Understanding UK Artificial Intelligence R&D commercialisation and the role of standards

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Executive Summary

1 The Department for Digital, Culture, Media and Sport's (DCMS) upcoming Digital Strategy and the National Artificial Intelligence (AI) Strategy (published in September 2021)[1] both acknowledge the transformational potential of AI technology to increase productivity and create long-term economic growth. Despite this promise, there are a number of barriers that potentially hamper the commercialisation of AI Research & Development (R&D). Understanding the ways in which AI R&D commercialisation can be supported is the core purpose of this research.

2 A key goal of this report is to help teams from across government, public funding bodies, universities' technology transfer offices, industry and other associated organisations understand what steps can be taken to support and increase the commercialisation of AI R&D in the UK. We present several considerations for policymakers and other stakeholders to address barriers to the commercialisation of AI R&D that emerged through the research.

3 This report identifies the most prevalent ways, or 'routes', by which AI R&D is commercialised in the UK:

- **University spinouts:** businesses that grow out of a university research project, which attempt to transform research into a commercial product or service;
- **Startups:** businesses in the early stages of operations, exploring a new business model, product or service;
- **Large firms that commercialise AI R&D:** 'Big Tech firms'[2], and also other large technology companies such as ARM, Graphcore, IBM, Netflix and Twitter; and,
- **Direct hire and joint tenure arrangements:** relationships between industry and academia that allow for a back and forth flow of AI talent between the two.

4 The report explores the main enablers, barriers and challenges for AI commercialisation through the specific routes above, and also generally across the commercialisation process as a whole. For each of these routes we investigated the key 'enabling institutions' (such as the Turing Institute and universities' Technology Transfer Offices), the role of public funding (Innovate UK, UKRI, etc.) and private funding (from 'angel' and venture capital investors).

1 https://www.gov.uk/government/publications/national-ai-strategy

2 Throughout this report, 'Big Tech firms' refers to Google (Alphabet), Amazon, Facebook (now Meta), Apple, and Microsoft.

5 Other issues that receive particular focus are:

- The role of Standards Development Organisations (SDOs). The development of technical standards for AI, though at a nascent stage, may potentially have an impact on the commercialisation of AI R&D in a similar way to the impact technical standards had on other digital and emerging technologies such as mobile.
- AI in healthcare and the life sciences. UK businesses have seen particular success with applied AI products in this area, in spite of the manifest challenges presented in such a 'high stakes' sector.

6 We derived insights through four strands of research:

a) The development of a taxonomy of the ways in which AI R&D is commercialised, or 'commercialisation routes';
b) Analysis of data sources giving insight into the activity of UK AI businesses;
c) Subsequent comparison with AI commercialisation activity in eight other countries: the United States, Canada, China, France, Germany, Israel, Japan, and South Korea;
d) Over 40 interviews that were conducted with representatives from ten categories of stakeholder. A list of the various stakeholder categories is available p.15.

Key findings

We identified the following key themes:

A The value of AI comes from its application to an existing problem.
AI techniques are rarely products in themselves, but create value in the marketplace when applied to a problem in a business or industry sector.

- **i.** Businesses seeking to implement an AI solution to a real world problem require access to sufficient compute resources (computing capability afforded by hardware, supercomputers, data centres, etc.).
- **ii.** Commercialisation of AI R&D depends on the availability of sector-specific data. The UK Biobank and NHS genomics dataset are good examples of such datasets, and also the digitalisation of existing data which can make AI commercialisation possible.

B AI businesses require a broad set of commercial and sector-specific skills in addition to technical AI skills.

- **i.** To successfully commercialise AI R&D, businesses require multi-skilled teams that combine technical expertise with other capabilities, such as commercial business experience, knowledge of applicable regulations and law, and experience of addressing customer needs.
- **ii.** Academics or 'research-founders', being specialists in the technicalities and in designing AI, tend to be ill-equipped to navigate these additional commercial or sector-specific challenges.

C The UK has successfully commercialised AI in challenging 'high-stakes sectors'.

- **i.** In high stakes sectors such as health, security, financial services, transport and nuclear energy, poor product execution can cause immeasurable harm. AI systems need to go through an extended period of training and testing before they pass competency and safety assessments before being deployed. Accordingly, financial success and profit take some time to materialise, which presents a challenge for potential investors.
- **ii.** Despite these challenges, the UK has notable commercial successes in applying AI in sectors of existing strength (e.g. healthcare, pharmaceuticals, financial technology or 'fintech').

D Universities' equity share in their AI spinouts presents an important commercial barrier. Universities are the locus of AI R&D in the UK, and spinouts present the most direct route by which that R&D can be commercialised. However, the value presented by university R&D may not be fully realised owing to large equity shares being retained by the parent university.

- **i.** In the spinout process, research-founders face challenges negotiating intellectual property (IP) and equity shares with Technology Transfer Offices (TTOs). Large equity shares retained by a university can discourage researchers from pursuing spinouts by reducing the personal financial incentive to do so, and also the attractiveness of the business to private investors.
- **ii.** In the US, universities take a far smaller share of spinout equity, an arrangement which US-based venture capital investors (VC) are more used to. The large equity share retained by UK universities presents a barrier to future investment in UK spinouts by VC.

E There is a significant flow of AI talent from universities to large technology firms. Interviews confirm that UK AI talent leaving academia for employment in large technology firms is a reality, and this is skewing the landscape of AI commercialisation.

- **i.** Graduates and researchers are highly incentivised to take up positions at large technology companies. This occurs in part because of earning potential.
- **ii.** Other influencing factors are that large technology companies provide access to both the compute resources necessary to develop AI at scale, and the large datasets that are a fundamental component of AI development.
- **iii.** Researchers, who might have founded a spinout, may instead choose to work for a large technology company. Contracts with large technology companies may place restrictions on the activities that the most talented AI researchers can pursue.
- **iv.** High competition for AI talent makes it difficult for smaller businesses to recruit and retain AI talent.

F Private and public funding are associated with differing outcomes for businesses. Private investment is largely focussed on areas of R&D that can quickly progress to commercialisation, whereas R&D supported by public investment can take a more long-term approach to commercialisation.

- **i.** Plausible explanations for this include the relative scarcity of private investors that are willing to fund R&D at a low level of tech readiness, and that public bodies have more 'patient' funding available given the positive externalities associated with many of these merit goods.
- **ii.** Criteria for public funding awards may not be well aligned with commercial considerations and market needs.

G Securing intellectual property protection for AI R&D is difficult. Software patents are difficult to secure both in the UK and elsewhere, which makes realising the value in novel AI highly challenging.

i. In the US, business process patents allow more of an AI's value to be captured through IP. Several interviewees expressed the view that the IP regime in the UK isn't well-suited to this. Further study of possible changes to IP law around software and business processes would be needed before specific recommendations could be made.

H Without trust, attempts to commercialise AI will be ineffective. Some AI systems are not easily explainable. Fostering public and industry confidence that AI systems work as intended and do not cause unintended harm is highly important.

i. The work of **Standards Developing Organisations (SDOs)** and the creation of technical standards for AI may play a central role in establishing trust amongst customers, users and between businesses in areas such as privacy, security, fairness and the removal of algorithmic bias.
ii. Technical standards may eventually support interoperability between the products and systems of different businesses, easing uptake of new products and thereby increasing their commercial value.
iii. However, interviewees noted that the potential impact of SDOs and technical standards on AI commercialisation is not yet well established; such technical standards are currently in the early stages of development.
iv. At present, our interviews indicated that engagement with SDOs is largely done by large technology companies.

Key considerations

The following considerations emerged through the course of the research, but further work would be required to assess the benefits and potential efficiencies of each proposal.

A Support a more fluid relationship between academia and industry. In the UK, pursuing industrial and business projects is not viewed as an accepted career path for academic success. A culture change would allow leading AI researchers to move into industry, direct companies, take secondments and sabbaticals, and interact more with private companies – without risking their academic career or credentials. The current status quo may be optimal for academic departments, but not necessarily for industry and the commercialisation of AI R&D. More career fluidity may also work to address some of the dynamics behind AI talent flows.

- **i.** At US universities like MIT or CalTech, industrial-focused labs (as opposed to theoretical ones) lead students to pursue a career in industry, and this does not prohibit their returning to university research at a later time.
- **ii.** Interviews and analysis has led to several policy considerations for creating an environment for 'entrepreneurial academics':
  - **Commercial AI Fellowships:** networks of tech entrepreneurs that work with universities and find novel AI researchers, then connect them with industry contacts to solve a business problem, perhaps in another sector;
  - **Permissive policies on forming new companies** and time to pursue industrial projects;
  - Support the development of creative **joint-tenure packages** that make it easier for top AI talent to work in and alongside industry on applied AI projects;
  - Support access to compute resources for founder-researchers, through a **National Research Cloud**.

B Make UK university AI researcher positions more attractive. AI researchers can be incentivised to work at UK universities by the following:

- **i.** Access to public datasets; greater access to compute resources; favourable access to public sector stakeholders for important research; and joint academic-public sector research programmes.

- **ii.** Lastly, adjusting pay scales was often suggested by interviewees, although an exploration of the potential negative externalities of creating higher salaries for AI researchers would be necessary.

