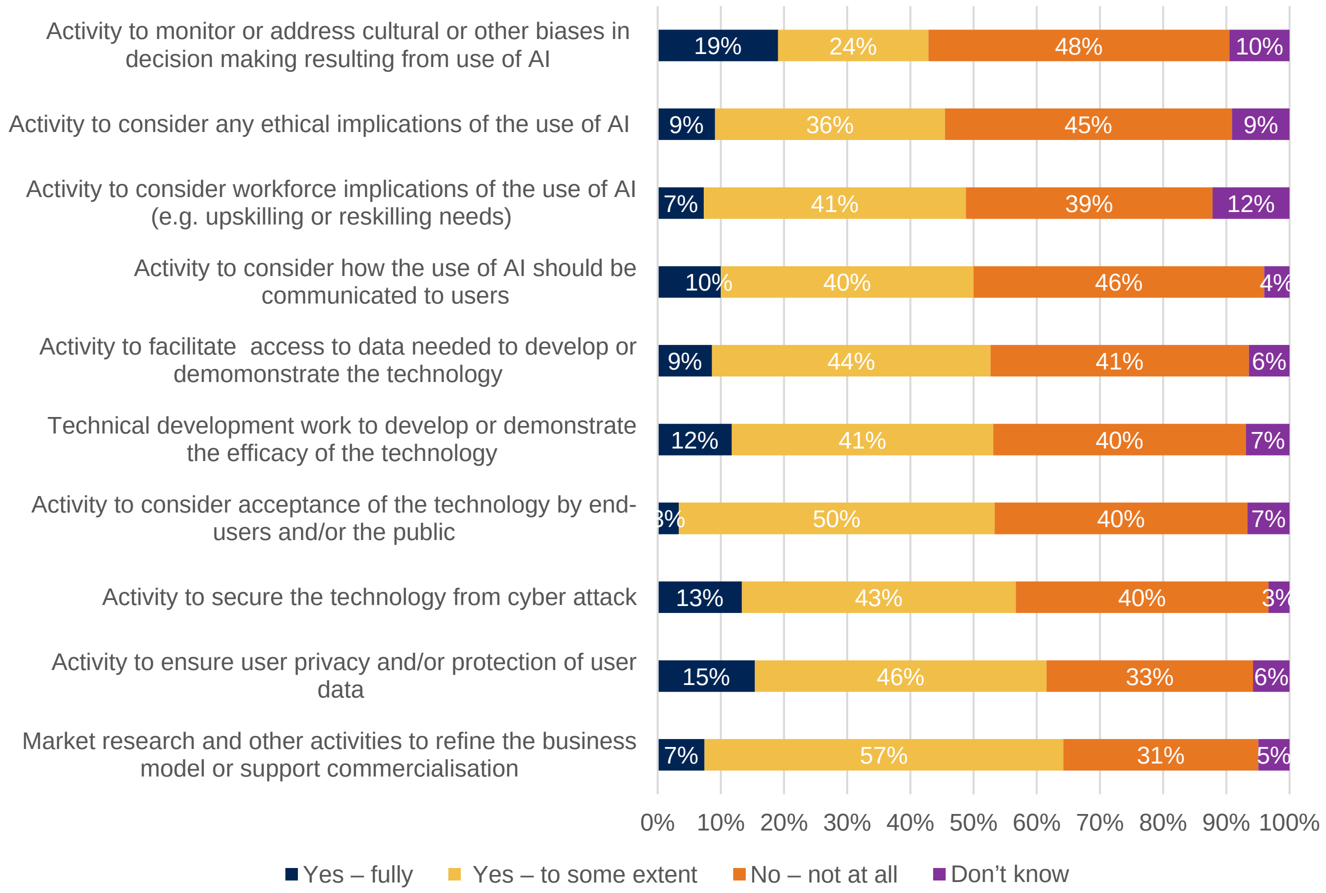
Innovate UK funding was expected to increase levels of spending on the development of AI technologies amongst firms receiving grants. This would be expected if Innovate UK's financial support leveraged additional resources into R&D projects that would not have otherwise been funded (or would not have been delivered at the same scale, over the same timescales, or in the UK).

4.6.1 Project progression without public support

Firms awarded funding considered that Innovate UK funding was critical in enabling projects to go ahead. Fifty-five percent of firms reported that they would not have been able to take the project forward without public sector support. Where projects would have gone ahead without funding, only 1 percent would have done so unchanged with 25 percent at a reduced scale, 21 percent with reduced scope and 27 percent at a slower pace. Seven percent would have gone ahead in a different country and 17 percent at a later date.

Respondents indicated that Innovate UK funding had broadly similar impacts in enabling most aspects of the work programme that formed part of the project, and there was no clear pattern in terms of elements that could or could not have been taken forward without public support. However, Innovate UK funding was most critical in enabling firms to explore, monitor or address bias in decision making and consider the ethical implications of the use of AI (where these aspects formed part of the work programme, noting that this was not a prominent feature in most projects).

Figure 4.11: To what extent would you have been able to take forward the following elements of your project had you not been awarded Innovate UK funding?



Source: Ipsos MORI (2021)

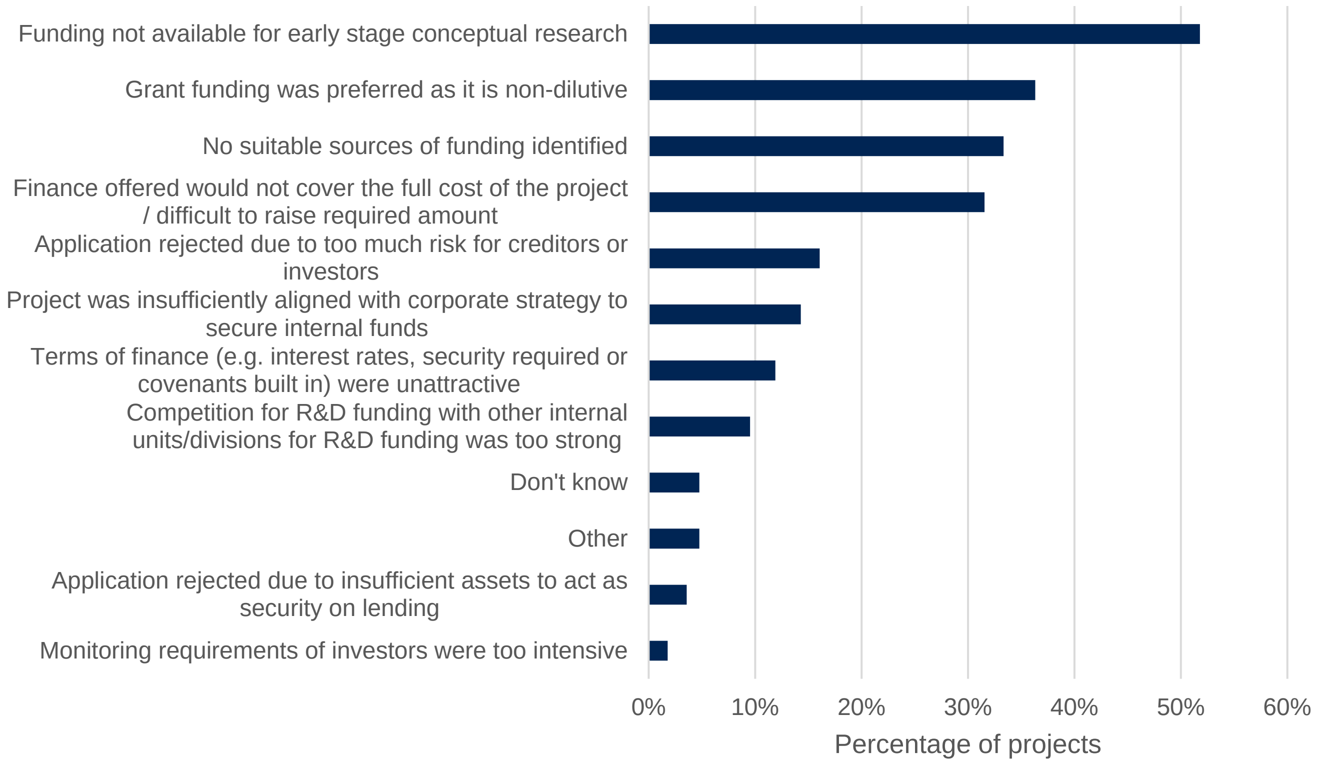
4.6.2 Challenges obtaining private funding

Respondents to the survey appeared to indicate that shortages of funding for early stage research was the main factor that constrained private funding for the project (or that they were unable to raise private funding in sufficient amounts or were unable to identify appropriate sources of funding). A reasonable share of respondents also articulated a preference for non-dilutive sources of funding. Given the large increases in VC investment in the UK AI sector observed in the late 2010s, there may be a case for:

- Closer scrutiny of the economic case for funding AI projects (i.e. how far public sector support is needed to enable the research programme to go forward), noting that some stakeholders reported that AI firms faced disadvantages relative to other technology firms driven by the lengthier development time required to reach the market and the underlying uncertainties associated with ever adapting models.

- Supporting some firms with ‘investment readiness’ through Innovate UK’s business support programmes to help them build skills in engaging with angel and VC investors.

Figure 4.12: Why private sector funding was deemed insufficient/inappropriate to take project forward

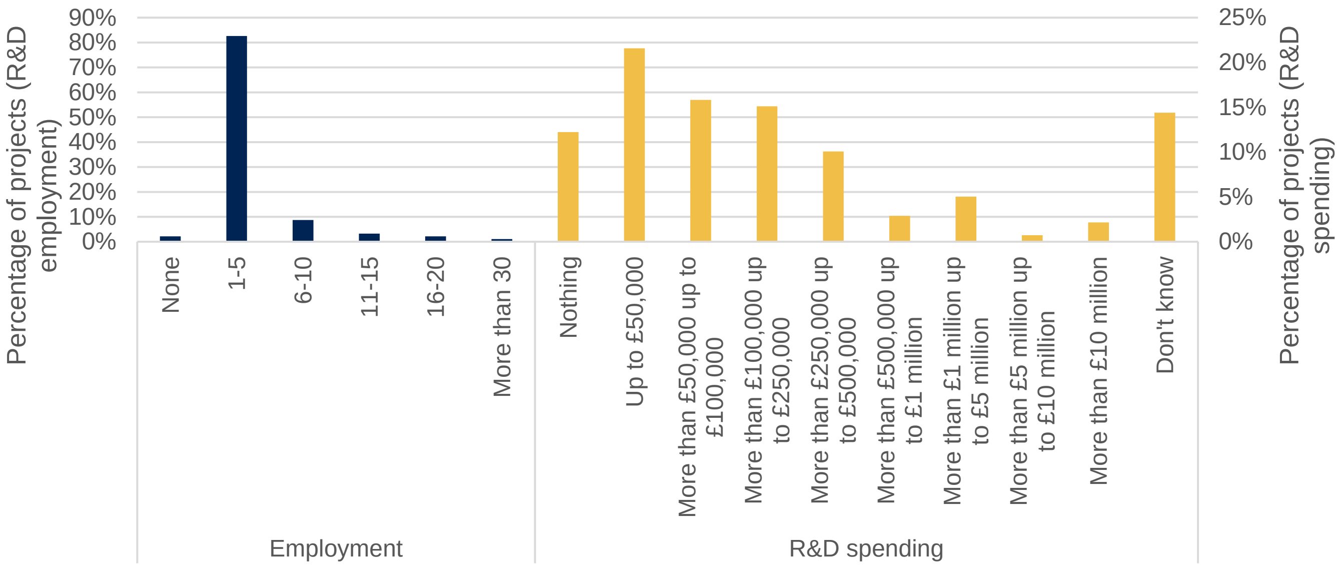


Source: Ipsos MORI (2021)

4.6.3 Impacts on R&D activity

Most firms responding to the survey indicated that they had increased their R&D spending (on the innovation forming the focus of the project) since being awarded a grant, as illustrated in the following figure.

Figure 4.13: Additional R&D expenditure and employment for the support of the innovation after Innovate UK funding ended



Source: Ipsos MORI (2021)

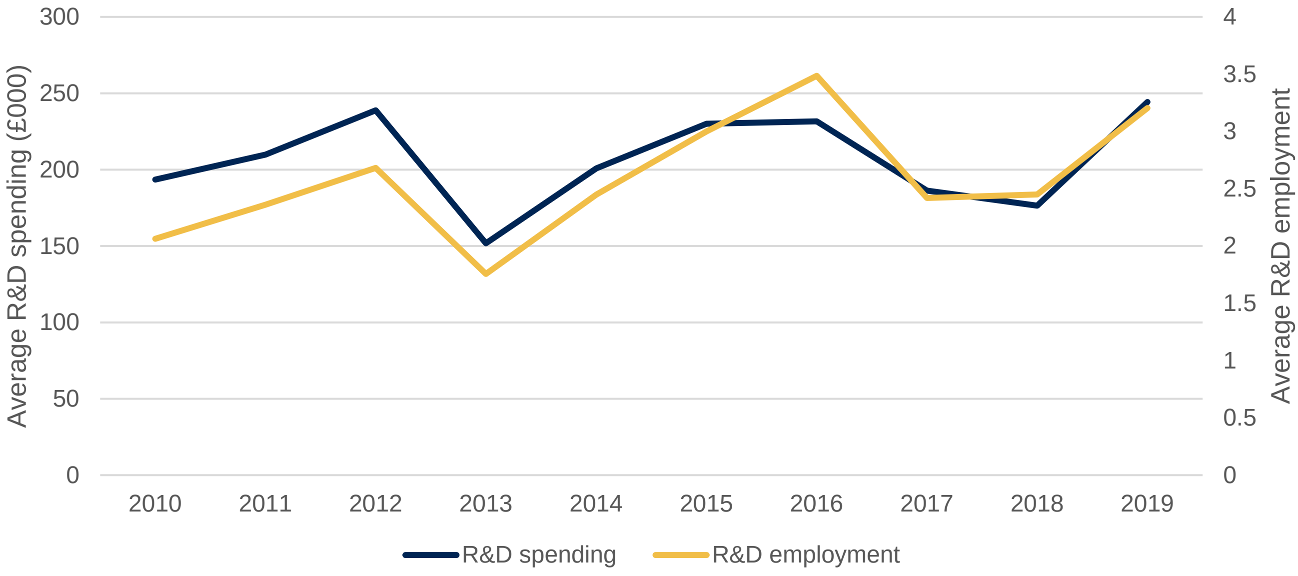
When asked about the number of additional R&D workers employed in technical roles as a result of the Innovate UK project, 45 percent of respondents also indicated that they had taken on 1 to 5 workers in such a capacity. Taken together these provide encouraging signs that Innovate UK funding in AI projects led to increased R&D activity associated with the projects funded.

4.6.4 Econometric analysis

Earlier findings provide indications that Innovate UK funding influenced the ability of applicants to take forward projects and those above indicate potential effects on R&D activity. A complementary series of econometric analyses were completed to help explore these issues in greater depth and help quantify the magnitude of the effects involved. These involved examining the overall R&D spending and employment of those awarded Innovate UK funding relative to two comparison groups (firms active in the AI vertical but not applying for Innovate UK funding and internal comparisons between those awarded funding at an early and later stage).

The data driving the analysis was gathered from the ONS Business Expenditure on R&D survey which measures total R&D activity – so while the analyses could explore volume effects, it was not possible to investigate other possible impacts (such as the diversion of R&D into AI specific technologies). Figure 4.14 below provides an overview of trends in average R&D employment and annual R&D spending across firms that were awarded grants using a trimmed mean (to remove the influence of some large firms in the sample of firms linked to the BERD that distorted patterns over time). It indicates that R&D spending and employment broadly rose over the period.

Figure 4.14: R&D employment and expenditure between 2010 and 2019, applicants for Innovate UK funding (2019 prices), trimmed mean



Source**:** ONS (2021). Ipsos MORI analysis of matched records to the Business Expenditure on R&D Survey.

The econometric analysis completed sought to control as far as possible for both observable and unobservable differences between firms awarded funding and the relevant comparison groups:

- **Effects on R&D spending:** There was evidence that Innovate UK support produced a temporary increase in the volume of R&D undertaken by those firms assuming the lead role. Each funded project led to:

- An estimated 9.0 to 9.8 percent increase in R&D spending in the year funding was awarded (although these effects were only weakly significant).
- Grants led to a 12.9 to 13.3 percent increase in R&D employment in the year funding was awarded. This effect fell to 9.2 to 9.7 percent in the year following the award of the grant.

- **Persistence:** No effects on R&D activity were visible two years post award suggesting that the effects of Innovate UK funding were temporary. This implies that grants brought forward that may have otherwise taken place at a later stage, though this is not consistent with other findings that suggested that Innovate UK grants had lasting effects (for example, on equity investment and employment). The result could be function of the relatively short time that had elapsed since funding was awarded. 2018 and 2019 saw the largest number of projects funded, and the effects of Innovate UK support may not yet be fully visible. An attempt was made to explore the impacts of older projects, but sample sizes were too small to identify statistically significant effects.

- **Effects by firm size:** The findings were broken down by size of firm to explore differential impacts across firms of different sizes. The results indicated that Innovate UK grants had an on-going effect on the R&D spending and employment of small businesses (i.e. those with 10 to 49 employees), of 18 percent and 14 percent respectively. No significant effects were found amongst businesses of other sizes, potentially suggesting that Innovate UK's grant funding for AI is most effective when targeted at smaller, earlier stage, companies.

- **Impact on total R&D spending:** The high level of variation in the findings creates some uncertainties in the terms of the basis for estimating the total effect of Innovate UK's support for AI on R&D spending. Full details are provided in Annex A, but estimates of the total increase in R&D spending driven by Innovate UK's support for AI range from £46m to £685m depending on the approach taken. These estimates also do not account for the possibility that Innovate UK funding placed pressure on prices, leading to reductions in R&D activity elsewhere.

- **R&D jobs:** There is also significant uncertainty around the scale of the impacts of Innovate UK's support for AI on total R&D jobs. Estimates ranged from 6,000 to 6,200 short-term jobs created to 80 on-going jobs created, depending on the approach. Again, full details are provided in Annex A.

Table 4.1: Estimated impact of Innovate UK grants for AI and machine learning on R&D activity

	Model 1	Model 2
Control sample	AI active non-applicants	Early vs later applicants (pipeline design)
Number of observations	1,939	1,824
Estimated % impact on R&D employment		
In year grant was awarded	0.133***	0.129***
One year after	0.097*	0.092*
Estimated % impact on R&D spending		
In year grant was awarded	0.098*	0.090*
One year after	-	-

Source: BERD, ONS, Ipsos MORI Analysis. *, **, *** show whether the estimated coefficient was significant at the 90, 95, and 99% level of confidence respectively.

5 Impacts of Innovate UK funding

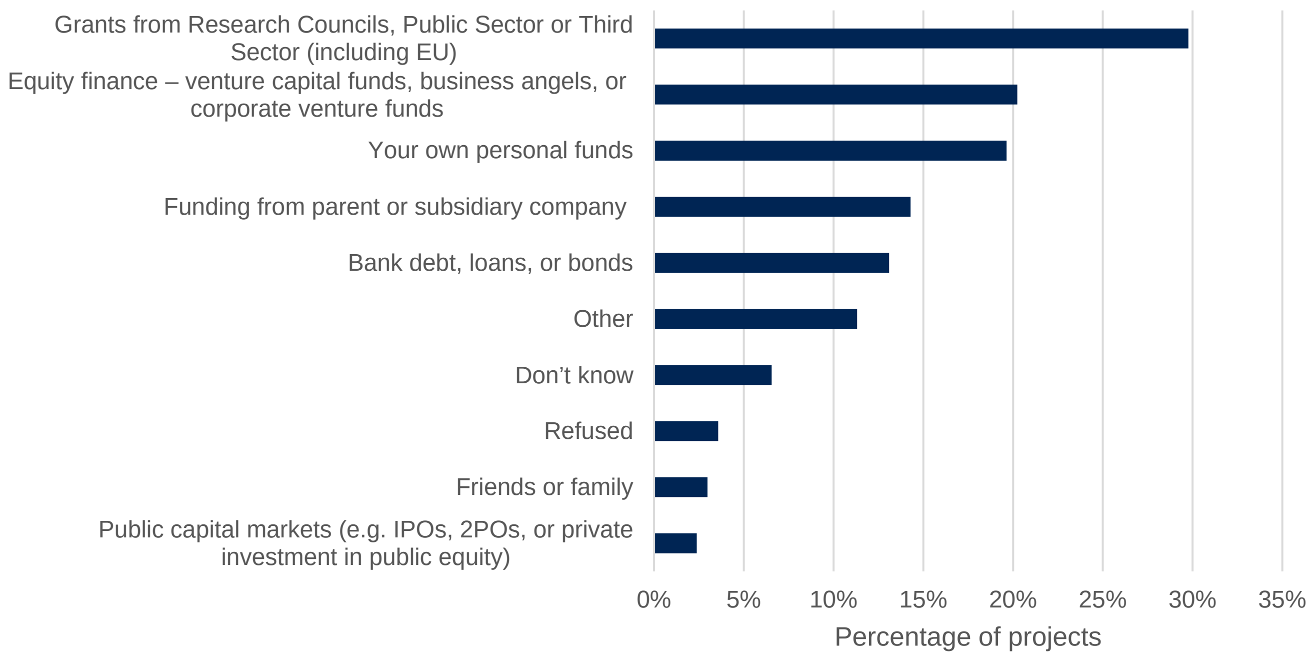
This section presents an analysis of how far Innovate UK funding has led to effects in supporting firms to raise further funding for follow-on development and commercialisation, and associated impacts on firm performance. Evidence for this section is taken from the programme of data-linking and econometric analysis, survey of successful Innovate UK applicants and analysis of monitoring records.

5.1 Further funding secured

5.1.1 Follow-on funding

Post-project completion, a high share of applicants (70 percent) secured additional funding to support the development of the innovation. The most common source of further funding was grant funding, which was obtained by 30 percent of funded firms. Equity finance was secured by 20 percent of firms whilst another 20 percent of projects used personal funds to support further development. Few firms (two percent) had progressed as far securing funding through public capital markets.

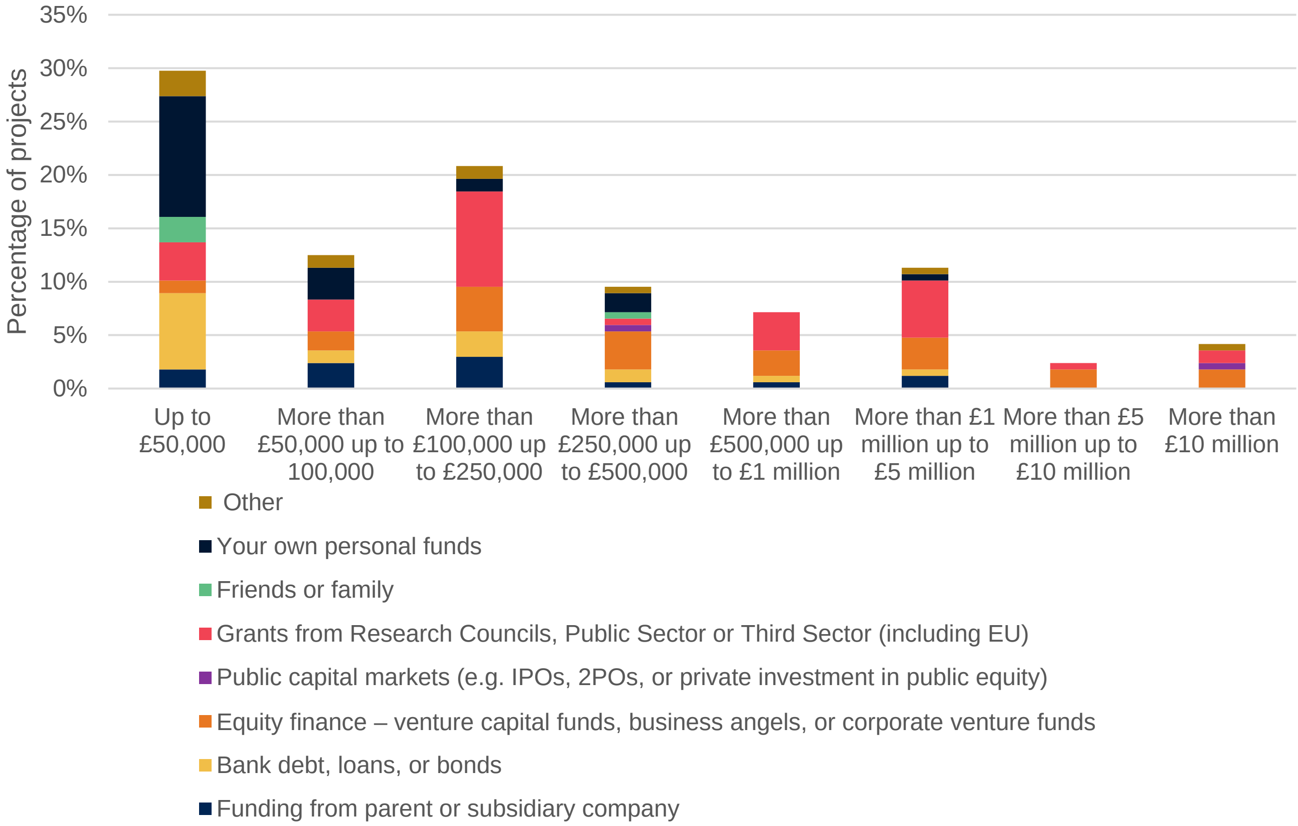
Figure 5.1: Sources of additional funding post project completion



Source: Ipsos MORI (2021)

Most sources of funding provided relatively small amounts of resources for follow on development (less than £250,000). In total, 25 percent of projects secured funding of over £500,000 from any one source. Grant funding and equity finance were the dominant source of funding for larger amounts (i.e. sums of funding exceeding £250,000). There was little evidence of firms self-financing further R&D from profits or from funds provided by parent companies, which is consistent with the profile of the firms supported by Innovate UK (i.e. predominantly disruptive start-up companies).

Figure 5.2: Amount of additional funding secured



Source: Ipsos MORI (2021)

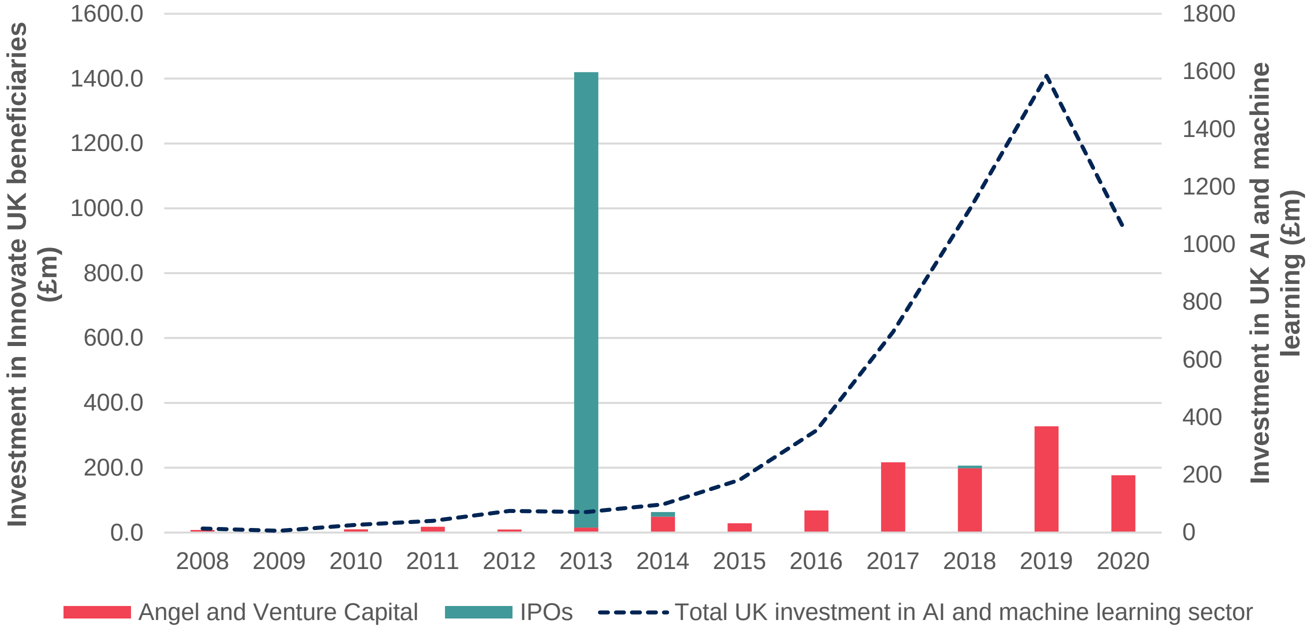
5.1.2 Equity investment

Data compiled from PitchBook indicated that 145 of 821 firms (18 percent) secured some form of equity finance after being awarded a grant by Innovate UK by July 2020. The overall amount raised by these firms totalled £2.3bn over 288 funding rounds. This covers both leads and collaborators and included some fundraising activity by collaborators that were not obviously linked to the grants awarded (particularly a £1.4bn IPO completed by Dun & Bradstreet in June 2020).

Investment in firms leading projects should provide a clearer signal of levels of investment that could plausibly be linked to the grants awarded. Restricting the analysis to firms that were the lead partner on at least one project showed that 128 of 493 firms (26 percent) attracted equity funding at some point after being awarded a grant. These companies raised a total of £758m over 259 funding rounds. The figure below shows total investment in these companies between 2008 and 2020 and illustrates that equity investment in these companies began to rise from 2017 onwards, slightly later than the general growth in investor interest seen from 2015.

It should be noted that not all Innovate UK beneficiaries are headquartered in the UK or necessarily classed as developers of AI or machine learning. For example, the IPO in 2013 related to the floatation of Zoetis, a US headquartered producer of vaccines and other health products for animals with UK operations in Leatherhead (which led a project to develop automated diagnosis of pig welfare problems in 2015). Nevertheless, UK headquartered companies accounted for £619m of the £758m raised following the grant award. £332m of the £758m was raised by companies classed as active in the 'artificial intelligence and machine learning' industry vertical. Again, this signals Innovate UK may be promoting broader adoption of the technology outside of the core AI and machine learning development community.

Figure 5.3: Equity investment raised by Innovate UK beneficiaries, 2008 to July 2020



Source: PitchBook, Ipsos MORI user defined query. Note that 2020 is an incomplete year.

Seven lead companies raised more than £30m after being awarded an Innovate UK grant, accounting for 42 percent of the investment raised. Details of these outlying successes are provided in the following table. Five of the seven companies benefitted from Innovate UK funding in 2015, and four of the seven received funding emerging from the historic Smart programme (funding for prototype development and proof of concept). None of the outlying successes were awarded funding before 2015. This could suggest that Innovate UK's support for the emerging technology required complementary interest from private investors to deliver significant investment impacts.

However, it should also be noted that AI and machine learning was not a specific policy priority for the agency in the 2010 to 2015 period. The framework of 'eight great technologies' developed as part of the Coalition Government's Industrial Strategy identified Big Data and Robotics and Autonomous Systems as technological priorities in 2013. However, actions to support growth focused on developing supporting infrastructure (such as the Digital Catapult) and funding for Centres of Excellence in academic institutions, rather than significant programmes of support for industrial R&D.

Table 5.1: Innovate UK beneficiaries raising more than £30m post grant award

Company	Amount raised since grant award (£m)	Innovate UK project(s)
Rigetti – a US headquartered developer of quantum computing integrated circuits intended to revolutionize computing speed and efficiency.	62.0	Rigetti UK was awarded funding in 2019 to collaborate with Oxford Instruments, Standard Chartered, Phasecraft, and University of Edinburgh to advance quantum computing in the UK.
Healthy.io – Israeli developer of a urinalysis mobile application designed to help users perform home-based urine tests.	49.2	Healthy.io received a grant in 2019 to test smartphone-based home urine testing for antenatal care in 100 women in the Royal United Hospitals Bath NHS Foundation Trust.
SoftIron – UK developer of task-specific hardware appliances designed for scale-out data center solutions.	44.4	SoftIron collaborated with the University of Portsmouth to produce an AI-based software agent that will work with SoftIron

Company	Amount raised since grant award (£m)	Innovate UK project(s)
		low energy storage servers to reduce the storage server energy requirements. Funding was awarded in 2015.
Tessian – UK developer of a next-generation email security platform designed to detect and prevent inadvertent data loss.	44.0	Tessian (formerly CheckRecipient) received proof of concept funding through Innovate UK's historic Smart programme in 2015. The project sought to transform its AI by incorporating natural language processing and machine learning technologies applied to the textual content present in email to improve the accuracy of predicting misaddressing errors.
Yoyo – UK developer of a mobile payment and loyalty marketing platform designed to combine mobile payment with loyalty programs.	42.0	Yoyo were awarded funded under the historic Smart programme in 2015 to develop a prototype platform to analyse data collected from mobile payments automatically.
Elvie – UK developer of feminocentric products designed to improve women's lives through smarter technology.	39.4	Elvie (formerly Chiaro Technologies) were awarded funding from the Smart programme in 2015 to develop proof of concept for adapting existing sensor technologies used in clinic settings to the consumer market, in particular for women.
Egress – UK developer of an email security platform designed to manage and protect unstructured data.	34.7	The aim of the Trust Network Platform (TNP) project was to demonstrate and evaluate various techniques that can significantly reduce the administrative burden of establishing encryption systems. The project was funded through the Smart programme in 2015.

Source: PitchBook, Ipsos MORI user defined query.