C Government to act as the 'first customer' to support the growth of AI businesses, potentially relocating grant funding to procurement. The UK government could use procurement to support the commercialisation of AI R&D, by being willing to be the 'first customer'.

- Interviewees reported that grants from public bodies do not always effectively incentivise startups to align with market needs. Put simply, a project's primary goal might be to justify funding, rather than to successfully commercialise. Several respondents expressed the view that criteria for grant awards do not sufficiently prioritise the commercial prospects of an applicant's project.
- Relocating funding from early stage funding to procurement may generate market value and create growth more readily than grant funding.
- A significant public sector first customer would support businesses who might otherwise struggle to reach scale by building market confidence, drawing investment, and encouraging the private sector to also become customers.

D Support spinout formation:

i. Create direct incentives. The UK government could opt to provide universities with a new Key Performance Indicator (KPI) which encourages spinout formation.
ii. Initiatives to link up research founders with commercial leadership through incubator and accelerator programmes should be continued and further developed.
iii. Public funding awards should include criteria that favour teams demonstrating a mix of technical, commercial and sectoral-specific skills and experience.
iv. Incubator and accelerator programmes should adopt a 'fail fast' approach – pulling funding and support from projects that fail to show the potential for commercialisation within a given timeframe. However, it should be noted that this does not mean that longer term, speculative research should be deprioritised. Commercialisation can only be a success by combining foundational, early-stage research with a commercialisation ecosystem that can shape and channel this research to meet market (and potential market) demand.

E Data and Regulatory Sandboxes. Support data availability in sensitive sectors through 'Regulatory Sandboxes': environments where private data can be used without infringing privacy rights and agreements.

i. Existing examples include programmes such as the proposed Kalifa 'Scalebox'[3], and the Financial Conduct Authority (FCA)'s regulatory sandbox[4].
ii. Such programmes enable public sector services to benefit from the use of novel AI applications.

3 https://www.gov.uk/government/publications/the-kalifa-review-of-uk-fintech, p.10
4 https://www.fca.org.uk/firms/innovation/regulatory-sandbox

F Explore the possibility of using the **Research Excellence Framework (REF)** to support engagement with Standards Developing Organisations for AI researchers and academics; and also consider the establishment of **AI innovation hubs** to foster engagement with and represent the voice of SMEs and startups in the standards development process.

G Although a thorough exploration of possible changes to the **IP regime for AI software** was beyond the scope of this project, we suggest it as an avenue for further research.

Contents

Accompanying materials
A 'technical appendix', with further information about the data sources and methods of analysis used in the research, is available as a separate document. This document also contains details of the questions asked in stakeholder interviews.

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Glossary of Acronyms

API	Application Programming Interface
BSI	British Standards Institution
Coadec	The Coalition for a Digital Economy
CDEI	Centre for Data Ethics and Innovation
CSET	Center for Security and Emerging Technology
DDE	Data-Driven Entrepreneurship Venture Builder
EIS	Enterprise Investment Scheme
EPSRC	Engineering and Physical Sciences Research Council
ETSI	European Telecommunications Standards Institute
FAIR	Facebook AI Research
FCA	Financial Conduct Authority
GAN	Generative Adversarial Network
GPU	Graphic Processing Unit
HAI	Stanford Institute for Human-Centred AI
IEC	International Electrotechnical Commission
IEEE	Institute of Electrical and Electronics Engineers
IP	Intellectual Property
IPO	Initial Public Offering
ISO	International Organisation for Standardisation
KTN	Innovate UK Knowledge Transfer Network
KTP	Knowledge Transfer Partnerships
KPI	Key Performance Indicator
JTC	Joint Technical Committee
LLM	Large Language Models
MIT	Massachusetts Institute of Technology
NFR	Non-functional requirements
NLP	Natural Language Processing
PDB	Protein Data Bank
RAEng	Royal Academy of Engineering
REF	Research Excellence Framework
RTO	Research and Technology Organisations
SDO	Standards Developing Organisation
SaaS	Software as a Service
SEIS	Seed Enterprise Investment Scheme
SME	Small and medium-sized enterprises
SRI	Stanford Research Institute
STEM	Science, Technology, Engineering and Mathematics
TRL	Technology Readiness Level
TTO	Technology Transfer Offices
UKRI	UK Research and innovation
VC	Venture Capital

Introduction

DCMS and the Office for Artificial Intelligence (OAI) commissioned Oxford Insights and Cambridge Econometrics to develop understanding of the ways in which AI Research & Development (R&D) is commercialised. The intended audiences for the resulting report are senior stakeholders at DCMS and the Office for Artificial Intelligence, public funding bodies involved in AI such as UKRI, and stakeholders in industry and academia – a policy audience, rather than a technical/scientific one.

Technological progress or innovation is the main driver of permanent increases in productivity.[5,6] Research in AI as well as commercial use of AI technologies have grown markedly[7], and the potential application of AI in all sectors of the economy is projected to create long-term increases in economic growth[8]. Both DCMS's upcoming Digital Strategy and the National AI Strategy, which sets out the UK government's ambitions for AI, acknowledge the transformational potential of AI technology.

The UK ranks 4th in the 2021 Global Innovation Index[9] and is a leader in starting and scaling new technology businesses; however, it is not always the case that research and development (R&D) will successfully be brought to market, and some indicators suggest that the UK may underperform in commercialisation compared with its performance in research[10] (i.e. knowledge creation vs knowledge diffusion). This report aims to develop an understanding of the process and routes by which AI R&D is commercialised, and suggest ways in which the effectiveness of those routes can be improved. This has led to a number of considerations and suggestions for policymakers and funding bodies as to how the UK can more effectively support the commercialisation process for R&D in AI – to ensure that AI research has maximum impact on the UK economy and the benefits of AI innovation are realised through increases in productivity and economic growth.

5 See the Solow-Swan model, (1956)

6 https://www.nber.org/digest/oct01/technology-and-productivity-growth

7 Stanford University, (2021), The AI Index 2021

8 BEIS, (2021), The Potential Impact of Artificial Intelligence on UK Employment and the Demand for Skills

9 Dutta. S, Lavin. B & Wunsch-Vincent. S, (2021), Global Innovation Index 2021

10 According to the Global Innovation Index, the UK ranks 8th for 'knowledge creation' (research output), but 15th for 'knowledge diffusion'. Knowledge diffusion is a measure that can be seen as comparable to commercialisation, containing metrics including: Intellectual Property receipts; exports of ICT; and high-tech exports.

The key components of the research are:

- A taxonomy of commercialisation routes for AI R&D.
- Analysis of a number of datasets to produce metrics that measure AI commercialisation activity in the UK economy. This establishes a foundation for understanding the most prevalent routes by which AI is commercialised.
- Over 40 interviews across ten stakeholder groups, including:
  - Private venture capital lenders;
  - Public funding bodies: EPSRC, UKRI, and Innovate UK;
  - Standards Developing Organisations – ETSI, BSI , IEEE and the UK's ISO/IEC mirror committee, ART/1-Artificial Intelligence (which mirrors the work of ISO/IEC JTC 1/SC 42);
  - Research and Technology Organisations – The Alan Turing Institute and The Royal Academy of Engineering;
  - Large technology firms – Microsoft, Nvidia, BT Group, Siemens Digital, and Deepmind;
  - NHS Transformation Directorate;
  - CEOs and MDs from a range of AI SMEs;
  - 'Research-founders' (academics who establish a business to apply their research) from a range of AI startups and University Spinouts;
  - Industry associations: The Coalition for a Digital Economy (Coadec); and
  - Academic Directors from Technology Transfer Offices at Edinburgh and UCL universities.
- A 'deep dive' on four 'priority routes' of commercialisation: University Spinouts, Startups, Large Firms that use AI, and Direct Hire/Joint Tenure.
- International comparisons of commercialisation activity with the United States, Canada, China, France, Germany, Israel, Japan, and South Korea.
- An investigation into the role of Standards Development Organisations (SDOs) in supporting or providing potential avenues for commercialisation through the development of technical standards for AI.
- A case study of applied AI in healthcare and the life sciences.

Definitions

This section outlines definitions for key vocabulary used in this report, and helps show the scope of the project (see 'commercialisation' in particular). The literature review (available as a separate supporting document) provides the basis for these definitions.

Artificial Intelligence (AI)

The use of digital technology to create systems capable of performing tasks commonly thought to require human intelligence. This includes the ability to learn and improve performance, as new or more data are accessed. We classify AI technology with the following four key sub-fields:

1. Language applications
2. Computer vision
3. Other predictive applications (e.g. scientific R&D, finance...)
4. Hardware innovations, including new types of chips etc but also robotics.

In this report, we focus on software-oriented technology, which typically involves the first three sub-fields. We also examine sector-based classifications of software-oriented AI technologies (e.g. digital health, transportation, financial technology, energy etc.) as a part of the study to determine the type of AI classification that is most relevant and useful to understanding differences in commercialisation challenges and approaches.

R&D

Research and development (R&D) comprises creative work undertaken on a systematic basis in order to increase the stock of knowledge (including knowledge of man, culture, and society) and the use of this knowledge to devise new applications.[11] Key institutions involved in R&D include universities, and research and technology organisations (RTOs). Firms also conduct R&D to varying degrees. Large multinationals have their own dedicated research departments; whereas start-ups or small and medium-sized enterprises have smaller numbers of staff involved in R&D.