5.1.3 Mergers and acquisitions

In addition to capital raised through equity investments, 37 firms were acquired after being awarded a grant by Innovate UK in transactions with a total value of £3.7bn. A large share of this was accounted for by the £2.7bn acquisition of Atkins in 2017 (a large engineering consulting firm) by SNC-Lavellin, which was not directly connected to the firm's activities in the technology area. However, there were several notable acquisitions of firms whose core business model centred on developing technologies involving the application of artificial intelligence. This included a £410m buy-out of Foundry Visionmongers by Roper Technologies, a £267m acquisition of Touch Surgery in 2019 by Medtronic, an £85m acquisition of ASV Global by L3 technologies, and a £70m take-over of Nanna Therapeutics by Astellas Pharma.

In addition, two Innovate UK supported firms developing AI related products, not within scope of the analysis, were acquired by tech industry leaders with a $250m acquisition of SwiftKey by Microsoft and a $150m buyout of Magic Pony Technology by Twitter.

5.1.4 Challenges obtaining funding

Firms reported four key challenges in obtaining follow-on funding. The primary reason given was that there were shortages of external funding (rather than a lack of interest in the sector amongst investors). This should be taken in the context of rapidly expanding overall levels of VC investment in the sector, and additional responses given by firms provides some indication of the reasons they may have experienced shortages:

- **Clarity of commercialisation plans:** There was evidence that a significant share of firms had not sufficiently developed their commercialisation plans. Around a fifth of firms reported that the route to market was not clear or that they had experienced challenges in demonstrating the commercial potential to investors. On the surface, this suggests that this group of firms could potentially benefit from enhanced commercialisation support and/or a greater focus on market validation as part of the projects funded by Innovate UK.

- **Risk:** A significant share of firms highlighted the level of risk associated with the innovation as a factor constraining investment. However, relatively small numbers suggested that the technology was not sufficiently developed for investors. This suggests that the level of commercial risk may have been a more significant factor, which may reflect issues relating to the maturity of commercialisation plans.

- **Gaps in funding:** As highlighted above, many firms sought further grant funding to continue the development of their projects. Depth interviews indicated that some firms were reliant on grant funding and did not seek private funding to support on-going development of their projects. This created gaps between phases of development as firms stalled development on completion of the project as they applied for follow-on grants.

Figure 5.4: Challenges securing additional funding post completion

Source: Ipsos MORI (2021)

5.1.5 Impacts on securing private finance

A series of econometric analyses using PitchBook data on equity investments secured by firms between 2008 and 2018 suggested that Innovate UK awards had a significant effect on the ability of firms to raise external funding:

- **Impact on equity investment:** The findings suggested that each Innovate UK grant increased the total equity investment raised by companies by 5.3 to 16.4 percent (with the most robust findings towards the lower end of this range). The estimated impacts were larger for lead applicants than collaborators (consistent with past studies).

- **Market conditions:** Grants awarded in 2015 or afterwards were more effective in leveraging additional equity investment than those awarded before this. This indicates that Innovate UK funding has complemented the growth of private investment, rather than crowding out investments that would have otherwise been made with private funding.

- **Total leverage:** The average amount of equity funding raised by firms was £4.1m by the end of 2019. This gives an estimated average impact on fundraising of £215,000 or a total effect of £212m when aggregated over the 984 awards in the scope of this analysis[39]. Despite the long timeframe of the analysis, this should be considered an estimate of the short-term effects of Innovate UK funding as most projects in scope were comparatively recently funded (i.e. from 2017 onwards).

Table 5.2: Estimated impact of Innovate UK grants for AI on equity investment raised

	Model 1	Model 2	Model 3
Fixed effects (firm level)	No	Yes	Yes
Fixed effects (year)	No	No	Yes
Number of observations	12,315	12,315	12,315
Estimated % impact of each Innovate UK grant on cumulative equity investment (£ms) raised			
All grants	0.153***	0.164***	0.053**
Leads	0.206***	0.217***	0.107***
Collaborators	0.056***	0.063***	-0.063**
Grants 2008-14	0.104***	0.117***	0.023
Grants 2015-19	0.170***	0.175***	0.062**

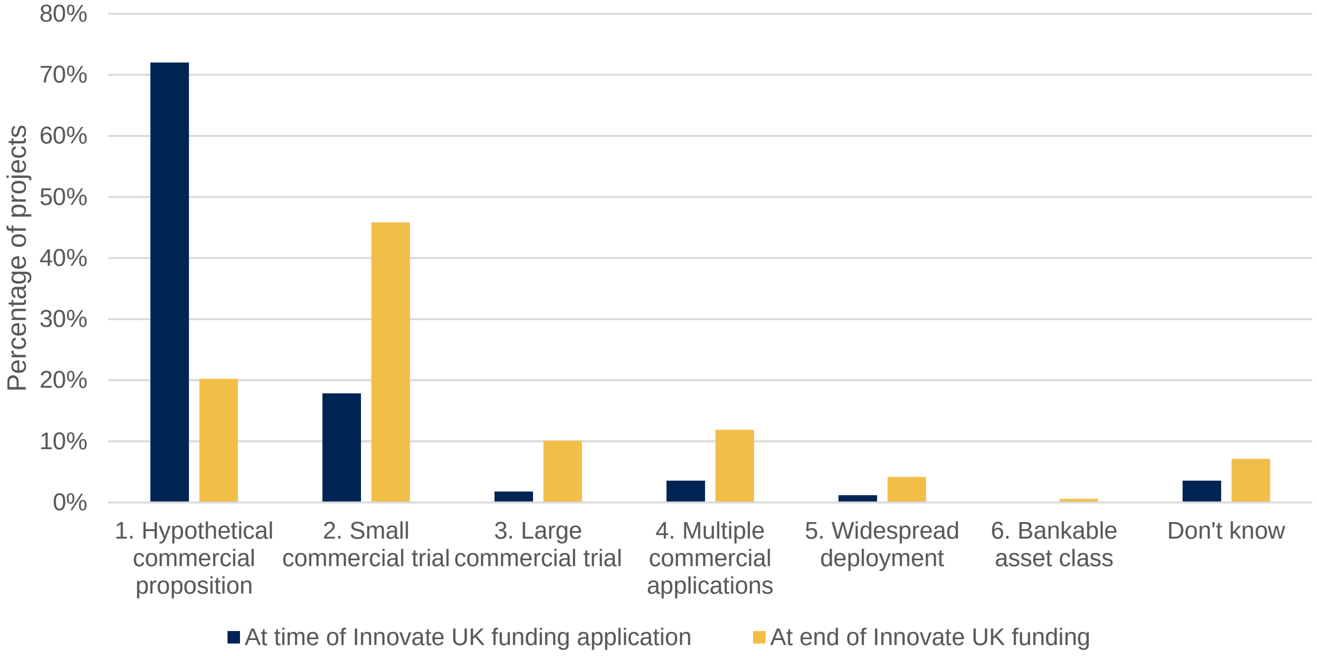
Source: Ipsos MORI. *, **, *** show whether the estimated coefficient was significant at the 90, 95, and 99% level of confidence respectively.

5.2 Commercialisation

Firms made significant advances in commercialising the innovations at the heart of their projects since being awarded the grant. While 71 percent of projects were reportedly a 'hypothetical commercial proposition' at the time the grant was awarded, the majority had at least reached small commercial trials and a small number had reached 'widespread' deployment. One of those projects reaching widespread deployment was a platform used to record and analyse sports related video to help develop and improve players, provided by Statmetrix Limited.

[39] Note that these 984 awards were awards made to leads in addition to those made to collaborators and so is greater than the 757 projects funded.

Figure 5.5: Commercial readiness from before application to after completion of the project

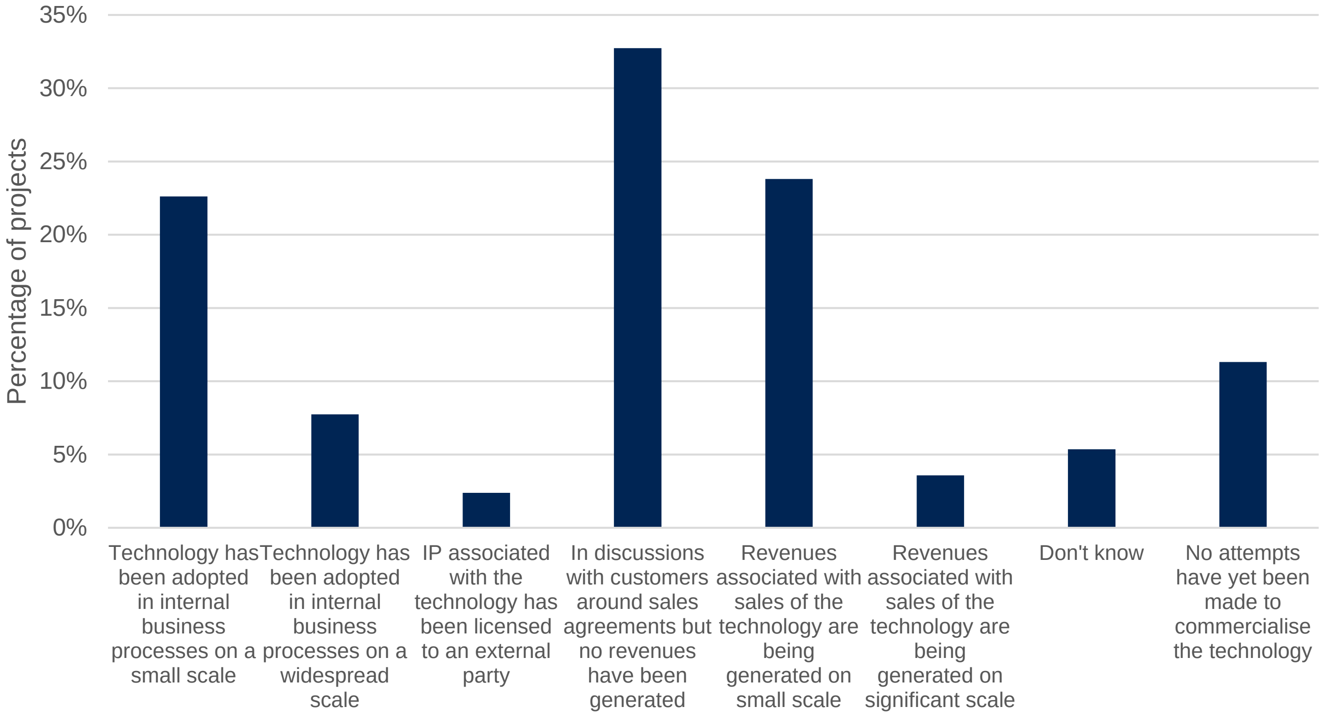


Source: Ipsos MORI (2021)

Most respondents indicated that they were involved in on-going discussions with customers or that they were generating revenues from the innovation at a small scale. Only 11 percent of projects had made no attempt to commercialise. However, this illustrates that most projects were yet to be widely adopted and generating revenues on a large scale.

The general picture was generally consistent with the depth interviews, which suggested that CR&D projects had progressed, but firms were some way from being able to demonstrate scalable revenues from the products. However, the interviews also indicated that some KTPs led to some rapid commercialisation impacts. In one example, the respondent indicated that algorithms to optimise search placement were deployed comparatively rapidly and contributed millions in additional revenues for the firm.

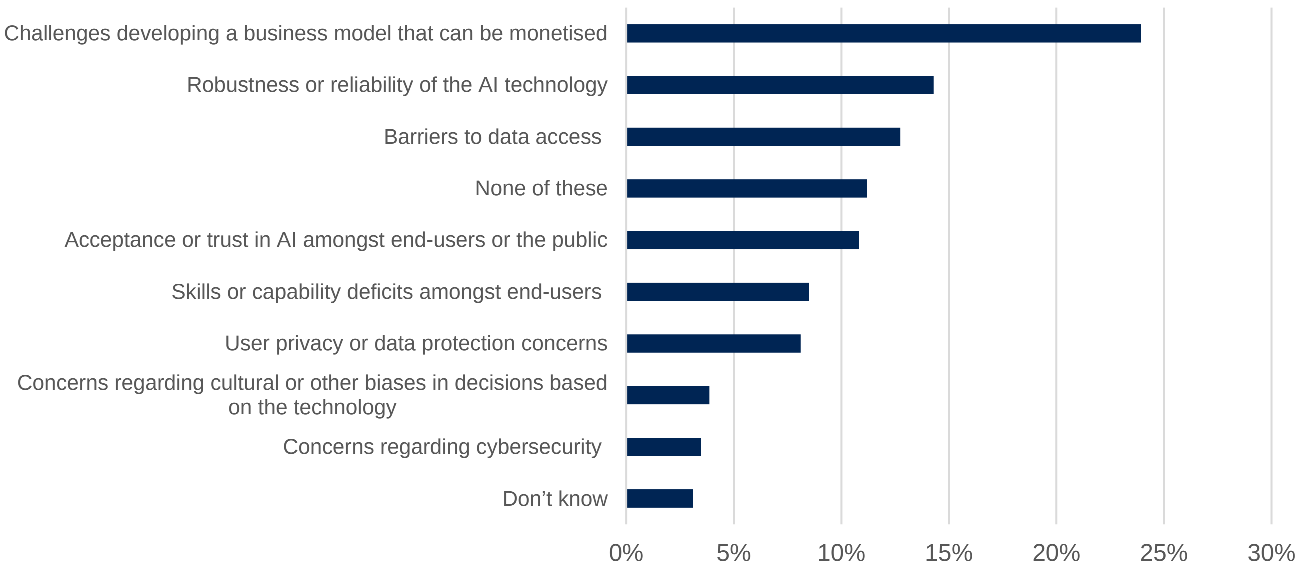
Figure 5.6: Progress made with commercialisation of the technology over the lifetime of the project



Source: Ipsos MORI (2021)

The most significant barrier reported by applicants was in developing a monetizable business model with almost 25 percent of projects citing this as a barrier in the survey. The robustness and reliability of the technology and barriers to data access were also widely reported. It should be noted that few firms considered issues of data security or ethical dimensions a significant barrier to commercialisation.

Figure 5.7: Barriers encountered to commercialisation of the technology



Source: Ipsos MORI (2021)

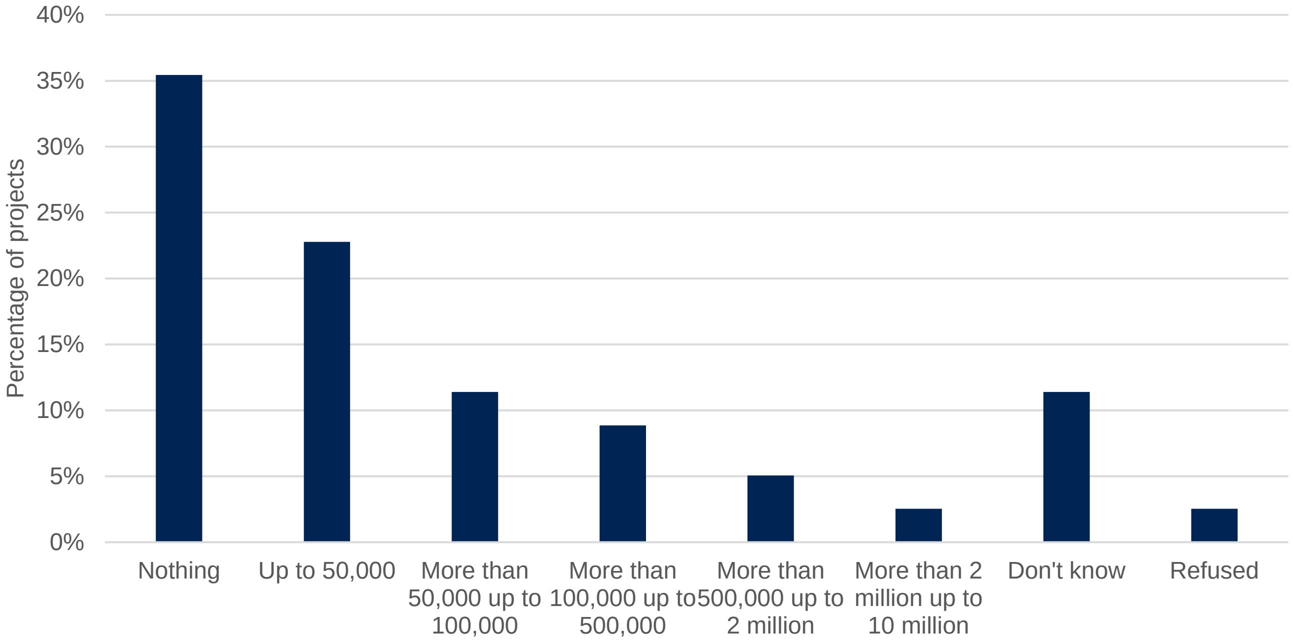
5.3 Impacts on firm employment, revenue and productivity

As described in the theory of change, successful exploitation of the IP developed would be expected to be visible in an expansion of the firm in terms of its turnover, output (GVA), and employment.