Commercialisation

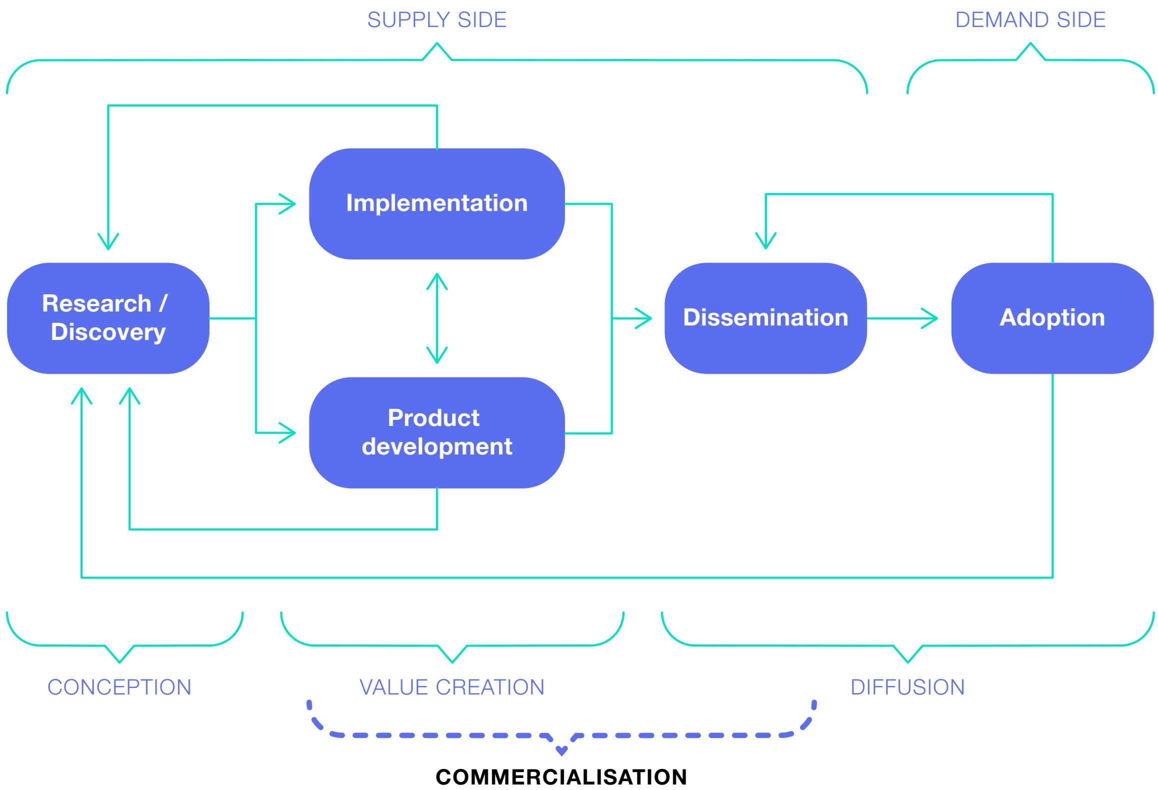
The process through which ideas or research are transformed into marketable AI products or services from which capital gains, income from licences, or revenue from sales can be realised. For the purposes of this project, "Implementation", "Product development" and "Dissemination" are the stages relevant to commercialisation. In the figure below, the dotted boxes with black font broadly show the area of research interest: factors that support the development of AI products and how AI technology is implemented, and then disseminated in the marketplace. R&D is not a central focus on this research; neither is adoption.

AI R&D Commercialisation in the UK

The study focuses on AI R&D originating from UK-based businesses, universities and other entities. It includes both UK-based R&D that is commercialised in the UK and also that which is commercialised overseas. Understanding factors that might lead UK AI R&D to be commercialised overseas is an area that the research aims to address.

11 https://www.oecd.org/sti/inno/frascati-manual.htm

Figure 1. Stages of AI innovation.



Technical Standards

Technical standards set out requirements, specifications, guidelines or characteristics that can be consistently applied to ensure that products, materials, processes and services are safe, efficient and fit for purpose. In digital technologies, technical standards establish uniform engineering or technical criteria, processes or practices. These specifications, which may include proprietary information, can be shared between and across organisations and businesses. Organisations that develop technical standards exist both at the national and international level.

There is a useful distinction to be made between 'de facto' industry standards (where a standard process, design or component developed by industry becomes dominant by public acceptance and/or market forces), and formal technical standards of the kind developed by Standards Development Organisations.

'Enablers' and 'Barriers' for Commercialisation

Discussion of enablers and barriers to commercialisation includes all those factors that positively and negatively influence the success of AI commercialisation attempts, including institutions, access to technological resources such as data access and compute capability, skills gaps, access to public and private funding, and others.

Summary of the Research Methodology

The approach to the research had four stages:

Stage 1: Taxonomy Development

We identified the different ways (hereafter referred to as 'routes') in which AI R&D moves towards commercialisation, and produced a taxonomy of commercialisation routes. This was initially based on a comprehensive literature review (see appendix 1), and was then further refined through conducting interviews with experts from academia, industry, government, Research and Technology Organisations (such as the Turing Institute), and funding bodies (such as UKRI). A list of interview contributors is available on p.12.

The final version of the taxonomy breaks commercialisation activity into three broad categories ('direct commercialisation', 'knowledge exchange', and, 'formal or de facto standards and IP') and sub-divides these into more specific routes (see p.20). It also identifies the roles of various 'enabling institutions' (Venture Capital investors, University Technology Transfer Offices, Knowledge Exchange Networks, SDOs, etc.) and the different 'actors' (researchers, spinouts, startups, SMEs, large businesses, etc.) within each of the routes.

Stage 2: Quantitative Analysis

A means for selecting a small number of these routes for in-depth study and analysis was devised. To do this, metrics for assessing the prevalence/importance of the various routes were designed by economists at Cambridge Econometrics, tailored to company-level data from a range of data platforms available to DCMS (details in the separately available technical appendix). Two key metrics were developed: i) 'absolute prevalence' measures the proportion of AI firms in our dataset using a given channel at least once; ii) 'relative prevalence' provides a comparative measure of route use between AI and non-AI firms. The results of this analysis fed into the selection of 'priority routes' for AI R&D commercialisation.

Stage 3: Qualitative Interviews

We conducted 41 interviews (stakeholder details found on page 12) in two waves between October 2021 and January 2022. A wide range of respondents were included from different stakeholder groups (see pp.15). The first wave of interviews aimed to capture a broad range of stakeholder types and wide-ranging discussions of all facets of AI commercialisation, to better refine our taxonomy, help identify the key areas of interest, and verify/corroborate the selection of 'priority routes' suggested by the quantitative analysis in stage 2. Second wave interviews focused on developing deeper understanding – a 'deep dive' into the workings of the chosen priority routes, and also on international comparison of the UK's AI commercialisation strengths and weaknesses against those of other countries.

Stage 4: Analysis of UK Strengths and Weaknesses

A SWOT analysis offering an assessment of the UK's Strengths, Weaknesses, Opportunities and Threats in the commercialisation process of AI R&D, based on insights from quantitative analysis extended to other countries including US, Japan, China, S Korea, Israel and Germany, qualitative interviews, and targeted desk research to build international case studies of examples of good practice.

Summary of Research Limitations

Interviews

Although the research interviews take in a relatively large number of respondents, from a wide variety of stakeholder groups, nonetheless the ideas and policy considerations that have been generated are based in large part on the subjective experiences and viewpoints of individuals.

Data timescale

The datasets on which the quantitative elements of the research are based provide a snapshot picture of activity in the various commercialisation routes at a single point in time. They are not truly longitudinal (i.e. do not follow a single cohort of businesses over a period of time), but rather present the present state of businesses all with different start dates, who may have reached different stages of progress and business evolution at the present moment in time. Comparing values across different stages of business evolution or business size bands and interpreting those as comparable journeys would require an assumption that each cohort is (broadly) identical and comparable, and experienced the same environment and conditions; both of which would be unwarranted assumptions. As such, it is fair to say that the quantitative elements of the research are at best indicative of trends in AI commercialisation activity.

Sample sizes

Beauhurst and CSET-PARAT datasets enabled analysis of different routes to commercialisation in aggregate. However, the sample size of some of the companies at different levels of maturity for each route was sometimes too small to draw strong conclusions between the different stages of a business's growth. Therefore, analysis only made such intra-route comparisons when the number of companies at a particular stage of growth was above 50. For some routes (for example, direct hire), it was not possible to obtain quantitative data on the prevalence of commercialisation for either AI or non-AI companies. As a result, our analysis placed greater weight on the results of interviews where quantitative data was limited.

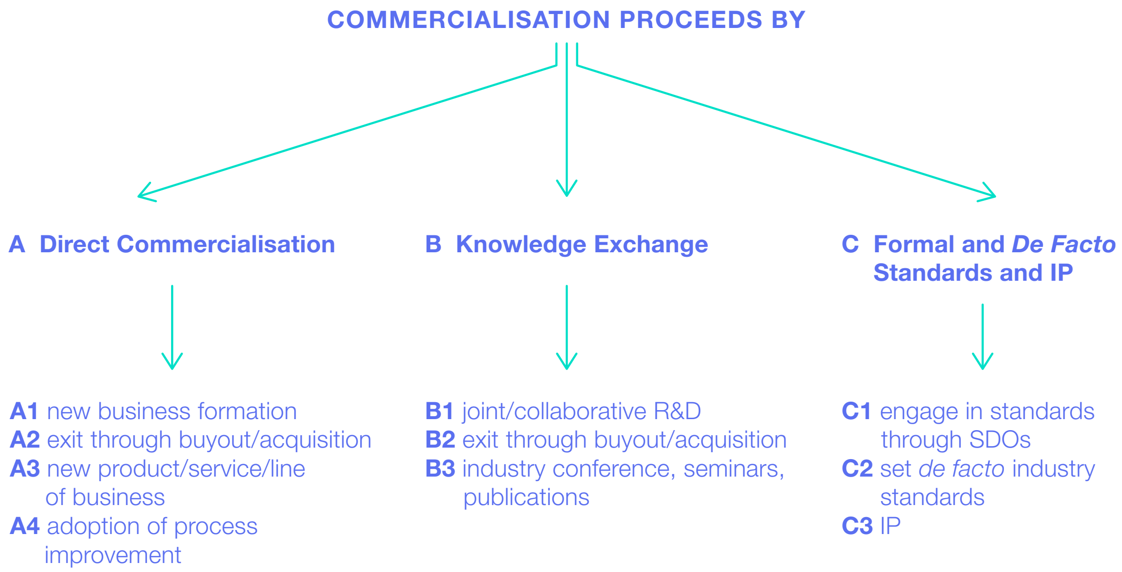
Open source software development

The research does not address commercial activity generated by specifically open source AI software (software released with a licence which allows users to freely change and redistribute the software). Open source development is a way to conduct R&D which facilitates collaboration amongst researchers and developers. Several respondents pointed to the frequency with which open source AI software is distributed by individuals, departments and informal associations of researchers, which then is taken up by many and varied businesses and put to commercial use. Commercial applications of open source software appear to be particularly relevant and accessible to small firms, and therefore its omission in this research biases discussion in favour of larger businesses. Interviewees indicated that standards for AI software may be emerging amongst open source AI researchers and developers; such standards appears to act as an enabler for small firms and new entrants – offering collaborative knowledge dissemination in developing off-the-shelf API/interoperability that is more accessible to smaller firms/individual actors than participating in SDOs.

There are two reasons for this omission. First, attempting to quantify commercial activity that makes use of open source software is very difficult, perhaps impossible, with the available datasets. Secondly, the use of open source software in the commercial sphere is not particular to AI software. This research is focused keenly on the commercialisation of specifically AI R&D, and not broadly on software commercialisation more generally.

Taxonomy of Routes to Commercialisation

Figure 2. Taxonomy of commercialisation routes



The figure above shows an overview of AI R&D commercialisation activities, or 'routes'.[12] These have been grouped into three broad categories: Direct commercialisation refers to commercialisation of a particular product, business or company function. Knowledge Exchange refers to the commercialisation of knowledge, usually through the commercial exchange of academic research. Formal or de facto standards can be understood as the systems of norms and technical requirements that can create new markets for commercial activity.

A Direct commercialisation

A1 New business formation

- This involves university spinouts based on R&D conducted by university researchers, as well as spinouts from existing companies based on R&D.
- University spinouts are often supported by university TTO with the university taking an equity share. Company spinouts may receive investment from the company it spun out of. Both university and company spinouts may fundraise through private funding such as VC (seed round) and public funding (innovate UK grants etc.) to get the business off the ground.
- This research focuses on university and company spinouts because these are environments where R&D can take place, unlike business formation not arising from an R&D basis.

A2 Exit through buyout or acquisition

- This often involves a large firm acquiring a smaller firm or startup, but can also refer to large firms being acquired.

12 This taxonomy is based on findings from the literature review (see appendix 1) and then revised in light of insights that emerged in a first wave of interviews with a broad range of stakeholders.

- "Acqui-hiring" is another form of acquisition that has emerged, which describes a process of acquiring a company primarily to hire its employees; this is closely related to route B3.
- Initial Public Offerings (IPOs) and other public share offerings also form part of this route.

A3 New product/service/line of business
- A company brings to market a new AI-based product/service (from R&D).
- This involves private sources of funding to enable the route, such as fundraising from venture capital or loans from banks, as well as internal funding in the case of a large firm.
- New products, services and/or line of business primarily involve grant-based public funding.

B Knowledge exchange

B1 Joint/collaborative R&D
- This includes shorter term consulting engagements of academic researchers with an AI-focused firm as well as longer term R&D collaboration with firms and university research teams/departments.

B2 Direct hiring and joint tenure
- Direct hire of academic researchers into a firm. Typically, firms more likely to conduct hires of this kind are large and possess significant data and computing resources.
- Joint tenure of academic researchers at university and at a, typically large, firm.

B3 Industry conference, seminars
- Monetised conference, seminar or speaking engagements to showcase new R&D.

C Formal or de facto standards and IP

C1 Engagement in standards through SDOs
- This can take the form of any actor attending committee meetings, and contributing to the development of technical standards.

C2 Set de facto industry standards
- Large firms may also increase the commercial value of their products and platforms by establishing de facto technical standards through market dominance; i.e. other businesses and developers may be compelled to use a particular process, platform or software. More research is needed to determine how relevant this route is in AI.

C3 Intellectual Property IP
- Use IP to establish protection around the development and use of AI technology. Examples of this include patents, copyright, and trade secrets.

Further in depth descriptions of these commercialisation routes can be found in the literature review presented in appendix 1.

Key actors and key enabling institutions

A group of key 'actors' and 'key enabling institutions' that interact with the routes described above emerged through the various interviews.

Table 1. Actors and Key Enabling Institutions

Actors	Key enabling institutions
• University researchers • Industry researchers • Startups • Small and medium sized firms • Large firms	• Private funding (e.g. VC, large firms) • Public funding (e.g. Innovate UK) • University Technology Transfer Office (TTO) • Knowledge Exchange Networks (e.g. KTN, The Alan Turing Institute) • Standards Developing Organisations (SDOs)

'Actors' are the groups of entities that conduct AI R&D, whereas 'key enabling institutions' are the organisations that play an important role in organising and directing the various enabling factors that help actors to commercialise research into marketable products and services.

The table overleaf explores in more detail the way that different actors engage with commercialisation routes, showing which actors and institutions are relevant to each route. Developing the taxonomy by adding these dimensions creates a more nuanced understanding of the AI commercialisation landscape.

Dark grey boxes indicate use of route, whilst light grey boxes indicate the potential use of a route in the future. This is especially relevant to standards development, as AI-specific standards are nascent and therefore have less established routes to commercialisation for actors and institutions.

Table 2. Intersection of Commercialisation Routes, Actors and Key Enabling Institutions

	Actors using routes of commercialisation					Key enabling institutions				
	University researcher	Industry researcher	Startups	Small and medium sized firms (SMEs)	Large firms	Private funding (e.g. VC, large firms)	Public funding (e.g. Innovate UK)	University Technology Transfer Offices (TTO)	Knowledge Exchange Networks (e.g. KTN, Alan Turing)	Standards Developing Organisations (SDO)
Route A – Direct commercialisation through…										
A1 …new business formation	e.g. university spinout	e.g. cofounder of university or company spinout			e.g. company spinout			e.g. supports university spinouts		
A2 …exit through buyout/acquisition						e.g. large firm acquiring smaller firm				

	Actors using routes of commercialisation					Key enabling institutions				
	University researcher	Industry researcher	Startups	Small and medium sized firms (SMEs)	Large firms	Private funding (e.g. VC, large firms)	Public funding (e.g. Innovate UK)	University Technology Transfer Offices (TTO)	Knowledge Exchange Networks (e.g. KTN, Alan Turing)	Standards Developing Organisations (SDO)
A3 …new product/service/line of business					e.g. large firms uses internal budget to develop and a new product	(a)	(b)			
A4 ...adoption of process improvement					e.g. large firm uses internal R&D budget to develop a new process					
Route B – Knowledge exchange through...										
B1 …joint/collaborative R&D							e.g. Knowledge Transfer Partnerships between University researchers and Innovate UK			
B2 …direct hiring/ joint tenure	e.g. university professor having joint tenure with a large firm									
B3 …industry conference, seminars, publications				e.g. CTO presents at NeurIPS						
Route C – Formal or de facto standards and IP…										
C1 …engagement in standards through SDOs	University professors securing funding for participating in standards development									
C2 …set de facto industry standards										
C3 ...IP										

KEY	Light grey	Route used
	Dark grey	Potential for route use

Assessing Route Prevalence

After constructing the taxonomy of commercialisation routes, we use a combination of quantitative and qualitative analysis to determine which routes were of greatest importance to the commercialisation process.

Quantitative Analysis

From the quantitative analysis of Beauhurst, Pitchbook, and CSET-PARAT data, in which we identified high-growth AI firms in the UK, a comparison of routes was produced, based on 'absolute' and 'relative' prevalence measures. Full details of these metrics are found in appendix 2, along with details of route scoring and explanations of the data sources used.