Sales

In total, 65 percent of projects reported that they were generating revenues associated with it, although in most cases these were typically small (up to £500,000). Around 35 percent of projects reported no additional revenues generated through sales or licensing in the 2019/20 financial year. A small number of projects reported large revenues in excess of £2m including the Energy Superhub Oxford involving the construction of an Electric Vehicle (EV) charging network and first of its kind hybrid battery underpinned by an Optimisation and Trading Engine to control the activity of the battery and charges to use cheaper and cleaner electricity when available.

Figure 5.8: Value of additional revenues earned from sales or licenses associated with the innovation in 19/20 financial year

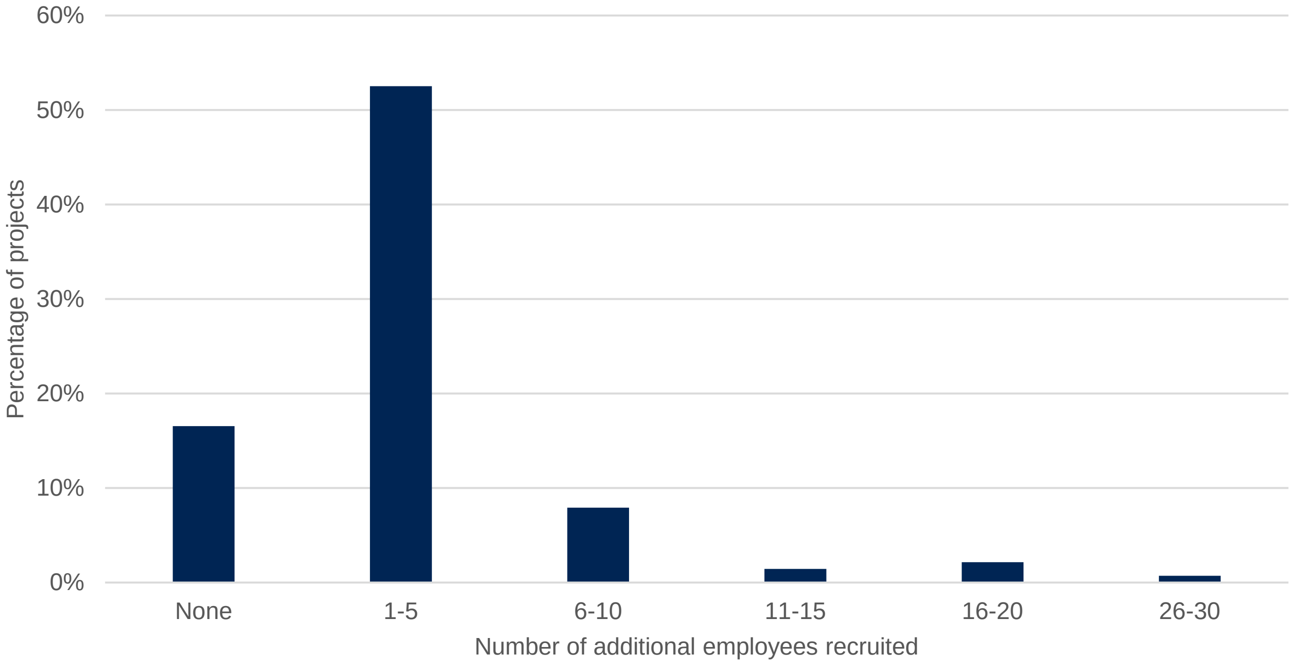


Source: Ipsos MORI (2021)

Employment effects

Respondents to the survey reported similar levels of growth in overall employment as employment of R&D workers. This would suggest that the majority of additional employment taken on as a result of the project would be in R&D and technical roles.

Figure 5.9: Number of additional workers recruited to support further development or commercialisation of innovation since application for Innovate UK funding



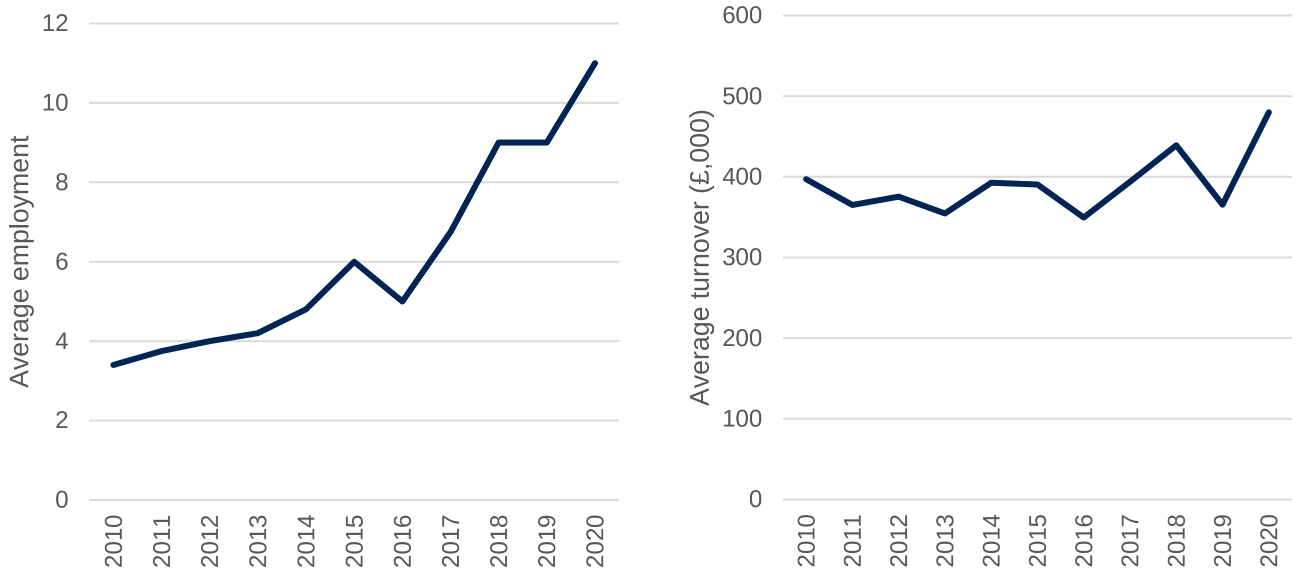
Source: Ipsos MORI (2021)

5.3.2 Econometric analysis

As above, the findings presented above are based upon self-reported responses to survey questions and do not involve a counterfactual. The econometric analysis was used to provide the further of evidence of the impacts of the programme on the expansion of firms (as visible in employment and turnover).

The following analysis was based on data from the Business Structure Database, an annual snapshot of the Interdepartmental Business Register that provides yearly observations of employment and turnover of all firms registered for PAYE or VAT. The following figure provides an overview of trends in these measures between 2010 and 2020 for firms that were awarded grants. These figures indicate that those firms awarded grants saw rapid growth in employment from 2010 to 2019 (though growth in turnover was less rapid).

Figure 5.10: Average employment and turnover of firms awarded for Innovate UK funding, 2010 to 2020 (2019 prices)



Source: ONS (2019). Ipsos MORI analysis of applicant linked records to the Business Structure Database.

The findings of the econometric analysis indicate that the programme led to significant employment impacts for both leads and collaborators:

- **Employment:** Each grant was estimated to have led to an ongoing expansion in employment of 6.4 to 8.3 percent. This effect was larger for leads (8.8 percent to 12.8 percent) than for collaborators (4.8 to 6.7 percent). The findings of the pipeline approach and comparisons to other companies active in the AI sector were broadly similar. These effects were also stable and persistent over time.

  Aggregating these results to population of firms awarded grants suggests that Innovate UK support led to the creation of 6,200 to 8,000 jobs. When compared to the effect of the programme on R&D jobs, it would suggest that the bulk of positions created were in non-R&D occupations. This would be explained if firms were preparing for further commercialisation and were investing in teams to support sales generation in advance.

- **Turnover:** The results did not show any statistically significant effects on turnover at the overall level or for leads or collaborators. It should also be noted that the observations of turnover taken from BSD are often based on VAT returns and are known to be subject to lags (and commercialisation effects may not yet be visible in the data). There were also signs of positive effects on turnover arising five years after grants were awarded, suggesting Innovate UK's grants may contribute to positive commercialisation benefits in the longer-term.

- **Turnover per worker:** The findings are consistent with a scenario in which Innovate UK grants have supported firms to progress to scaling up their business models and recruiting workers to support the commercialisation process (though have not yet progressed to generating significant amounts of revenues). The short-term nature of impacts on R&D activity would also be consistent with this scenario. At this stage of the commercialisation process, the expected effect on productivity would be negative as firms incur losses to support their expansion and this is consistent with the findings in relation to turnover per worker (where the estimated effect of Innovate UK grants were negative across most models).

When compared to the effect of the programme on R&D jobs, this would suggest that the bulk of these positions were in non-R&D occupations (potentially contradicting the survey results). This would be explained if firms were preparing for further commercialisation and were investing in teams to support sales generation in advance. It should also be noted that these are gross additional rather than net additional effects and have not been adjusted for either displacement or crowding out.

- **Leads and collaborators:** The findings did not find any turnover impacts present for lead or collaborator firms across the portfolio. This would be consistent with the modest levels of commercialisation reported in the survey, though it should also be noted that the observations of turnover taken from BSD are often based on VAT returns and are known to be subject to lags (and commercialisation effects may not yet be visible in the data).

Table 5.3: Estimated impact of Innovate UK grants for AI on employment and turnover

	Model 2	Model 3
Fixed effects (firm level)	Yes	Yes
Fixed effects (year)	Yes	Yes
Comparison sample	Comparisons to AI active non-applicants	Pipeline
Number of observations	1,028	985
Estimated % impact of each Innovate UK grant on employment		
Estimated impact (Lead)	0.088***	0.128***
Estimated impact (Collaborators)	0.048***	0.067***
Estimated % impact of each Innovate UK grant on turnover		
Estimated impact (Lead)	-0.035	0.055
Estimated impact (Collaborators)	0.033	0.0823**

Source: Business Structure Database, ONS, Ipsos MORI Analysis. *, **, *** show whether the estimated coefficient was significant at the 90, 95, and 99% level of confidence respectively.

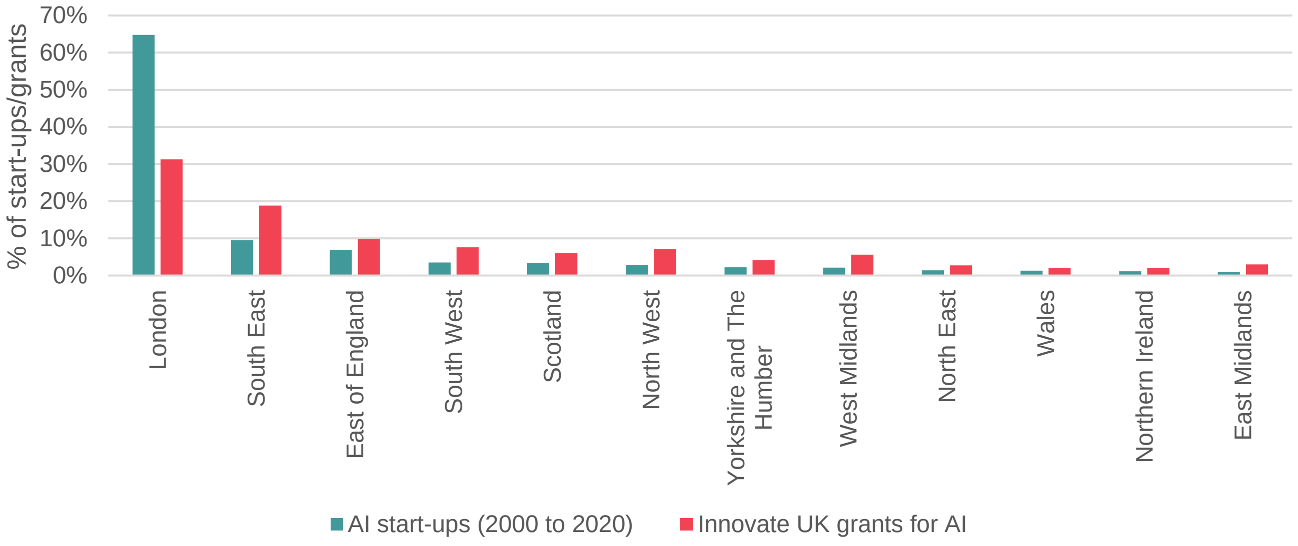
5.4 Clustering and spatial impacts

This section explores how far there is evidence of any broader spillovers arising from Innovate UK's support for the AI technology area in the form of evidence of clustering effects and other economic spillovers.

5.4.1 Regional distribution of Innovate UK grants for AI development

The following figure illustrates that Innovate UK's support for AI development was less concentrated in London and the South East than the industry itself. While London accounted for 65 percent of start-ups in the technology area since 2000, just 31 percent of Innovate UK's awards were directed at companies located in the capital.

Figure 5.11: Regional distribution of AI start-ups since 2000 and Innovate UK grants for AI development since 2004



Source: Innovate UK monitoring, PitchBook

5.4.2 Clustering effects

There was a variety of evidence from econometric analyses that Innovate UK's grants for AI development have increased firm formation rates in the AI sector. These effects were stronger outside of London than in London, suggesting that Innovate UK's support for the sector has helped contribute to the growth of clusters outside of the capital (though London may have developed in a similar rate without the support of the agency).

The econometric analyses explored how far the number of start-ups in the AI sector in a given local authority could be explained by the cumulative number of grants awarded to firms located in that area (as a proxy for the stock of knowledge and capabilities supported by Innovate UK)[40]. The analysis was driven by data on companies founded in the AI and machine learning 'industry vertical' derived from PitchBook records and details of the locations of firms awarded Innovate UK grants.

Comparisons between areas that did and did not receive grants from Innovate UK are potentially biased, as those areas receiving grants from Innovate UK may have unobserved properties that also influence the formation of new firms in the AI sector. For example, areas that have stronger skills supply or academic institutions may be both more likely to secure Innovate UK grants and see higher rates of formation of new firms in the sector. This issue was mitigated by limiting comparisons to local authorities that received support from Innovate UK at some point between 2004 and 2019). Additionally, models also controlled for unobserved, but time specific, shocks that could affect the start-up rate in all local authorities (such as the broad increase in investor interest in the technology area observed in the late 2010s).

The findings of the econometric analyses are set out in the following table:

- It was estimated that each grant awarded by Innovate UK increased the start-up rate (i.e. the number of new start-ups in the AI sector per annum) within the Local Authority by 2.4 to 8.1 percent (with more robust estimates towards the lower end of this range).

[40] The underlying econometric model took the form:

- There were differential effects inside and outside London. Outside London, each grant awarded led to an increase in the start-up rate of 8.3 percent (equivalent to around one new business per annum). However, inside London, there were no statistically significant effects.

- This suggests that while Innovate UK support may not have had any impacts on the emergence of a significant cluster of firms in the AI sector in London, it has supported the emergence of secondary clusters elsewhere in the UK. These findings have potentially broader significance in terms of the government's 'levelling-up' agenda, as it suggests that Innovate UK's support for emerging technology areas can help promote their growth outside of dominant clusters.

Table 5.4: Estimated impact of Innovate UK grants on local authority start-up rates

	Model 1	Model 2	Model 3	Model 4	Model 5
Fixed effects (LA level)	No	Yes	Yes	Yes	Yes
Fixed effects (year)	No	No	Yes	Yes	Yes
Areas included	LAs with at least one AI start-up since 2000	LAs receiving Innovate UK awards for AI development	LAs receiving Innovate UK awards for AI development	LAs receiving Innovate UK awards for AI development (outside London)	LAs receiving Innovate UK awards for AI development (inside London)
Model	Negative Binomial	Negative Binomial	Negative Binomial	Negative Binomial	Negative Binomial
Number of observations	4,780	3,700	3,700	3,140	560
Estimated effect on the incident rate ratio (a value of 1 implies no effect)					
Estimated impact of each additional grant	1.081***	1.078***	1.024***	1.083***	1.015

Source: PitchBook, Ipsos MORI Analysis. *, **, *** show whether the estimated coefficient was significant at the 90, 95, and 99% level of confidence respectively.

5.4.3 Economic spillovers

The econometric analyses also explored how far there was evidence of local economic spillovers arising from the support provided by Innovate UK for the development of AI. This was explored by adapting the models used to examine the direct impact of Innovate UK grants on firms to explore if similar effects were visible in the employment, turnover, turnover per worker, and hourly wages paid by, firms located in the same Output Area[41] as firms awarded grants and in other areas nearby (within 0-1km, 1-5km, and 5-10km).

The analyses (set out in the following table) suggested that:

- **Low productivity areas:** Innovate UK support for the AI sector had positive economic impacts in lower productivity areas of the country

[41] A small area accounting for 10 to 12 postcodes on average.

- **Local impacts:** These impacts were highly localised. Each Innovate UK grant increased employment in the area in which the applicant was located by just over 6 percent, indicating that there were limited levels of displacement at the very local level. Grants also led to an increase in wages paid by local firms (with hourly earnings increasing by 4.6 percent in response to the grants awarded).

- **Supply chain impacts:** There was also evidence of impacts of local supply chain impacts, with the employment and turnover of firms located within 0-1km of firms supported rising by 1.2 to 1.3 percent in response to each grant awarded.

▪ **High productivity areas:** There was limited evidence that Innovate UK support produced positive local economic impacts in high productivity areas (which would include London). This suggests that while Innovate UK support may have positive effects on the expansion of firms in these areas, it is likely that more intensive competition for resources in these areas has meant other firms have been 'crowded out'.

▪ **Medium productivity areas:** The patterns of impacts were less clear in areas with moderate productivity levels. While Innovate UK support appeared to reduce employment in areas close to the applicant, there was also evidence of positive wage spillovers in nearby areas.

These findings align with those above on clustering and suggest that Innovate UK's support may have more significant local economic development outcomes when directed at lower productivity areas outside of London.

Table 5.5: Estimated percentage impact of Innovate UK grants on local levels of employment, turnover, turnover per worker, and hourly earnings, by distance from the applicant

	Model 1	Model 2	Model 3
Fixed effects (LA level)	Yes	Yes	Yes
Fixed effects (year)	Yes	Yes	Yes
Areas included	Low productivity areas (LAs with 33% lowest average wages)	Medium productivity areas (LAs with average wages between 33% and 66% highest)	High productivity areas (33% of LAs with highest average wages)
Model	OLS	OLS	OLS
Employment			
In OA of applicant	6.21**	-2.73***	1.39
0-1km	1.24***	0.21	0.22*
1-5km	-0.12	-0.03	0.00
5-10km	-0.29***	-0.09***	-0.03**
Turnover			
In OA of applicant	0.52	-2.25	1.39
0-1km	1.27**	0.13	0.28
1-5km	-0.16	-0.05	-0.00
5-10km	-0.01	-0.13***	-0.00
Turnover per worker			
In OA of applicant	-0.23	1.62	0.01
0-1km	0.01	0.08	0.06
1-5km	-0.01	-0.02	0.00
5-10km	0.01*	-0.04**	0.02***
Wages (hourly earnings)			
In OA of applicant	4.6***	0.52	0.36
0-1km	0.49	0.94**	0.24
1-5km	-0.17	0.23**	0.01
5-10km	0.12	0.00	0.00

*Source: ASHE and BSD, ONS, Ipsos MORI Analysis. *, **, *** show whether the estimated coefficient was significant at the 90, 95, and 99% level of confidence respectively.*

6 Economic evaluation

This section provides an indicative economic evaluation of Innovate UK's support for the development of AI. This considers its efficiency in leveraging additional resources to support further development and scale-up, alongside an indicative cost-benefit analysis.

Comparisons are drawn below to support provided by Innovate UK for other technology areas to provide insight into the relative cost-effectiveness. These comparisons are based on the available evaluation evidence. While these studies cover programmes using similar funding mechanisms, they typically consider impacts over longer timeframes than considered in this study. As the impacts of Innovate UK support are frequently a function of the time, it should be noted that the findings presented below will understate the effectiveness of Innovate UK's support for AI relative to the available benchmarks. This is considered in the interpretation of findings.

6.1 Leverage of private R&D spending

As set out in Section 5, Innovate UK's support for AI is estimated to have led to a temporary increase in R&D spending of between £46m and £685m by the end of 2019. As highlighted, this is finding is subject to significant uncertainty and is highly sensitive to the method of aggregation.

Monitoring data indicated £174m[42] of project costs were funded by the public sector. At the upper bound, this implies that the Innovate UK's support for AI leveraged £511m in additional private R&D spending, equivalent to between £2.94 per £1 of public sector spending. However, at the lower bound, Innovate UK's support for AI is estimated to have crowded out £128m in private R&D spending (or £0.74 per £1 of public sector spending).

Table 6.1: Estimated leverage ratios (increase in R&D spending per £1 of Innovate UK spending)

Estimate	Estimated impact on total R&D spending by 2019 (£m)	Expenditure of Innovate UK grant awards by 2019 (£m)	Implied increase in private R&D spending (£m)	£s of additional private R&D spend per £1 of Innovate UK grant spending
Upper bound	685	174	511	2.94
Lower bound	46	174	-128	-0.74

Source: Ipsos MORI (2019). Analysis to aggregate R&D effects across the funded projects under review.

This table below benchmarks this result against a range of other programmes of public support for R&D, although the uncertainty involved makes it difficult to reach a definitive conclusion as to how efficiently Innovate UK's support for AI leverages additional R&D spending. At the upper bound, Innovate UK's support for sector would be among the most efficient instruments for promoting R&D spending. However, at the lower bound, public spending largely crowds out private R&D.

[42] This represents actual spend on projects relative to the £323m committed spend

Table 6.2: Leverage ratios (increase in R&D spending per £1 of Innovate UK spending)

Scheme	Estimated impact on total R&D spending (£m, low to high)	Public spending on the scheme (£m)	Implied increase in private R&D spending (£m, low to high)	£s of additional private R&D spend per £1 of public spending (low to high)
Innovate UK support for AI (2004 to 2020, with most grants awarded from 2017 onwards)	47 to 661	174	-128 to 511	-0.74 to 2.94
Innovate UK grants for CR&D and Feasibility Studies (2012 to 2018)	58 to 167	109	-51 to 58	-0.47 to 0.53
Biomedical Catalyst (2011 to 2017) [43]	248 to 350	141	107 to 2019	0.76 to 1.48
General public support for R&D (effect over 20 years) [44]	N/A	N/A	N/A	1.96 to 2.34
R&D tax relief for SMEs (effect over one year) [45]	N/A	N/A	N/A	0.75 to 1.28

Source: Ipsos MORI (2019). Analysis to aggregate R&D effects across the funded projects under review.

6.2 Leverage of equity investment

The efficiency of Innovate UK's support for AI can also be considered in terms of the £s of additional equity investment leveraged per £1 of public spending. Innovate UK's support for AI was estimated to have led to an increase in equity investment of £212m, which equates to a leverage ratio of £1.21 of additional equity investment per £1 of public spending.

There are few directly relevant comparators as the broader literature tends to focus on R&D expenditure rather than equity investment. The few comparators available indicate that Innovate UK's support for AI was:

- As effective in leveraging equity investment into companies as the ICURe programme. It should also be noted that the ICURe evaluation covered start-ups established between 2013 and 2018. These predate many of the grants covered by this evaluation, and the leverage ratios associated with Innovate UK support for AI are likely to rise above this benchmark with time.

- Less effective in leveraging investment into companies than the Biomedical Catalyst, which produced a leverage ratio of £4.99 to £6.36. This is partly a function of time elapsed (i.e. the Biomedical Catalyst evaluation covered the period from 2012 and 2018 and the firms concerned generally had more time to raise funding than those covered in this review). However, it also reflects the much larger capital requirements of firms in the biotechnology area. For example, the Biomedical

[43] Innovate UK and MRC (2019) Biomedical Catalyst Impact Evaluation
[44] BEIS (2020) The Relationship Between Public and Private R&D funding
[45] HMRC (2020) R&D Tax Relief for SMEs Evaluation

Catalyst supported Adaptimmune and Immunocore, both of which closed more than £150m in private and public fundraisings after being awarded Innovate UK funding.

Table 6.3: Estimated leverage ratios (increase in equity investment per £1 of Innovate UK spending)

Scheme	Estimated effect on equity investment (£m, low to high)	Public spending (£m)	£s of additional private R&D spend per £1 of public spending (low to high)
Innovate UK support for AI (2004 to 2020, with most grants awarded from 2017 onwards)	212	174	1.21
Biomedical Catalyst (2012 to 2018)	703	111 to 141	4.99 to 6.36
ICURe (2013 to 2018)[46]	19 to 21	18	1.04 to 1.16

Source: Ipsos MORI (2019). Analysis to aggregate R&D effects across the funded projects under review.

6.3 Indicative cost benefit analysis

In line with the guidance set out in the HM Treasury Green Book, the economic benefits of this type of programme would normally be understood in terms of the productivity gains realised by firms benefitting from the programme. While Innovate UK's support for AI increased investment in R&D and leveraged private investment into firms, it did not increase the turnover of participating firms and there was no extensive evidence of commercialisation at the time of the analysis. This implies that the programme had not produced increases in economic output or productivity at the time of writing.

A forward-looking approach is needed to understand the potential economic benefits involved. This was explored by examining the effect of the programme on the underlying value of firms receiving Innovate UK support. Assuming a well-functioning financial market, the value of the firm will represent the present value of expected future profits over and above the risk-free rate of return. If R&D investments are expected to increase the future profitability of the business, the present value of future profits will be capitalised into the value of the firm. Changes in valuations attributable to Innovate UK can be understood as a partial measure of the net benefits of the programme (while the future expansion of the firm may displace competitors, the economic activities displaced can be assumed to be earning a 'normal' rate of return).

Data was compiled from PitchBook on changes in the valuations of firms supported by Innovate UK to assess these impacts. This data was not complete – valuations are only observed for the subsample of firms that attracted equity investments (and only when the relevant details were disclosed). The econometric analysis was restricted to those firms for which a valuation was observed both before and after Innovate UK support was provided. This is likely to produce biased measures of the average impact of Innovate UK support, as it may be reasonable to assume that firms attracting equity investment are associated with higher underlying values than those that do not. As such, the estimated impacts on the valuations of firms should be treated as indicative:

[46] Innovate UK (2020) ICURe Evaluation Report 2020

- It was estimated that each grant led to an increase in the underlying value of firms of £6.2m.

- To avoid overstating the total impact of Innovate UK support, this is taken as a measure of the average impact of Innovate UK funding on lead applicants that received equity investment after receiving a grant. A total of 145 firms attracted equity investment after the grant, giving an estimate of the total economic value created of £899m.

- This was not robust to the addition of unobserved time-specific shocks so should be treated as indicative.

Table 6.4: Estimated impact of Innovate UK grants on firm valuations (lead applicants)

	Model 1	Model 2
Fixed effects (firm level)	Yes	Yes
Fixed effects (year)	No	Yes
Model	OLS	OLS
Number of observations	1,027	1,027
Estimated impact of each additional grant (£m)	6.226***	15.491

Source: PitchBook, ONS, Ipsos MORI Analysis. *, **, *** show whether the estimated coefficient was significant at the 90, 95, and 99% level of confidence respectively.

An indicative social welfare analysis has been completed by comparing the effects of Innovate UK's support for AI on R&D investment to the total increase in economic value implied by its effects on the valuations of firms:

- The increase in R&D spending attributable to Innovate UK support was estimated at between £313m and £661m.

- Comparing this to the estimated economic value of £899m, this gives an indicative Benefit to Cost Ratio of £1.36 to £2.87. The midpoint of these results (£2.12) exceeds the hurdle rate of return normally applied in the economic appraisal of these types of programme. It also represents a short-term measure of economic efficiency. It is likely to significantly understate the total value of Innovate UK support as it does not capture any economic value that has not been capitalised into observed valuations (and excludes any value created by firms that have not yet attracted follow-on investment).

The findings are also subject to the following limitations:

- Using firm valuations as a measure of economic benefit assumes that financial markets are well-functioning. However, public programme itself is predicated on an assumption that markets do not price investments in clean technologies effectively. If so, then firm valuations may not provide a reliable guide to the economic benefits of Innovate UK's support for AI.

- Firm valuations only capture private benefits to the investor. This measure of benefit will not capture other economic benefits that may arise from future exploitation of the technologies (e.g. wage benefits for workers or knowledge spill-overs).

Annex A: Technical Appendix

This Annex sets out the findings of a series of econometric analyses exploring the impacts of Innovate UK's grant funding for the development of artificial intelligence (AI) between 2004 and 2019. The analyses exploit the long timescales over which grants were awarded (2005 to 2019), with impacts inferred from comparisons between firms that were awarded grants at different points in time. The analysis is driven by longitudinal data on R&D spending, equity investment, employment, and turnover derived from the Business Expenditure on R&D Survey (BERD), the Business Structure Database (BSD), and data compiled on the PitchBook platform.

Key hypotheses being tested

The following table sets out the key hypotheses being tested in the review.

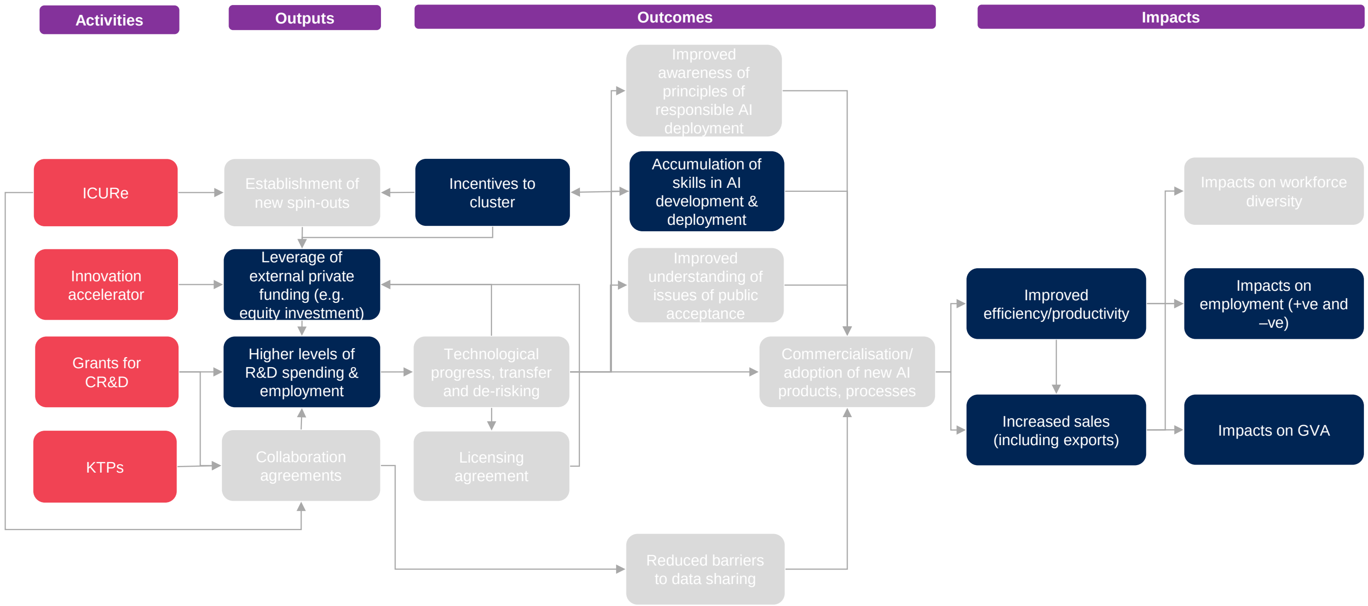
Table A.1: Hypotheses being tested

Number	Description
#1	Innovate UK's grants for artificial intelligence address market failures leading to socially suboptimal levels of investment in R&D, leading **to a net increase in R&D spending**
#2	Innovate UK's grants for artificial intelligence support technical and commercial de-risking of innovations applying artificial intelligence, **stimulating follow-on equity investment by the private sector to support further development and commercialisation.**
#3	As a result of #1 and #2, firms supported **employ larger number of workers, both in R&D and increasingly in sales and marketing occupations** as firms progress to commercialisation.
#4	Innovate UK's grants also help accelerate the commercialisation process and firms **increase their turnover as they generate increasing revenues from artificial intelligence technologies.** In the short-term, increases in future expected profitability will also be reflected in an increase in valuation of firms.
#5	Innovate UK's support for the development of artificial intelligence supports an accumulation of knowledge, skills, and other assets that create incentives for other firms to locate in proximity and facilitate the formation of new firms aiming to exploit artificial intelligence. These effects contribute to **more rapid growth of clusters (agglomeration effects).**

Source: Ipsos MORI

The available data only permitted a partial assessment of the links in the logic model used for this evaluation using econometric methods. The following figure highlights which aspects have been tested (highlighted in dark blue) and those elements that have been explored using other approaches (highlighted in grey).

Figure A.1: Logic model and hypotheses tested using econometric analysis



Source: Ipsos MORI. Elements covered by the review in dark blue, aspects not explored in grey.

Data

The following table provides an overview of the data used in this analysis. The BERD and BSD datasets were accessed via the ONS Secure Research Service. Data from PitchBook was obtained using queries defined by Ipsos MORI (and figures may not match PitchBook publications).