Absolute prevalence – The proportion of AI firms in our dataset using a given channel at least once.

Relative prevalence – a comparison of the use of a route by AI firms relative to its use by other kinds (non-AI) of firms in the wider economy.

Highest scoring routes in terms of absolute prevalence were:

- Privately-funded development of new products/ services (A3a)
- Knowledge exchange through academic publications (B4)
- Publicly-funded development of new products/services (A3b)

Highest scoring routes in terms of relative prevalence were:

- Commercialising through IP (Patenting) (C3)
- Publicly-funded development of new products/ services (A3b)
- New business formation, specifically university spinouts (A1)
- Privately-funded development of new products/ services (A3a)

Qualitative Analysis

Routes with highest levels of discussion

Through qualitative analysis of interview responses, the following routes emerged as most significant:

- New business formation, specifically university spinouts (A1)
- Publicly-funded development of new products/ services (A3b)
- Privately-funded development of new products/ services (A3a)
- Direct hire/joint tenure (B2)

Routes with a moderate amount of discussion

Commercialising through IP (Patenting) (C3)

Several respondents point to a weakness in the understanding of software IP in the UK, and that it is uncommon for AI firms in the UK to effectively commercialise on the basis of IP/patenting.

> *"And the IP side is very difficult to get patents now in the software space. You can get them granted but can't necessarily protect them or enforce them…the traditional elements of commercialization, I think probably don't apply to a lot of AI technologies. So, certainly patents are not really used that much."*
>
> *– Startup*

Routes least discussed

Knowledge exchange through publications and conferences (B3) has not been discussed much in interviews, which contradicts the high prevalence scores reached in the quantitative data analysis. Our conclusion thus far is that, although many firms are engaged in knowledge exchange through these mediums, the effect of commercialisation success is not obvious or important to industry stakeholders.

Buyouts/exits (A2) was not a significant area of discussion. This may indicate that the startups interviewed are at a relatively early stage, though large firms interviewed also did not discuss buyouts.

Setting de facto industry standards (C2) is indirectly discussed by certain stakeholders, particularly in the standards community, who recognise that large incumbent firms play a big role in shaping de facto industry standards by simply being first-to-market. Thus newer players benefit from conforming with these standards to operate in the industry.

Joint-collaborative R&D (B1) is mentioned, particularly in the context of large technology firms which cultivate close relationships with universities and fund research centres at universities. While important for R&D, this channel is not emphasised with clear importance for commercialisation.

Synthesis of findings

The following routes emerged as most prevalent/important across the two components:

- New business formation, specifically university spinouts (A1)
- Publicly-funded development of new products/services (A3b)
- Privately-funded development of new products/services (A3a)

In addition to these routes, we also take forward

- Direct hire/joint tenure (B2)

Direct hire/joint tenure could not be captured in the quantitative analysis; however interviewees have particularly pointed to this phenomenon for AI researchers, which warrants further analysis.

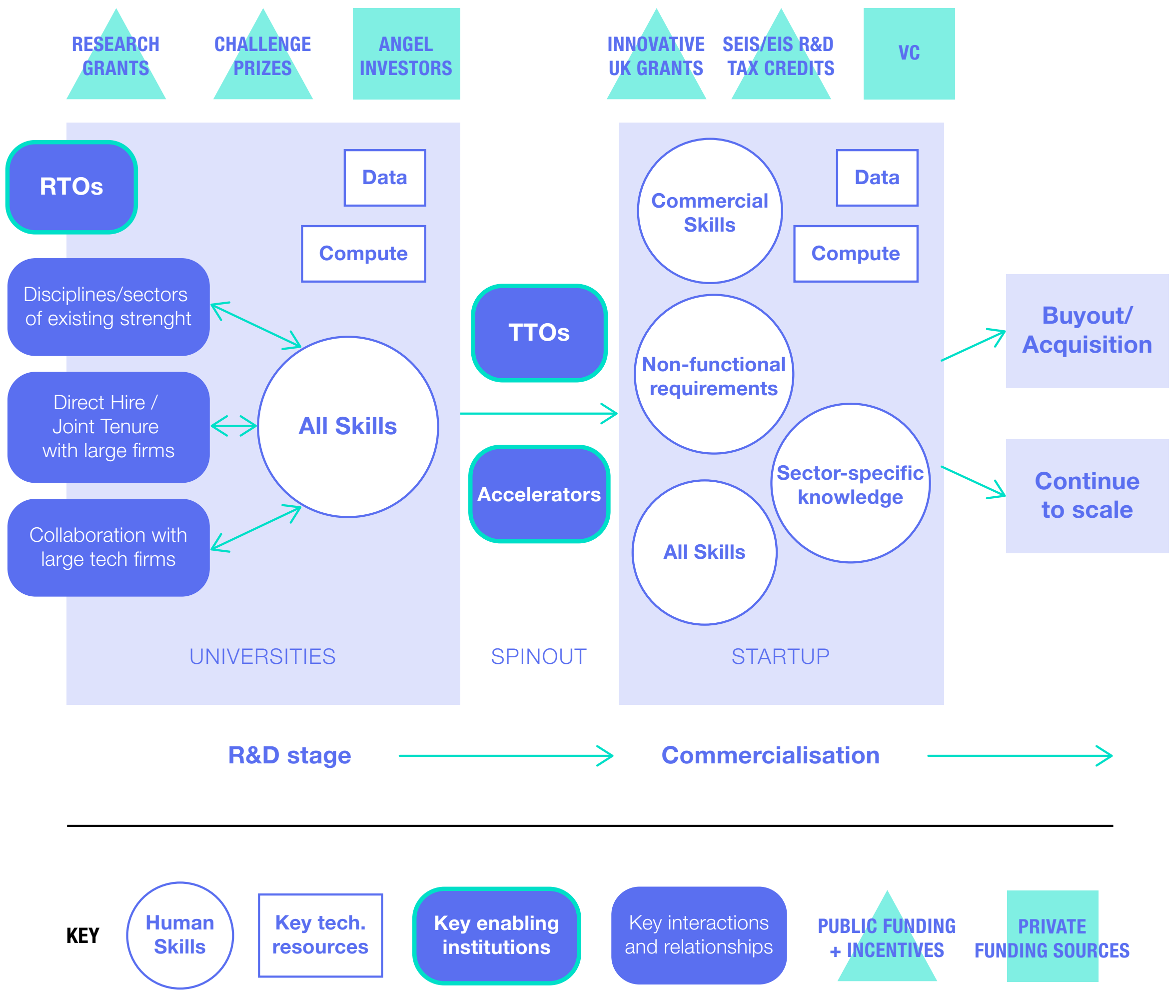
- Engaging in standards through SDOs (C1)

Discussions with different stakeholders point to the impact of SDOs and AI technical standards being at a nascent stage; but also a clear groundswell of opinion noted that AI standards will only grow in importance given the far-reaching and growing applicability of AI technology, and also in light of the need for standards to develop trust in AI and address the ethical implications that are already beginning to surface.

- Commercialising through IP (Patenting) (C3)

We examine its role in the context of the routes, rather than as a route on its own.

Figure 3. Overview of the commercialisation process for AI R&D, including enabling institutions, key barriers and enablers, resources.



Interviews and analysis of quantitative data resulted in a number of general insights into the commercialisation process that are not specific to any particular route. This section discusses the 'cross-cutting themes' that apply to several of the taxonomic routes. More route specific insights are given in the section beginning on page 34.

This overview depicts AI R&D commercialisation beginning at universities. This is where the initial research is often completed, though large technology firms and RTOs are also significant players here. Sources for funding at this early stage include grants, challenge prizes, and angel investment.

To reach the next stage often requires 'spinning out' research from the university into a fully-fledged company. The key enabling institutions that facilitate this initial commercialisation stage include TTOs and accelerator programmes. Alongside AI knowledge, in order to develop commercially valuable AI systems, companies often require skills such as sector-specific knowhow, commercial acumen, and the ability to meet non-functional requirements. Access to technological resources such as data and compute capability are also essential.

The next stage for a spinout, should they not go out of business, has two potential paths. Either they continue to scale, with the help of funding from Innovate UK grants, R&D tax credits, and venture capital, or they are eventually acquired by a larger firm.

'Real life' applications

AI researchers are increasingly motivated by impactful work – generating AI applications with real-life impact. Previously, researchers were primarily interested in improving benchmarks of AI performance; game environments with clear rules of success were the preferred medium (e.g. AlphaGo). Today, researchers seek interdisciplinary collaborations to develop applications to save lives, solve climate change, as well as more incremental, real-world applications such as fraud detection.

In the UK, this trend has effectively interacted with and built on top of existing areas of strength in fundamental research, including the life sciences. The UK is widely recognised as a global leader in life science-related AI applications, which include (but are not limited to) healthtech, medtech, biotech, and pharmatech.

Universities continue to be a key enabler of these processes, particularly in the dense networks of the Golden Triangle of London, Oxford and Cambridge. AI and science researchers at universities are able to engage, freely exchange ideas and collaborate on R&D. Open source development frameworks and off-the-shelf algorithms appear to facilitate this collaboration.