Table A.2: Overview of datasets

Dataset	Description and role in the study
Grant data (Innovate UK)	Innovate UK identified a population of 808 projects aiming to develop artificial intelligence funded through grants for Collaborative Research and Development (CR&D), Knowledge Transfer Partnerships, the ICURe programme, and Investment Partnerships between 2005 and 2020. Eighty-seven percent of these projects were funded in 2017 or afterwards. These projects were identified through keyword searches of the abstracts provided by the lead applicant in their applications for funding. This automated process for identifying projects is likely to understate Innovate UK's total contribution to the development of artificial intelligence, as abstracts have not been retained for all projects (with omissions more prevalent in the early years of the timeframe for analysis). Additionally, the search process may also fail to identify some relevant projects if the relevant keywords were not mentioned in the abstract. It was assumed that the omission of potentially relevant projects would not bias findings (i.e. that the non-retention of projects abstracts was effectively random in relation to the impacts of grants on R&D activity and commercialisation). The project sample included details of 1,617 participants (including leads and collaborators). As the focus of these analyses are on the business impacts of the grants, grants awarded to universities, the public sector, and RTOs were removed from this sample, giving a final sample of 821 private enterprises supported. The data included the Companies House Reference number for 819 of the 821 firms, which was to support onward linking to the Interdepartmental Business Register and the datasets described below.
Business Expenditure on Research and Development Survey (ONS)	The BERD is an annual survey undertaken by ONS comprising a panel of known R&D performers and a random probability survey of other firms to capture information on their expenditure on R&D activities and related measures. This was used to construct an unbalanced longitudinal panel dataset describing the evolution

Dataset	Description and role in the study
	of R&D activity amongst firms supported by Innovate UK. Data was obtained for 297 of the 819 firms (a matching rate of 36 percent), giving 1,824 observations over the 2010 to 2019 period. The survey is delivered using random probability sampling. Consequently, it is assumed that the incomplete coverage of the population does not introduce systematic non-response or attrition bias.
Business Structure Database (ONS)	The Business Structure Database is annual snapshot of the Interdepartmental Business Register, providing measures of employment and turnover for all firms registered for VAT and PAYE, and covers 99 percent of economic activity in the UK. The underlying data is drawn from both administrative data (VAT and PAYE returns to HMRC) and ONS' regular surveys (the Business Register Employment Survey and the Annual Business Survey). 771 of the 819 firms (a matching rate of 94 percent) were successfully matched to the IDBR giving close to complete coverage of the population of firms awarded grants. Data was extracted for the 2010 to 2019 period, giving a total of 5,705 observations over the period. The data (particularly observations of turnover) is associated with reporting lags, and in some cases, measures of turnover may be two years out of date. Given the concentration of grants in the later years of the timeframe of interest, this is likely to lead to an understatement of their effects on turnover.
PitchBook (equity investment and valuations)	PitchBook captures and structures records of equity investments that have been disclosed (through press releases, on-line searches, as well as information captured directly from fund managers). Details of firms awarded grants were linked to these records (and firms were assigned to their parent company where they were a subsidiary of larger group) to obtain details of equity investments secured (covering angel and VC investments, and initial and secondary public offerings). A total of 447 firms in the sample (54 percent) were tracked by PitchBook. 293 of the 446 firms were the lead organisation for at least one project. A database of 844 equity investments in those companies was assembled. An assumption was made that any firm not tracked by PitchBook did not raise any equity investment. PitchBook was also used to obtain information on the underlying valuations of firms awarded grants. This data was not complete – valuations are only observed for the subsample of firms that attracted equity investments and only when the relevant details were disclosed. A total of 500 observed valuations were obtained for a sample of 227 firms awarded grants. Valuations were treated as unobserved prior to the first observed valuation and as unchanging until a new observation was available. The econometric analysis was restricted to those firms for which a valuation was observed both before and after Innovate UK support was provided. This may produce biased measures of the impact of Innovate UK support on valuations, as it may be reasonable to assume that firms attracting equity investment are associated with higher underlying values than those that do not.
PitchBook (clustering)	PitchBook was also used to identify the population of UK headquartered start-ups active in the 'artificial intelligence and machine learning' industry vertical. This served two purposes: ▪ Providing a counterfactual group of UK headquartered firms active in the 'artificial intelligence and machine learning' industry vertical that were not supported by Innovate UK to augment the core findings. A total of 667 AI active firms were identified that were linked to the IDBR and associated datasets. ▪ Providing evidence on the number of UK headquartered start-ups in the 'artificial intelligence and machine learning' industry vertical to support an analysis of clustering effects associated Innovate UK's support for the sector. This involved extracting details of 1,298 firms founded between 2000 and 2020. The postcodes associated with headquarter locations were assigned to local authorities using the ONS Postcode Directory.

Source: Ipsos MORI. Elements covered by the review in dark blue, aspects not explored in grey.

Econometric approach

Selection bias

A credible quantitative assessment of impact requires comparisons between those benefitting from Innovate UK's grant funding and an appropriate group of firms that did not, to help determine what may have occurred in its absence. As grants were awarded on a non-random basis, the selection of this group needs to address the potential issues of bias caused by 'selection into treatment'.

Applicants 'self-select' by submitting applications for Innovate UK funding and will differ from non-applicants in systematic ways that influence the outcomes of interest. As an example, non-applicants may not be exposed to the same forms of financial constraints faced by applicants to the programme, which could reflect unobserved properties of the firms or the projects, such as the relative level of risk associated with the technologies. Non-applicants may not have been engaged in any innovation effort requiring venture finance. In these cases, comparing firms awarded grants to non-applicants would overstate the effect of the grants, as the latter would be less likely to raise obtain alternative funding to progress their R&D activities regardless of the funds awarded.

This problem can often be mitigated by drawing the sample of comparator firms from the population of declined applicants (as both successful and declined applicants can be assumed share similar characteristics motivating their applications for funding). However, this was not feasible in this case as details of firms applying for funding for AI and machine learning projects were not available.

To address this problem the following approach was adopted:

- **Pipeline:** A 'pipeline' approach (also known as a phased counterfactual) was adopted in which firms benefitting from awards in later years were used as a counterfactual for those benefitting in earlier years (on the basis that those awarded funding first should experience their impacts first). As comparisons are only made between firms awarded funding, this mitigates possible issues of bias driven by systematic differences between groups. However, it depends on an assumption that there are no systematic differences in the characteristics of firms awarded funded.

- **AI active firms not supported by Innovate UK:** Checks on this core approach (in some analyses) were completed by augmenting the pipeline approach with comparison sample of 667 firms active in the 'artificial intelligence and machine learning' industry vertical that were not supported by Innovate UK. This sample was extracted from the PitchBook data platform using user-defined queries (as highlighted above).

Econometric model

While the selection of comparison groups as described above helps address some sources of possible bias, there will be residual concerns regarding possible differences between groups of applicants that could distort comparisons (particularly since the dataset constructed contained little information on the characteristics of firms beyond their pre-programme fund raising activity). Further steps to minimise possible sources of bias were taken by specifying the following econometric model:

$$Y_{it} = \alpha + \beta A_{it} + \partial X_{it} + \alpha^{i} + \alpha^{t} + \varepsilon_{it}$$

This model describes the relationship between the outcomes of interest (e.g. employment) for firm i in year t (Y_{it}) as a function of the cumulative number of Innovate UK awards received (A_{it}). As A_{it} is a cumulative value, the coefficient β measures the long-term effect of the programme. Where data permitted, controls were also added for the sector and region of the firm (X_{it}). The model is also given a fixed effects interpretation, allowing for both any unobserved differences between firms that do not change with time (α^i) and any unobserved time specific shocks (α^t) affecting all firms in the same period (e.g. a general improvement in fundraising conditions). All models were estimated with robust standard errors.

The time distribution of impacts was explored for some outcomes by adapting the model as follows:

$$Y_{it} = \alpha + \sum_{j=0}^{5}(\beta_j A_{it-j}) + \partial X_{it} + \alpha^i + \alpha^t + \varepsilon_{it}$$

The key difference between this and the preceding model is that the treatment variable (A_{it}) takes the value of 1 in year in which the grant is awarded and 0 otherwise. The time distribution of effects was explored by including lags of this variable in the model (five lags were included in the following analyses).

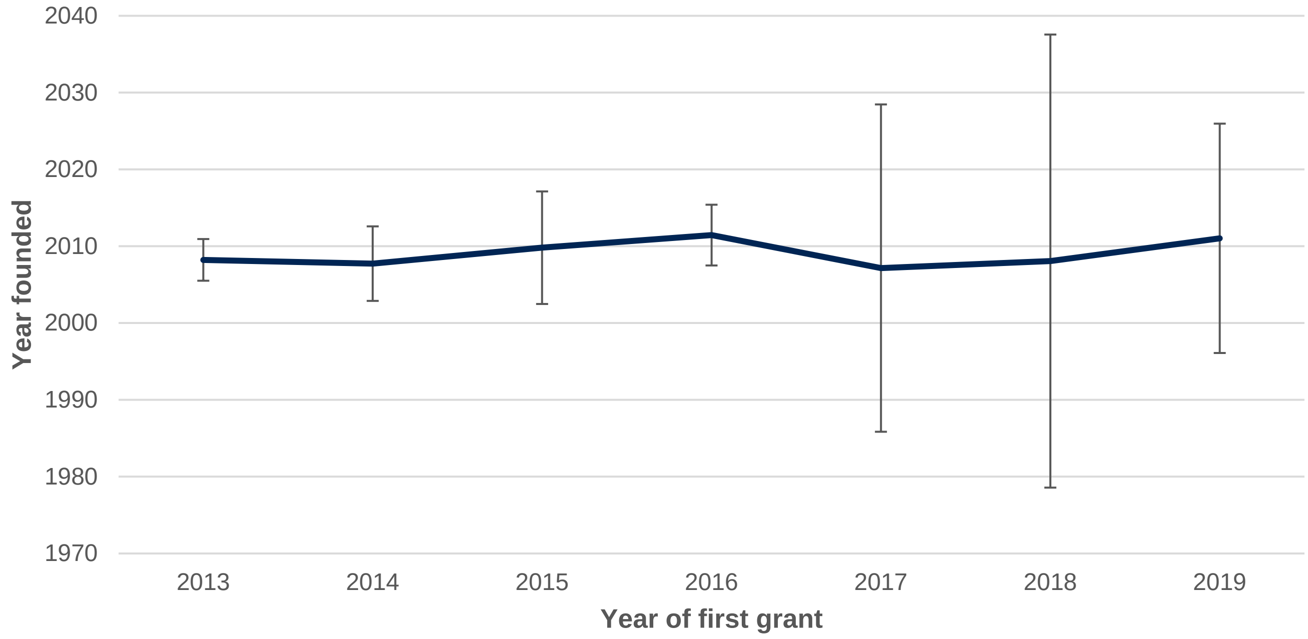
Validity of pipeline model

The pipeline approach outlined above will produce unbiased findings if there are no systematic differences between firms awarded funding at different points in time. This section provides some analysis of the observed characteristics of firms supported in different years to explore the validity of this assumption.

The analyses below are based on data compiled from PitchBook and provided coverage of 54 percent of the firms awarded funding. The analyses are limited to firms awarded grants after 2013 owing to the small number of observations available for firms supported prior to this date. Any systematic differences between firms that were not tracked by PitchBook are not observed in the data below. Additionally, there is a possibility that there are unobserved differences between firms that could introduce bias. This possibility (by definition) cannot be tested and should be borne in mind when considering the findings that follow.

The following chart shows average year in which firms were founded by the year in Innovate UK grants were awarded. As highlighted by the error bars, there were no statistically significant differences in the age of firms supported by Innovate UK in different years. As such, it is possible to discount the possibility that findings were biased by an increasing share of start-ups in the population of firms supported by Innovate UK over time.

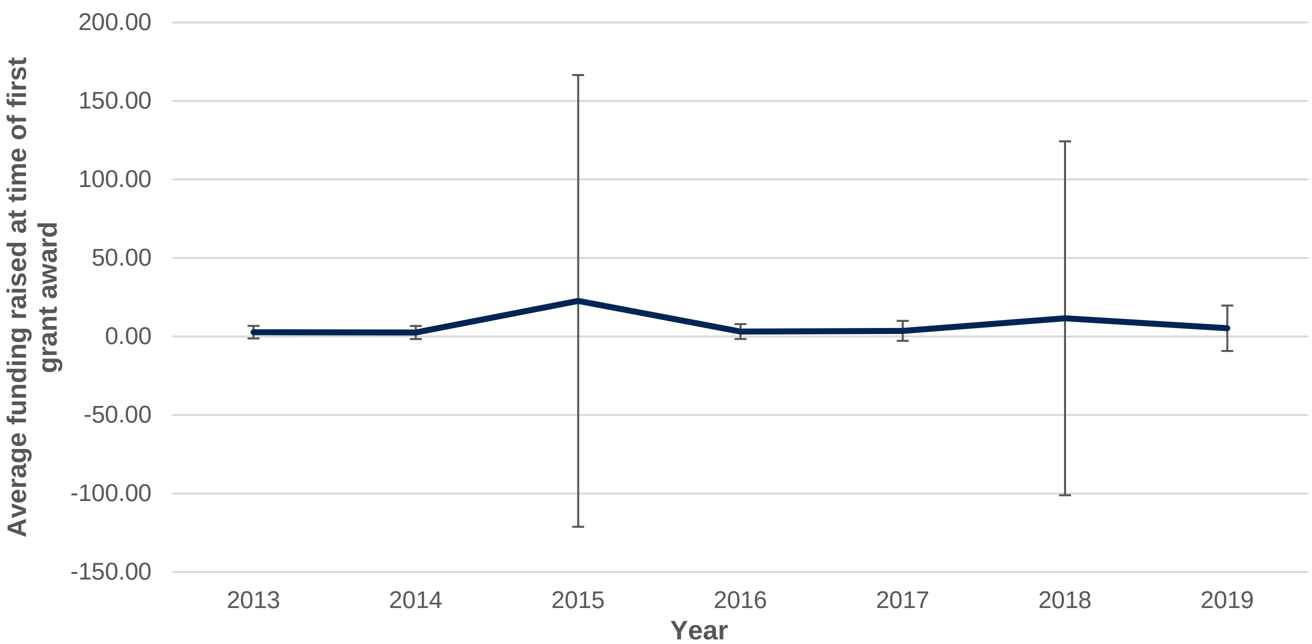
Figure A.2: Average year of establishment by year of first grant award



Source: PitchBook based on user defined query by Ipsos MORI.

The findings could potentially be biased if firms supported in later years had access to greater levels of capital resources than those supported in earlier years due to growing investor interest in the sector. In this case, the pipeline design will likely overstate the impacts of Innovate UK support (as firms in later years would have been more likely to progress their projects without public funding). The following figure provides information on the average level of equity funding raised by firms supported by firms awarded grants in different years. Although there is volatility, there are no statistically significant differences in the level of capital raised by firms supported in different years. As such, it is unlikely that findings are potentially distorted by systematic differences in the underlying capitalisation of firms supported in different years.

Figure A.3: Average funding raised at time of grant award, by year of first grant award

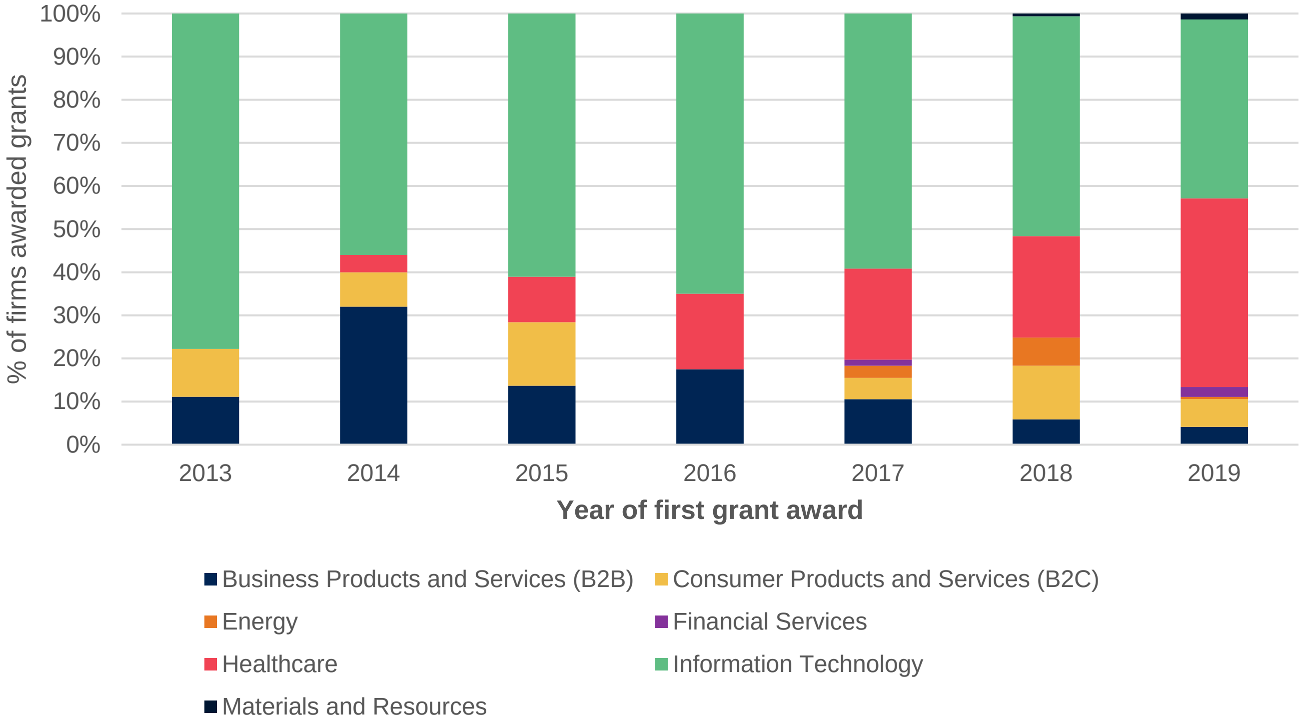


Source: PitchBook based on user defined query by Ipsos MORI.