Furthermore, interviewees noted that the digitisation of a given sector was the most important factor in determining whether AI would be commercialised in a given sector.

> *"So I would think it [the key determinant of which kind of AI is commercialised] would be the underlying digitisation of the sector or the sub sector. Then it would be the data availability. So how robust is the collection? Can that data be used? And then choosing which type of technique."*
>
> *– The Alan Turing Institute, Research and Technology Organisation (RTO)*

Statements of this kind were reflected across the industry, from investor to academic to entrepreneur.

Another key finding relates to 'high-stakes' sectors, where lives and national security are at stake. In areas such as health, security and nuclear energy, poor product execution can cause immeasurable harm. AI is being increasingly commercialised in these sectors, hereby posing a different set of regulatory challenges to lower risk domains. With the UK boasting particular strengths in such high-stake commercial applications of AI, such challenges are especially relevant.

Leadership and commercial experience

University incubators and accelerators, along with surrounding 'angel' investing networks and VCs play a role in mitigating the barriers outlined, by providing researchers in the process of founding AI businesses with business and commercial training and introductions into key sector-specific networks. In some cases, founding teams brought on an experienced CEO at early stages to mitigate the lack of commercial and fundraising experience. There is an indication that sector-specific accelerators, or innovation hubs, are particularly valued in the commercialisation process. This reflects the deep sector understanding and networks that are crucial to building and funding successful AI spinouts or startups.

Data issues, ethics and constraints

As AI technology has become increasingly adopted into sectors that affect human lives, the quality of datasets that are used to train AI models have been called into question. Concerns have risen around the population representativeness of datasets, including how ethnic minorities, women, LGBTQ+ and differently abled groups are represented in datasets. At the same time, ethical concerns are called into question around how data have been collected and used in developing machine learning models with little to no knowledge or consent of the people whose faces, physical features and other digital traces may have been scraped from various databases. Further, there is increasing concern around the unpredictable and unexplainable nature of AI, combined with general applicability of AI technologies, as they are adopted to replace human decision-making in safety-critical sectors where lives and national security are at stake. It is widely acknowledged in the communities of SDOs in Europe and the US that developing AI technical standards is of utmost importance to manage ethical and safety-critical risks.[13]

The role of universities

Universities continue to be a key foundational hub of AI talent, R&D and resources for research commercialisation.

It is worthwhile to note that universities are diverse entities. The strategy, commercialisation or innovation support provided to researchers and students varies widely across institutions.

AI Talent

While general software development talent has become relatively more widely available, through a dispersed global pool of programming and development capabilities, high-skilled AI talent continues to be concentrated at top universities. Many interviews have remarked that the UK is a global leader in producing AI talent at its top universities.

This means that there is tremendous international competition for this talent pool as companies race to build and scale their AI applications. This competition materialises in salary and compensation pressures for academics, graduates seeking employment, and prospective academic entrepreneurs.

The substantial salary and compensation differences between academia and industry are pull factors that may entice AI researchers to seek industry employment. Large technology firms can offer large compensation packages to attract and retain AI talent.[14]

> *"The difference in salaries for academics compared to the salary of an AI researcher at a large tech firm is huge… From what I know, a researcher working in AI has the same salary as, for example, an academic in a field like sociology, and so on. In those fields, there is no such huge gap between the industry, academia, and the market."*
>
> *– Large Technology Firm*

Joint-tenure arrangements

Joint-tenure at corporations and universities appears more common in the AI context than for other technology fields. Retaining university positions may mitigate some of the consequences of universities completely losing talented AI researchers who contribute to the pipeline of development of future talent as well as an overall healthy AI innovation ecosystem. This phenomenon may also reflect the fierce competition for skilled AI talent, which could enable established researchers to negotiate mutually beneficial contracts that allows researchers to retain a degree of autonomy in research direction by keeping their faculty position. This arrangement is also beneficial for corporations as it helps them to stay close to the innovative R&D taking place at universities.

Effect on Spinout Formation

Global competition for talent could also influence university spinouts in a few different ways. R&D-based spinouts will tend to have strong AI talent in its founder or co-founder, without the need to bring on additional AI talent until further growth. However, researcher-founders may also face a decision between starting their own company or taking a high-salaried position, where they may still have an opportunity to further develop and bring their research to market. This could reduce startup formation in the UK.

> *"I think down the line, it could lead to a reduction of companies appearing from the UK because if all the most talented people are going to these tech giants, we won't have many people to work on developing startups"*
>
> *– University*

13 European Commission, (2020), Ethics Guidelines for Trustworthy AI

14 Gofman. M & Jin. Z, (2020), Artificial Intelligence, Education, and Entrepreneurship

Technology Transfer Offices (TTOs) in a global market

The global competition for AI means that UK universities increasingly face pressures to replicate best international practice in structuring their TTOs and their equity split with university spinouts in order to stay globally competitive as an enabler of AI innovation.

Such a development could have upstream implications on where researchers choose to attend institutions for graduate research or academic appointments. TTOs face pressure since they typically play an important role in helping to facilitate fundraising to ensure that the spinout is successful or at a high valuation. If VCs are coming from the US, or are influenced by US spinout investment structures, then they are likely to push back on demands from universities for higher equity shares.

Several interviews pointed to a conflict between researchers and TTOs. TTOs traditionally play a role of supporting and enabling research commercialisation at the university through varying degrees and types of support depending on the office. Support includes facilitating introductions to key funding and industry networks, supporting business model and regulatory research, and guiding fundraising processes. One of the most contentious issues is the allocation of equity. Prospective founders want to be able to grow a business, whereas TTOs are typically structured to be, at least partially, compensated through the equity share to enable the office to stay financially viable. These objectives can create tension as founders do not want to give up a significant amount of their company early on, in part because this could make them less attractive to private investors and could present challenges for later rounds of fundraising in the UK and beyond.

In the US, universities take a far smaller slice of spinout equity. Some interviews point to TTOs having a different approach to financial viability in the US, wherein they can far offset taking a smaller share of equity through supporting more numerous spinouts that achieve varying levels of success. In response to these criticisms, the University of Oxford, for example, has recently announced that it will reduce its spinout equity requirements to 10% in some instances (compared to 20% normally).[15]

According to interviewees, in the US, TTO's have more employees from a commercial background than in the UK. As a result, this means that there is more of a 'shared understanding' of incentives between US TTO staff and the prospective entrepreneurs over issues such as equity demands.

Intellectual Property conflicts

Another conflict is around IP ownership. University spinouts are often based on R&D that was developed during a researcher's time at university; so the university may claim to own the IP. In enabling the spinout, the university offers a form of (free) IP licensing as part of the equity agreement.

This is contentious as software generally cannot be patented in the UK. Interviews pointed to a general lack of understanding of software IP in the UK. Moreover, if IP is established and owned by the university, this could raise issues in the fundraising process, especially with venture capital investors who may see the IP arrangement as problematic.

Further, some university professors claimed that the idea of IP ownership is outdated when it comes to AI – with a new approach being necessary for a technology that is so often published as open source.

> *"They [TTOs] are a little bit shackled by this mental model, the characterization of academics having to be owners of slices of an intellectual property. It doesn't really make sense."*
>
> *– University*

Here, AI is different from other research fields. According to founders interviewed, it is unlikely that a machine learning-focused business is born out of 15 years worth of university research. Additionally, AI is often made open source. As a result, AI businesses can always threaten to make information open source, so they have a strong lever when it comes to negotiating a better IP deal.

Analysing patent data also shows that as AI firms grow, they are increasingly likely to hold IP. This could reflect an increasing likelihood of having an innovation worth protecting and/or more resources to secure a patent, as a firm grows.

15 https://www.medsci.ox.ac.uk/.../equity-share-policy-for-new-spinouts

Compared with other countries, DCMS analysis of Pitchbook data showed that the UK achieved a middling performance when it comes to commercialising IP relative to the likes of the US and Canada. A potential explanation of this could be due to the ability for the US and other countries to use business process patents, unlike the UK.

University-Multinational collaboration

Large multinational technology companies also point to joint-collaboration with universities around the world in AI research and development being an important component of their R&D strategy. From these collaborations, these companies are also able to draw on relevant in-country networks for commercialisation of applications. Researchers at large companies also point to being motivated to increase the impact of their work by working collaboratively with academic partners.

The importance of data and compute

AI innovations premised on data availability

High quality, digitised, publically available datasets are important enablers of AI R&D commercialisation. As researchers move into different sectors of application, accessing large amounts of data in that sector is critical to developing useful applications. This is a common need across different types of actor – spinouts, large firms, SMEs, etc. For example, AlphaFold's development has been based on the freely accessible Protein Data Bank (PDB)[16], which is a database for the three-dimensional structural data of large biological molecules, which has been curated and managed by institutions in the US and UK over many years.

Large firms may have advantages owing to holding and having access to large amounts of proprietary data (although this can depend on the type of application researchers aim to build).