Finally, the following shows the sector distribution of firms awarded grants by Innovate UK over time. The figure indicates that the share of grants awarded to firms active in the healthcare sector increases with time while the share of grants awarded to firms in the general IT sector falls. The extent to which these patterns are significant are dependent on the relative commercialisation prospects of general AI technologies relative to those aimed at the healthcare sector. If firms in the healthcare sector were more likely to grow without Innovate UK support than other firms, then the estimated impact of Innovate UK's support will be overstated using the pipeline approach.

This was explored further by comparing the average valuations of firms in the healthcare sector to those in other sectors (where available). The average post-money valuation of firms awarded grants in the healthcare sector was £91.7m at the point at which they first received funding (95% confidence of £86.3m to £97.0m). This was higher than the average valuations of firms in other sectors (an average of £69.0m and a 95% confidence interval of £66.7m to £71.3m). This would suggest that there is a risk that the pipeline approach carries a degree of upward bias, highlighting the need for robustness checks by augmenting the analysis with comparisons to other firms active in the AI sector.

Figure A.4: Sector distribution of firms awarded grants, by year of first grant award



Source: PitchBook based on user defined query by Ipsos MORI.

Results

R&D spending and employment

Estimates of the on-going effects of Innovate UK grants on R&D spending and employment are set out in Table A.3 below. The modelling found that Innovate UK grants had no on-going effects on R&D spending or employment over the 2010 to 2019 period. This held regardless of whether the findings were based on a pipeline approach or on comparisons to other firms in the artificial intelligence industry vertical not supported by Innovate UK. The result also held across the population of firms supported and in subgroups of leads and collaborators.

Table A.3: Estimated on-going impacts of Innovate UK grants on R&D spending and employment

Model (~)	Controls				Estimated impact (%)			
	Control sample	Firm fixed effects	Year fixed effects	Sector and region	R&D spending	St. Err	R&D employment	St. Err
					Overall effects			
#1 (1,824)	Pipeline	Yes	Yes	Yes	0.023	0.625	0.040	0.241
#2 (1,939)	PitchBook control sample	Yes	Yes	Yes	0.033	0.478	0.043	0.205
					Lead applicants			
#3 (1,142)	Pipeline	Yes	Yes	Yes	0.029	0.683	-0.011	0.802
#4 (938)	PitchBook control sample	Yes	Yes	Yes	0.058	0.403	0.008	0.861
					Collaborators			
#5 (1,142)	Pipeline	Yes	Yes	Yes	-0.035	0.797	-0.042	0.624
#6 (938)	PitchBook control sample	Yes	Yes	Yes	-0.027	0.842	-0.040	0.636

Source: Business Expenditure on Research and Development Survey, Office for National Statistics, Ipsos MORI analysis. (~) Number of observations in parentheses. *, **, *** indicates whether the estimated coefficient was significant at the 90, 95, or 99 percent level of confidence.

However, analyses focusing on the time distribution of the effects of Innovate UK grants suggested they had a short-term effect on R&D activity:

- Each grant appeared to lead to a 9.0 to 9.8 percent increase in R&D spending in the year funding was awarded (although these effects were only weakly significant).
- Grants led to a 12.9 to 13.3 percent increase in R&D employment in the year funding was awarded. This effect fell to 9.2 to 9.7 percent in the year following the award of the grant.
- There were no significant effects on R&D spending beyond the first year following the award of the grant. This indicates the Innovate UK grants have provided a temporary stimulus to R&D activity in artificial intelligence sector.
- This could be explained if grants bring forward activity that would have otherwise taken place later, though this explanation is not entirely consistent with other findings in this review. It should also be noted that the population of grants were largely awarded from 2017 onward, so estimates of the longer-term effects of grants are based on sample sizes that are insufficiently large to detect effects of the magnitude expected.

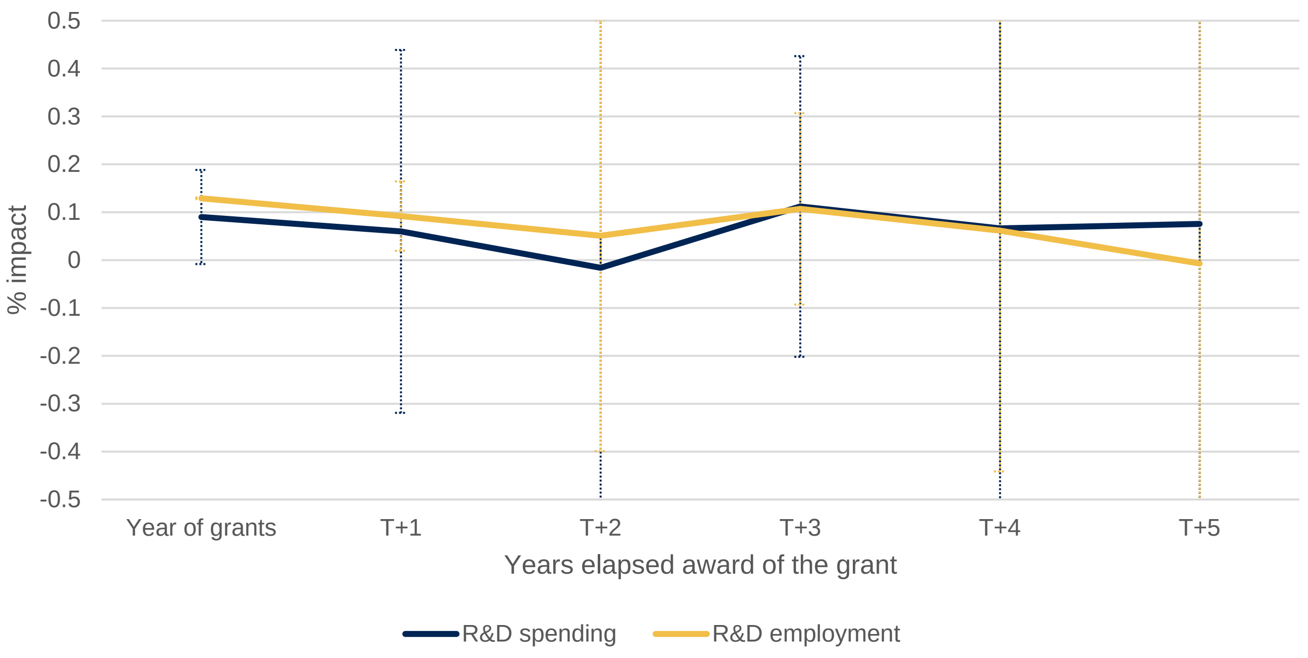
Table A.4: Estimated short-term impacts of Innovate UK grants on R&D spending and employment (first two years only)

Model (~)	Controls				Estimated impact (%)			
	Control sample	Firm fixed effects	Year fixed effects	Sector and region	R&D spending	St. Err	R&D employment	St. Err
Year of the grant								
#1 (1,824)	Pipeline	Yes	Yes	Yes	0.090*	0.098	0.129***	0.001
#2 (1,939)	PitchBook control sample	Yes	Yes	Yes	0.098*	0.070	0.133***	0.001
Year following the grant								
#3 (1,824)	Pipeline	Yes	Yes	Yes	0.060	0.379	0.092*	0.073
#4 (1,939)	PitchBook control sample	Yes	Yes	Yes	0.067	0.315	0.097*	0.056

Source: Business Expenditure on Research and Development Survey, Office for National Statistics, Ipsos MORI analysis. (~) Number of observations in parentheses. *, **, *** indicates whether the estimated coefficient was significant at the 90, 95, or 99 percent level of confidence.

The estimated effects of Innovate UK grants on R&D spending over time (with associated confidence intervals) are shown in Figure A.4 below.

Figure A.4: Estimated impacts of Innovate UK grants on R&D spending and employment by number of years elapsing since grants were awarded



Source: Business Expenditure on Research and Development Survey, Office for National Statistics, Ipsos MORI analysis. Findings based on the pipeline approach.

Finally, the findings were broken down by size of firm to explore differential impacts across firms of different sizes. The results indicated that Innovate UK grants had an on-going effect on the R&D spending and employment of small businesses (i.e. those with 10 to 49 employees), of 18 percent and 14 percent respectively. No significant effects were found amongst businesses of other sizes.

Table A.5: Estimated short-term impacts of Innovate UK grants on R&D spending and employment (first two years only)

Model (~)	Controls				Estimated impact (%)			
	Control sample	Firm fixed effects	Year fixed effects	Sector and region	R&D spending	St. Err	R&D employment	St. Err
Micro-businesses (0 to 10 employees)								
#1 (422)	Pipeline	Yes	Yes	Yes	-0.053	0.633	-0.024	0.584
#2 (439)	PitchBook control sample	Yes	Yes	Yes	-0.036	0.742	-0.017	0.710
Small businesses (10 to 49 employees)								
#3 (538)	Pipeline	Yes	Yes	Yes	0.181**	0.016	0.141***	0.001
#4 (565)	PitchBook control sample	Yes	Yes	Yes	0.184**	0.014	0.138***	0.001
Medium sized businesses (50 to 249 employees)								
#1 (304)	Pipeline	Yes	Yes	Yes	0.169	0.248	0.217	0.124
#2 (333)	PitchBook control sample	Yes	Yes	Yes	0.098*	0.070	0.066	0.469
Large businesses (250 or more employees)								
#3 (560)	Pipeline	Yes	Yes	Yes	-0.173*	0.078	-0.018	0.841
#4 (602)	PitchBook control sample	Yes	Yes	Yes	-0.149	0.124	-0.016	0.855

Source: Business Expenditure on Research and Development Survey, Office for National Statistics, Ipsos MORI analysis. (~) Number of observations in parentheses. *, **, *** indicates whether the estimated coefficient was significant at the 90, 95, or 99 percent level of confidence.

Equity investment and valuations

Estimates of the impacts of the programme on follow-on equity investment (from angel investors, VC funds, and fundraisings on public capital markets) and valuations were driven by data compiled from the PitchBook data platform (and covered to 2000 to 2019 period):

- **Equity investment:** The findings suggested that each Innovate UK grant increased the total equity investment raised by companies by 5.3 to 16.4 percent. The most robust findings, which allow for unobserved shocks to investor sentiment, are at the lower end of this range.

- **Leads and collaborators:** The estimated impacts were larger for lead impacts than for collaborators. The most robust models suggested that the effects on collaborators was negative (reducing equity investment by 6.3 percent).

- **Period:** Grants awarded in 2015 or afterwards were more effective in leveraging additional equity investment than those awarded before this. The most robust models indicated that grants awarded between 2008 and 2014 had no effect in leveraging equity investment into the firms concerned.

- **Valuations:** Owing to sample size constraints, the analysis of impacts on valuations was limited to lead applicants. It was estimated that each grant led to an increase in the underlying value of firms of £6.2m. However, this finding was not robust to the addition of unobserved time-specific shocks so should be treated as indicative.

Table A.6: Estimated impacts of Innovate UK grants on cumulative equity investment and valuations

Model (~)	Controls			Estimated impact (% / £m)			
	Control sample	Firm fixed effects	Year fixed effects	Cumulative equity investment (%)	St. Err	Valuations (£)	St. Err
All applicants							
#1 (12,315)	Pipeline	No	No	0.153***	0.014		
#2 (12,315)	Pipeline	Yes	No	0.164***	0.019		
#3 (12,315)	Pipeline	Yes	Yes	0.053**	0.021		
Leads							
#4 (12,315)	Pipeline	Yes	No	0.217***	0.026	6.226***	2.051
#5 (12,135)	Pipeline	Yes	Yes	0.107***	0.027	15.491	39.300
Collaborators							
#4 (12,315)	Pipeline	Yes	No	0.063***	0.023		
#5 (12,135)	Pipeline	Yes	Yes	-0.064**	0.026		
Grants awarded between 2008 and 2015							
#4 (12,315)	Pipeline	Yes	No	0.114***	0.037		
#5 (12,135)	Pipeline	Yes	Yes	0.023	0.037		
Grants awarded between 2015 and 2019							
#4 (12,315)	Pipeline	Yes	No	0.175***	0.023		
#5 (12,135)	Pipeline	Yes	Yes	0.062**	0.026		

Source: PitchBook, Ipsos MORI defined user query. (~) Number of observations in parentheses. *, **, *** indicates whether the estimated coefficient was significant at the 90, 95, or 99 percent level of confidence. Note that estimates of impacts on valuations were driven by a sample of 1,027 observations.

Employment, turnover, and turnover per worker

The findings of the econometric analysis indicated that Innovate UK's grants for AI development led to significant expansions in employment for both leads and collaborators:

- **Employment:** Each grant was estimated to have led to an ongoing expansion in employment of 6.4 to 8.3 percent. This effect was larger for leads (8.8 percent to 12.8 percent) than for collaborators (4.8 to 6.7 percent). The findings of the pipeline approach and comparisons to other companies active in the AI sector were broadly similar.

- **Turnover:** The results did not show any statistically significant effects on turnover at the overall level or for leads or collaborators. It should also be noted that the observations of turnover taken from BSD are often based on VAT returns and are known to be subject to lags (and commercialisation effects may not yet be visible in the data).

- **Turnover per worker:** The findings are consistent with a scenario in which Innovate UK grants have supported firms to progress to scaling up their business models and recruiting workers to support the commercialisation process (though have not yet progressed to generating significant amounts of revenues). The short-term nature of impacts on R&D activity would also be consistent with this scenario. At this stage of the commercialisation process, the expected effect on productivity would be negative as firms incur losses to support their expansion and this is consistent with the findings in relation to turnover per worker (where the estimated effect of Innovate UK grants were negative across most models).

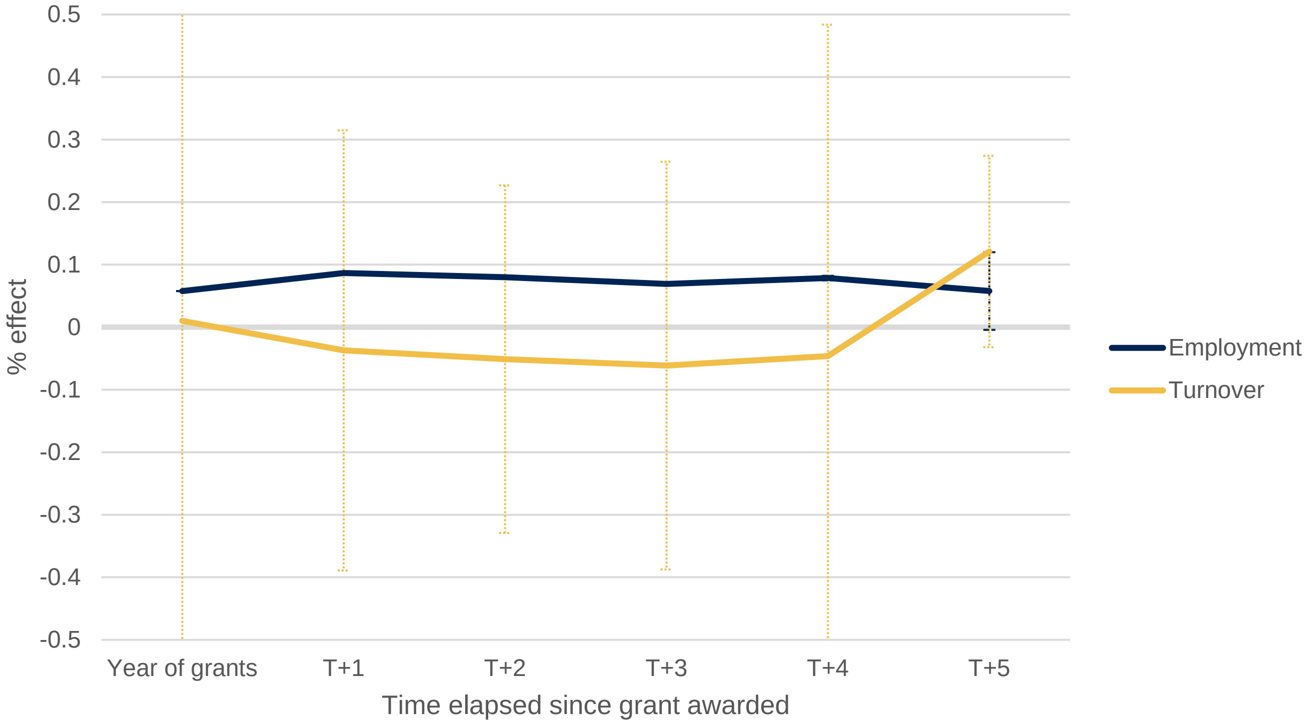
Table A.7: Estimated impacts of Innovate UK grants on employment, turnover and employment

Model (~)	Controls				Estimated impact (%)					
	Control sample	Firm fixed effects	Year fixed effects	Sector and region	Emp.	St. Err	Turn.	St. Err	Turn. per work.	St. Err
Overall effects										
#1 (5,705)	Pipeline	Yes	Yes	Yes	0.064***	0.000	-0.010	0.708	-0.074***	0.004
#2 (7,452)	PitchBook control sample	Yes	Yes	Yes	0.083***	0000	0.021	0.386	-0.062***	0.008
Lead applicants										
#3	Pipeline	Yes	Yes	Yes	0.088***	0.000	-0.035	0.411	-0.123***	0.004
#4	PitchBook control sample	Yes	Yes	Yes	0.128***	0.000	0.033	0.347	-0.095***	0.006
Collaborators										
#5	Pipeline	Yes	Yes	Yes	0.048***	0.003	0.0554	0.165	0.007	0.853
#6	PitchBook control sample	Yes	Yes	Yes	0.067***	0.000	0.0823**	0.018	0.016	0.629

Source: Business Structure Database, Office for National Statistics, Ipsos MORI analysis. (~) Number of observations in parentheses. *, **, *** indicates whether the estimated coefficient was significant at the 90, 95, or 99 percent level of confidence.