There is increasing interest in new, novel, publicly accessible databases – including opening access to previously proprietary data owned by private companies – and the digitisation of as-yet-undigitised records and sources. Successful commercialisation of AI R&D in novel areas and sectors will require new sources of data to be collected, curated and made available. Governments and associated organisations are seen as having an important role to play in facilitating this.[17]

Compute need

Compute needs have only grown as AI technology has advanced and richer sources of real-world data are collected and used as inputs. Researchers indicate that accessing reliable compute capacity is a tremendous barrier in building AI applications in both the UK and US alike. According to academics interviewed, compute clusters at universities do not hold nearly enough computing power to develop new AI applications; public research institutes often supplement their ownership of computational infrastructure with subscriptions to cloud computing services. This is an area where many interviewees suggested that government has a clear role to play in supporting the development of compute capacity; particularly as this is a barrier that is faced acutely by university researchers, spinouts and startups.

Data and compute resources draw talented researchers to large firms

Large data and compute resources give large firms an edge in competing for AI talent. Academic researchers working in fields of AI which require particularly high levels of data and reliable compute will receive many benefits in going to work for a firm with access to those resources.

> *"There are advantages like data sets, and big compute infrastructures. Especially now in deep learning with AI, we need large compute infrastructures. We had to build up our own GPU cluster. During COVID, some of them broke."*
>
> *– University*

16 https://alphafold.ebi.ac.uk/

17 The Economic and Social Research Council (a council of UK Research and Innovation) has been developing a nd maintaining a data infrastructure that provides access to a wider variety of datasets. ESRC has a small number of collaborative data service investments that focus on the creation, access and use of digital exhaust data: Consumer Data Research Centre, Urban Big Data Centre, Social Science Data Lab and HateLab.

A Closer Look at Applied AI in the Life Sciences

One of the sectors with particularly advanced examples of commercialised and applied AI in the UK is healthcare. Healthcare is seen by many AI experts as 'the next fintech', and one of the areas in which the UK could be a world leader in commercialising AI. Internationally, machine learning is increasingly being applied to problems in biology. This area has access to huge amounts of data for both imaging and sequencing. Furthermore, machine learning reduces human error, making processes and experiments more repeatable and thereby cheaper. As a result, AI is reducing the amount of time it may take, for example, for a drug to come to market.

The UK as a Global Leader in Life Sciences AI
Pharmatech firm Exscientia was the first company to automate drug design and the first to have an AI-designed molecule enter clinical trials.[18] London-based company Causaly[19] uses machine learning to analyse and connect papers and clinical trials to help clinicians solve specific healthcare problems. Recently, genomics group Oxford Nanopore had an IPO with one of the biggest London listings in 2021.[20]

Enabling institutions
Europe's leading universities and research institutions in healthtech are predominantly in the UK. Five of the world's top 25 universities for life sciences and medicine are in the 'Golden Triangle' of London, Oxford and Cambridge.[21] As a result, AI spinouts working on medical problems are able to flourish in Britain.

Healthtech specific incubators enable this commercialisation process. Digital Health London supported 2013 startup Babylon Health, which develops AI-powered diagnoses and remote consultations with NHS clinicians, and has gone on to sell services to clients around the world including in the USA, China, Canada, and partnered with the Bill and Melinda Gates Foundations in Rwanda. KQ Labs at the Crick Institute is accelerating the likes of Eczemado machine learning and personalised coaching to predict and prevent eczema flare ups.

18 https://www.dundee.ac.uk/stories/exscientia

19 https://www.causaly.com/

20 https://www.reuters.com/business/oxford-nanopore-eyes-47-billion-market-value-london-debut-2021-09-30/

21 https://business.london/invest/sectors/life-sciences-and-healthtech

Table 3. Healthtech accelerators in the UK

Incubator	Headquarters
Healthbox	London
Atlantic Accelerator	Cambridge
Digital Health London	London
Dotforge Health + Data	Manchester
Startupbootcamp	London
Digital Health Incubator	Birmingham

NHS Transformation Directorate (previously NHSX) plays a unique international role in facilitating the exchange of knowledge to the market. NHS Transformation Directorate Skunkworks, as part of their AI Lab, aims to ensure that AI adoption in the NHS can be done safely, effectively, and ethically. Examples of their work include a forecasting model which uses Generative Adversarial Networks (GANs) to forecast the length of stay of patients. Most of this AI is procured from UK suppliers, such as Aylesbury-based Polygeist in the long stayers modelling system.

Regulatory Sandbox

NHS Transformation Directorate is at the forefront of innovative new techniques to develop transformative technologies, such as regulatory sandboxes that enable the testing of products with real customers. In a sandbox, regulators monitor events closely and allow only controlled access to the sandbox in order to ensure safety.

The UK Fintech industry has already seen the benefits of sandboxes, with the FCA having launched their own sandbox in 2016. The Kalifa Review of UK Fintech recommended that the FCA sandbox be enhanced to provide more value to firms.[22]

Healthcare, a highly regulated sector, can often require an established legal team to keep up with changing regulation, excluding smaller businesses from entering the market. Sandboxes could be particularly useful in addressing a key challenge to commercialisation in healthcare: that data sharing is often still sealed. As a result, regulatory sandboxes could allow data to be shared between a patient's online GP and their regular NHS service, generating better datasets for AI systems to be trained on and a more personalised healthcare response.

22 https://www.gov.uk/government/publications/the-kalifa-review-of-uk-fintech

Challenges

Further challenges for commercialisation of AI firms in the healthcare industry still remain. First and foremost is the safety-critical nature of the industry. This challenge is twin-pronged in the UK, in both the risk that healthcare operations/products can pose to patients if poorly applied, but also the accountability question that naturally arises given the taxpayer-funded obligations of the NHS to the public.

Moreover, health records are notoriously difficult to parse. Often, these records are an amalgamation of handwritten notes and database entries. In the UK, the majority of the social care sector is unable to readily access digitised medical records.[23] For AI, these digitised records are particularly important when training AI models on a large, population-level dataset.

The role of IP

Healthtech is an example of a relatively IP-intensive sector, which could include obtaining patent protection on discovered drugs as a business model. However, the use of AI technology in speeding up drug discovery also has implications for IP considerations. IP has been developed based on protecting inventions of human creators. Therefore, as unexplainable deep learning models advance in drug discovery capabilities, the ability to attribute the discovery to human inventors will become more tenuous over time, opening novel implications for IP and how it will have to adapt to a future of increasing human-AI collaboration in inventions.[24]

23 https://www.nhsx.nhs.uk/blogs/a-market-for-digital-social-care-record-solutions/

24 https://www.gov.uk/government/consultations/artificial-intelligence-and-ip-copyright-and-patents

Route specific insights

The following section describes the insights generated by the 'deep dive' into the four 'priority routes'.

Route A1 – University spinouts

Description of route

Interviewees that had experience in commercialising UK AI University spinouts largely focused on healthcare (including pharmaceuticals and biotechnology), fintech, defence and security, and advertising (adtech). Those forming and investing in spinouts consider the sector of application an important factor in determining approaches to commercialisation. Computer vision and natural language processing (NLP) were found to be the AI technologies most commonly used in spinout applications.

4.3% of all UK AI firms are formed by university spinouts[25]. This route is much more important for AI firms than non-AI firms, at every stage of business evolution. This higher relative prevalence may be down to specialist AI knowledge being more likely to develop in universities compared with non-AI spinouts.

AI firms that are university spinouts are more likely to be in the 'established' stage than AI firms that are not university spinouts (and non-AI firms that are university spinouts). While this could suggest better performance of spinouts, it could also indicate that university spinouts are a more mature route of commercialisation in the UK, i.e. they have been in existence longer and are therefore more likely to be represented in the 'established' stage.

Founders of AI-based spinouts have an academic background ranging from early career researchers to established professors with a strong STEM representation of founder backgrounds.

Key Enabling Institutions

A number of key enabling institutions are important in the spinout route. These include; universities; technology transfer office (TTOs); research and technology organisations (RTOs); and innovation and funding agencies (such as UKRI).

Additionally, university affiliate organisations have emerged with a focus in scaling AI spinouts, including the Machine Learning Research Group at Oxford University and the Edinburgh AI Accelerator Cohort.

Typically, the spinout journey begins as a research-led idea from a university academic, who then has to negotiate technology transfer between other parties, involving at least the university's Technology Transfer Office, and perhaps also external investors.

During the process of spinning out, founders often seek support from grant funding (such as from Innovate UK), venture capital funding and support, as well as accelerator support affiliated with the university, or technology-relevant accelerator programmes.

There are numerous criteria that funders look at when judging the commercial success of an AI spinout, including; viability of business model; revenue generation; product uptake; and leverage of follow-on investment. Both public and private funders consider these metrics. Additionally, public funders such as EPSRC will also pay attention to knowledge spill-overs and agglomeration effects increasing wider labour market efficiencies where this can be measured, as well as broader distributional outcomes that may pertain to geographic, class, gender, age, and racial disparities.

Universities in the UK are independent, but are funded by the government. As a result of government funding, they tend to have precise Key Performance Indicators (KPIs). This is not the case in countries such as the US, where there is less public funding.

This is a potential advantage to the UK, if considered wisely. Interview respondents suggested that if the government decided to add new KPIs on spinouts, this could create a new incentive regime which other countries could not replicate, thus gaining a commercial advantage on the international market.

25 See technical appendix supporting document.

Enablers of commercialisation

Accelerator programmes

Institutions that can coordinate connections, and funnel monetary and non-monetary resources towards researchers looking to spinout, help spinouts to perform particularly well when commercialising AI R&D.