Figure A.5 shows the time distribution of the estimated effects of Innovate UK grants on employment and turnover (i.e. by the number of years elapsing since grant funding was awarded). This shows that the effect of grants on employment is both consistent and persistent in the five years following the award of the grant (implying that workers initially recruited into R&D occupations may be being redeployed into other roles as the firm progresses). It also highlights signs of positive effects on revenues five years after the grant was awarded (this result was on the threshold of statistical significance), suggesting the possibility of more significant effects on turnover in the longer term.

Figure A.5: Estimated impacts of Innovate UK grants on employment and turnover by number of years elapsing since grants were awarded



Source: Business Structure Database, Office for National Statistics, Ipsos MORI analysis. Findings based on the pipeline approach.

Clustering

The econometric analyses explored how far the number of start-ups in the AI sector in a given local authority could be explained by the cumulative number of grants awarded to firms located in that area (as a proxy for the stock of knowledge and capabilities supported by Innovate UK). The analysis was driven by data on companies founded in the AI and machine learning 'industry vertical' derived from PitchBook records and details of the locations of firms awarded Innovate UK grants. The model took the following form:

$$Y_{it} = \alpha + \beta A_{it} + \alpha^{i} + \alpha^{t} + \varepsilon_{it}$$

In this model, the number of AI start-ups in local authority i in period t (Y_{it}) is explained by the cumulative number of Innovate UK grants awarded to firms located in that local authority (A_{it}).

Comparisons between areas that did and did not receive grants from Innovate UK are potentially biased, as those areas receiving grants from Innovate UK may have unobserved properties that also influence the formation of new firms in the AI sector. For example, areas that have stronger skills supply or academic institutions may be both more likely to secure Innovate UK grants and see higher rates of formation of new firms in the sector. This issue was mitigated by limiting comparisons to local authorities that received support from Innovate UK at some point between 2004 and 2019.

The models also allowed for unobserved differences between Local Authorities that do not change over time (α^{i}). Additionally, models also controlled for unobserved, but time specific, shocks (α^{t}) that could affect the start-up rate in all local authorities (such as the broad increase in investor interest in the technology area observed in the late 2010s).

The findings of the econometric analyses are set out in the following table:

- It was estimated that each grant awarded by Innovate UK increased the start-up rate (i.e. the number of new start-ups in the AI sector per annum) within the Local Authority by 2.4 to 8.1 percent (with more robust estimates towards the lower end of this range).

- There were differential effects inside and outside London. Outside London, each grant awarded led to an increase in the start-up rate of 8.3 percent (equivalent to around one new business per annum). However, inside London, there were no statistically significant effects.

- This suggests that while Innovate UK support may not have had any impacts on the emergence of a significant cluster of firms in the AI sector in London, it has supported the emergence of secondary clusters elsewhere in the UK. These findings have potentially broader significance in terms of the government's 'levelling-up' agenda, as it suggests that Innovate UK's support for emerging technology areas can help promote their growth outside of dominant clusters.

Table A.8: Estimated impact of Innovate UK grants on local authority start-up rates

	Model 1	Model 2	Model 3	Model 4	Model 5
Fixed effects (LA level)	No	Yes	Yes	Yes	Yes
Fixed effects (year)	No	No	Yes	Yes	Yes
Areas included	LAs with at least one AI start-up since 2000	LAs receiving Innovate UK awards for AI development	LAs receiving Innovate UK awards for AI development	LAs receiving Innovate UK awards for AI development (outside London)	LAs receiving Innovate UK awards for AI development (inside London)
Model	Negative Binomial	Negative Binomial	Negative Binomial	Negative Binomial	Negative Binomial
Number of observations	4,780	3,700	3,700	3,140	560
Estimated effect on the incident rate ratio (a value of 1 implies no effect)					
Estimated impact of each additional grant	1.081***	1.078***	1.024***	1.083***	1.015

Source: PitchBook, Ipsos MORI user defined query. *, **, *** show whether the estimated coefficient was significant at the 90, 95, and 99% level of confidence respectively.

Economic spill-overs

The econometric analyses also explored how far there was evidence of local economic spillovers arising from the support provided by Innovate UK for the development of AI. This was explored by adapting the models used to examine the direct impact of Innovate UK grants on firms to explore if similar effects were visible in the employment, turnover, turnover per worker, and hourly wages paid by, firms located in the same Output Area[47] as firms awarded grants and in other areas nearby (within 0-1km, 1-5km, and 5-10km).

[47] A small area accounting for 10 to 12 postcodes on average.

These effects were estimated using the following model:

$$Y_{it} = \alpha + \sum_{j=1}^{4}(\beta_j A_i^j) + \partial X_{it} + \alpha^i + \alpha^t + \varepsilon_{it}$$

In this model, the outcomes of interest (e.g. employment) in Output Area i in period t are explained by the number of grants awarded to firms in the same Output Area (j = 1) and three distance bands (j = 2, 3, and 4) of increasing distance from the Output Area (i.e. 0-1km, 1-5km, and 5-10k).

As with the clustering analysis, possible risks of bias arising from comparisons between areas that do and do not receive Innovate UK grant funding were mitigated by limiting the sample only to Output Areas within 10km of firms awarded grants. The models also allowed for unobserved differences between Local Authorities that do not change over time (α^i). Additionally, models also controlled for unobserved, but time specific, shocks (α^t) that could affect the start-up rate in all local authorities (such as the broad increase in investor interest in the technology area observed in the late 2010s).

The analyses (set out in Table A.8) suggested that:

- **Low productivity areas:** Innovate UK support for the AI sector had positive economic impacts in lower productivity areas of the country:
  - **Local impacts:** These impacts were highly localised. Each Innovate UK grant increased employment in the area in which the applicant was located by just over 6 percent, indicating that there were limited levels of displacement at the very local level. Grants also led to an increase in wages paid by local firms (with hourly earnings increasing by 4.6 percent in response to the grants awarded).
  - **Supply chain impacts:** There was also evidence of impacts of local supply chain impacts, with the employment and turnover of firms located within 0-1km of firms supported rising by 1.2 to 1.3 percent in response to each grant awarded.
- **High productivity areas:** There was limited evidence that Innovate UK support produced positive local economic impacts in high productivity areas (which would include London). This suggests that while Innovate UK support may have positive effects on the expansion of firms in these areas, it is likely that more intensive competition for resources in these areas has meant other firms have been ‘crowded out’.
- **Medium productivity areas:** The patterns of impacts were less clear in areas with moderate productivity levels. While Innovate UK support appeared to reduce employment in areas close to the applicant, there was also evidence of positive wage spillovers in nearby areas.

These findings align with those above on clustering and suggest that Innovate UK’s support may have more significant local economic development outcomes when directed at lower productivity areas outside of London.

Table A.9: Estimated percentage impact of Innovate UK grants on local levels of employment, turnover, turnover per worker, and hourly earnings, by distance from the applicant

	Model 1	Model 2	Model 3
Fixed effects (LA level)	Yes	Yes	Yes
Fixed effects (year)	Yes	Yes	Yes
Areas included	Low productivity areas (LAs with 33% lowest average wages)	Medium productivity areas (LAs with average wages between 33% and 66% highest)	High productivity areas (33% of LAs with highest average wages)
Model	OLS	OLS	OLS
Employment			
In OA of applicant	6.21**	-2.73***	1.39
0-1km	1.24***	0.21	0.22*
1-5km	-0.12	-0.03	0.00
5-10km	-0.29***	-0.09***	-0.03**
Turnover			
In OA of applicant	0.52	-2.25	1.39
0-1km	1.27**	0.13	0.28
1-5km	-0.16	-0.05	-0.00
5-10km	-0.01	-0.13***	-0.00
Turnover per worker			
In OA of applicant	-0.23	1.62	0.01
0-1km	0.01	0.08	0.06
1-5km	-0.01	-0.02	0.00
5-10km	0.01*	-0.04**	0.02***
Wages (hourly earnings)			
In OA of applicant	4.6***	0.52	0.36
0-1km	0.49	0.94**	0.24
1-5km	-0.17	0.23**	0.01
5-10km	0.12	0.00	0.00

Source: ASHE and BSD, ONS, Ipsos MORI Analysis. *, **, *** show whether the estimated coefficient was significant at the 90, 95, and 99% level of confidence respectively.

Grossing-up

The findings of the above analyses were used to provide estimates of the total impacts of Innovate UK support for AI as follows.

R&D employment and expenditure

The findings were not entirely consistent across the different models. Results at the level of the overall population indicating that Innovate UK's support had only temporary effects on R&D spending and employment. The results broken down by firm size indicated that Innovate UK's support may have had ongoing effects on R&D spending but only for small firms. The findings were aggregated to the population using two approaches to reflect this uncertainty.

- **Overall results:** Estimates of the temporary effect on R&D spending and employment were derived by multiplying the total number of grants awarded to businesses (984 including collaborators), average R&D spending or employment prior to the award of the grant, and the estimated effects of grants. A trimmed mean excluding the 5 percent smallest and largest observations was used to exclude outlying values (as the presence of some very large firms in the population increased the population mean[48]). This gave an estimated short-term effect on R&D spending of between £629m and £685m and the creation of between 6,000 and 6,200 (short-term) R&D jobs.

Table A.10: Estimated total effects on R&D spending and employment based on overall results

	Number of grants awarded	Mean R&D activity before grants awarded*	Estimated % effect per grant awarded		Estimated total effect	
			Low	High	Low	High
R&D spending	984	£7,104,000	0.090	0.098	£629m	£685m
R&D employment	984	47.4	0.129	0.133	6,017	6,203

*Source: Ipsos MORI analysis. * 90% trimmed mean*

- **On-going effects on small firms:** The findings by firm size could not be aggregated to the population directly as only information on the number of grants awarded to SMEs was available in Innovate UK monitoring data[49]. The effects of Innovate UK grants at the level of SMEs overall were estimated by developing a weighted average, assuming no effects on small and medium sized firms. As illustrated in the table below, the estimated effects of Innovate UK grants on the annual R&D spending and employment of SMEs are 5.5 and 3.3 percent respectively. Applying this to the average R&D spending and employment of SMEs before grants were awarded, gives a per grant effect of £16,100 in annual R&D spending and 0.1 R&D jobs created.

[48] For example, the average R&D spending of firms in the population (weighted by firm size) was £36.1m.

[49] Information on the overall size distribution of firms supported was available via the ONS SRS, but detailed data on the annual distribution of grants awarded could not be taken from the ONS SRS due to disclosure concerns.

Table A.10: Estimated total effects on R&D spending and employment based on results broken down by firm size

Size of business	% of SMEs supported	Effect on annual R&D spending per grant (%)	Effect on R&D employment per grant (%)
Micro	0.60	0	0
Small	0.31	0.181	0.184
Medium	0.09	0	0
Weighted average		**0.055**	**0.033**
Average R&D activity of SMEs supported		£291,000	2.9
Estimated effect per grant		**£16,100**	**0.1**

Source: Ipsos MORI analysis.

- These results were aggregated to the number of grants awarded to SMEs (853). This gave an estimate of (on-going) R&D jobs created of 81. As the estimated impact on R&D spending was on-going, the result was applied to the cumulative number of grants awarded to SMEs to reach an estimate of the total effect on R&D spending. As illustrated in the table below, this approach implies a total effect on R&D spending on £45.9m.

Table A.11: Estimated total effects on R&D spending based on on-going effects estimated for small firms

Year	Grants awarded to SMEs	Cumulative grants awarded	Total effect on R&D spending (£m)
2006/07	1	1	0.0
2007/08	2	3	0.0
2008/09	1	4	0.1
2009/10	2	6	0.1
2010/11	9	15	0.2
2011/12	10	25	0.4
2012/13	11	36	0.6
2013/14	32	68	1.1
2014/15	77	145	2.3
2015/16	54	199	3.2
2016/17	71	270	4.4
2017/18	201	471	7.6
2018/19	280	751	12.1
2019/20	102	853	13.7
Total	**853**	**2847**	**45.9**

Source: Ipsos MORI analysis.

These results indicate that there is a large amount of uncertainty regarding the total effect of Innovate UK's support for AI on R&D activity, estimates of which are highly sensitive to the approach taken.

Employment

The findings set out above indicated that Innovate UK's grant support for AI increased employment by between 6.4 and 8.3 percent. Applying this to average employment of 98 jobs prior to the award of the grant, and the number of firms awarded grants (987 including collaborators), gives an estimate of the total number of jobs created of between 6,200 and 8,000.

Table A.11: Estimated total effects on R&D spending and employment based on overall results

	Number of grants awarded	Mean employment before grants awarded	Estimated % effect per grant awarded		Estimated total effect	
			Low	High	Low	High
Employment	984	98	0.064	0.083	6,194	8,000

*Source: Ipsos MORI analysis. * 90% trimmed mean.*

Conclusions

The findings of the analysis are summarised in the following table against the key hypotheses defined at the start of this Annex.

Table A.12: Key findings

Number	Hypothesis	Findings
#1	Innovate UK's grants for artificial intelligence address market failures leading to socially suboptimal levels of investment in R&D, leading to a net increase in R&D spending	The findings indicated that Innovate UK support for artificial intelligence led to a short-term effect on R&D activity. This included raising R&D spending by around 9 percent in the year in which the grant was awarded, and increasing R&D employment by around 13 percent (an effect that persisted into the year following the award of the grants). However, these effects appeared to be transitory and the findings suggested there were no on-going effects on R&D activity associated with Innovate UK grant funding. This could be interpreted as a sign that Innovate UK funding accelerated R&D activity that would have otherwise taken place later without public support. However, this is not consistent with other findings that suggest that Innovate UK support had a lasting effect on overall employment levels. A more likely explanation is that firms quickly transition from development activity to scale-up and commercialisation activities, involving the diversion of workers from R&D activities.
#2	Innovate UK's grants for artificial intelligence support technical and commercial de-risking of innovations applying artificial intelligence, stimulating follow-on investment by the private sector to support further development and commercialisation.	The support provided by Innovate UK for AI development contributed to an increase in equity investment in companies supported. It was estimated that each grant awarded increasing the total equity investment raised by companies by 5.3 to 16.4 percent (over and above the amounts they may have raised anyway).

Number	Hypothesis	Findings
#3	As a result of #1 and #2, firms supported employ larger number of workers, both in R&D and increasingly in sales and marketing occupations as firms progress to commercialisation.	Innovate UK's support has also supported rapid scale-up and the firms supported expanded their overall employment by 6.4 to 8.3 percent as a direct result of the funding provided. The effects of grants on overall employment levels are substantially larger than their effects on R&D jobs, indicating that Innovate UK funding has enabled firms to progress as far as establishing significant sales and marketing functions.
#4	Innovate UK's grants also help accelerate the commercialisation process and firms increase their turnover as they generate increasing revenues from artificial intelligence technologies. In the short-term, increases in future expected profitability will also be reflected in an increase in valuation of firms.	There was limited evidence that Innovate UK's support for artificial intelligence has contributed to increases in revenues. This this is not unexpected given the maturity of the companies at the point funding was awarded, and the analysis provided signs that positive effects on revenues were beginning to emerge five years after the award of grants.
#5	Innovate UK's support for the development of artificial intelligence supports an accumulation of knowledge, skills, and other assets that create incentives for other firms to locate in proximity and facilitate the formation of new firms aiming to exploit artificial intelligence. These effects contribute to more rapid growth of clusters.	There was evidence from econometric analyses that Innovate UK's grants for AI development have increased firm formation rates. These effects were stronger outside of London than in London, suggesting that Innovate UK's support for the sector has helped contribute to the growth of clusters outside of the capital (though London may have developed in a similar rate without the support of the agency).

Source: Ipsos MORI

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