For example, accelerator programmes run by universities and RTOs were seen as integral to helping many AI spinouts bring their research to the market. The likes of Cambridge Enterprise, Edinburgh's Data-Driven Entrepreneurship (DDE) Venture Builder, and the Enterprise Hub at the Royal Academy of Engineering were frequently cited as having successful spinout models, offering money, entrepreneurial advice and a wealth of industry contacts for programme participants.

Funding of this kind can vary. Examples include equity-free funding, educational vouchers to help develop leadership skills, and regional talent hubs which support technology enterprises across the UK.

This is especially important for the general purpose nature of AI. Often spinouts operating in one particular sector may not recognise that there is a similar use case related to their prospective spinout in another sector. Joining up cross-sectoral expertise and insight is therefore especially important for a technology which is embedded across different industries.

Accelerator example – Cambridge Enterprise

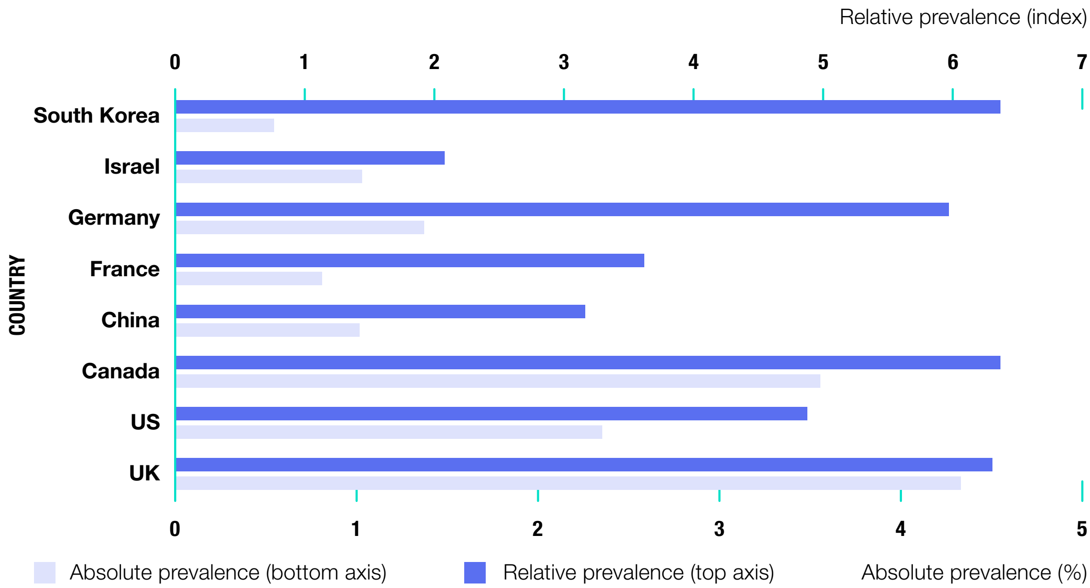
In 1995, Cambridge Enterprise, based at the University of Cambridge, began with a £2m fund. Since 2011, companies spunout from the University of Cambridge have raised £1.9b in equity investment since 2011.

Cambridge Enterprise advises on: how to coordinate resources; developing a business plan and commercialisation strategy; and IP management. The fund also has developed partnerships with the Cambridge Judge Business School in the areas of social enterprise within the NHS locally to promote innovation in medical technology.

Examples of AI spinouts that have secured funding from Cambridge Enterprise include:

- Cambridge Touch Technologies – a leading developer of AI-driven, 3D multi-touch sensing technologies for smart devices. In 2018, they received $5.5m Series A1 investment from Cambridge Enterprise and other investors. In 2019, They received a further $10.2m in Series B funding.
- Intellegens – develops proprietary algorithms which allow neural networks to be trained on a fragmented or incomplete database.

Figure 4. Prevalence of channel A1, New business formation through university funding (selected countries)



Internationally, the UK performs very strongly when it comes to spinning out new AI companies. This is partially explained by the strength of UK universities, particularly in sectors such as life sciences where AI is beginning to take hold.

Interestingly, of the comparator countries analysed, Canada has the highest relative prevalence of AI spinouts. The North American nation has built 5 technology commercialisation superclusters around the country, specialising in areas such as climate tech. Germany, with their Fraunhofer Institutes venture programmes, also perform well. Fraunhofer Venture, the tech transfer division of the Fraunhofer Society, has recently launched new venture accelerator programmes specifically focused on AI as a key spinout area.

Open source data

Open source data has been consistently cited as a useful enabling condition for commercialisation. Interviewees referred to its ability to foster joint collaboration, such as in Knowledge Transfer Partnerships (KTPs) for Masters and PhD students from disciplines such as computer and information sciences; help in updating the AI community when there is an issue with a particular technology; and helps researchers to improve their datasets.

A recent example of such a KTP project was at the University of Brighton, where AI expertise developed a triage system to underpin a novel model of family law provision.[26]

Barriers to commercialisation

Sector-specific

Many challenges and barriers to commercialisation of AI spinouts are sector specific. These include: the length of time it takes to yield a profit; suitable choice of business models; the level of digitisation of the sector; and the level of regulation of the sector.

For example in healthcare, high levels of regulation can place a series of constraints on many important enablers for commercialisation. These may make it more difficult to access datasets due to patient confidentiality, as well as placing other legal requirements on providers that generate a higher level of costs, relative to other sectors.

Understanding of market

There was general agreement amongst interviewees that many spinouts are largely unsuccessful in those cases where founders do not have adequate understanding of the market that they were building an application for. R&D was sometimes characterised as ‘a solution in search of a problem’.

Having sectoral understanding of market forces, regulations and end-user needs is particularly challenging for AI founders who are not always developing applications in a sector that is of their discipline of study. This is due to the technology’s general applicability across a wide variety of sectors. The UK’s performance is weaker in this regard compared to Europe and the US. Interviewees pointed to the lack of porous movement between academia and industry.

Paths to academic entrepreneurship

One major theme in the US is that in universities such as MIT or CalTech, industrial-focused labs, rather than theoretical ones, can see students join a firm spunout from these labs and use it as a career path to become a professor. In the UK, this is not an accepted career path. Without a career path like this, British academics are not going to take the risks necessary to produce the next generation of great AI companies.

Level of technology-readiness

Another barrier to commercialisation was often the technology readiness level (TRL) of the AI being developed by a spinout. Many interviewees that we spoke to, including those having obtained public or private funding, would only invest in spinouts that had a TRL between 4 (laboratory validated) and 6 (demonstrated in a relevant environment). This means that getting to proof of concept and beyond is essential for being likely to acquire financial and other commercial support. This is a particular challenge for deep tech startups, which almost by definition have lower technology readiness today.

Potential Risks, Consequences and Tradeoffs

A large London investor audience, coupled with the innovation culture embedded within Oxbridge, means that venture capital deals do not materialise evenly across the country. On the one hand, this concentration could offer economies of scale in the AI innovation ecosystem;

26 Larkin. A, (2018), Divorce Final Toolkit:https://www.divorcefinancetoolkit.co.uk/child-maintenance-calculator/

However, this investment will often find a home in a handful of top universities. This means that the spinout resources, such as having strong TTO and accelerator institutions, and aspirations of the Golden Triangle will not be replicated elsewhere unless more targeted action is taken to build up new AI spinout clusters across the country. A geographically concentrated innovation centre could risk leaving out valuable considerations in the development of AI models that are often intended to be applied and adopted across different geographic and demographic areas.[27]

Moreover, should universities move towards a model with lower equity share demands, there is a potential financial sustainability risk if TTOs do not make up for lost equity with a more than proportional increase in total spinouts. Whilst the examples of the US showcase that universities can thrive financially from lower equity demands and a higher number of spinouts (and follow-on endowment investments from alumni), the right incentives must be in place to ensure that maximising the number of spinouts in a given window of time is a key aim of universities.

Route A3 – Startups

Description of route

Startups interviewed were in the process of obtaining, or had recently completed, Series B funding, and have therefore achieved a relatively clear level of commercial viability. They have previously been part of various incubators, whether as a university spin-out, or even a spin-in (where a startup is incubated by a university the founders were not previously affiliated with) such as the Edinburgh AI Accelerator.

Founder backgrounds are not just university academic researchers. Many of the startup founders interviewed for this project came from a range of different industries in the technology ecosystem, including advertising, finance and healthcare. Crucially, many startup leaders (who may not have founded the company, but have been brought in by founders at an early stage) had previous experience in successful fundraising and running venture capital-backed technology companies.

Enablers of Commercialisation

Key institutions that enable startup commercialisation include:

- Innovation agencies such as UKRI or Innovate UK;
- Venture capital investors, firms with money from sources such as corporations, individuals, private and public pension funds and foundations;
- Angel Networks, individual investors putting their own finances into business development;
- Development institutions such as the British Business Bank.

Analysis of Beauhurst data indicates that high proportions of AI firms have used private or public funding to commercialise AI R&D through the development of new products, services or lines of business, indicating the importance of funding for successfully commercialising AI R&D. It is broadly useful to distinguish between public and private funding of AI startups:

Public funding

94% of AI firms have received at least one round of private funding, whilst 25% of AI firms have received at least one round of public funding.

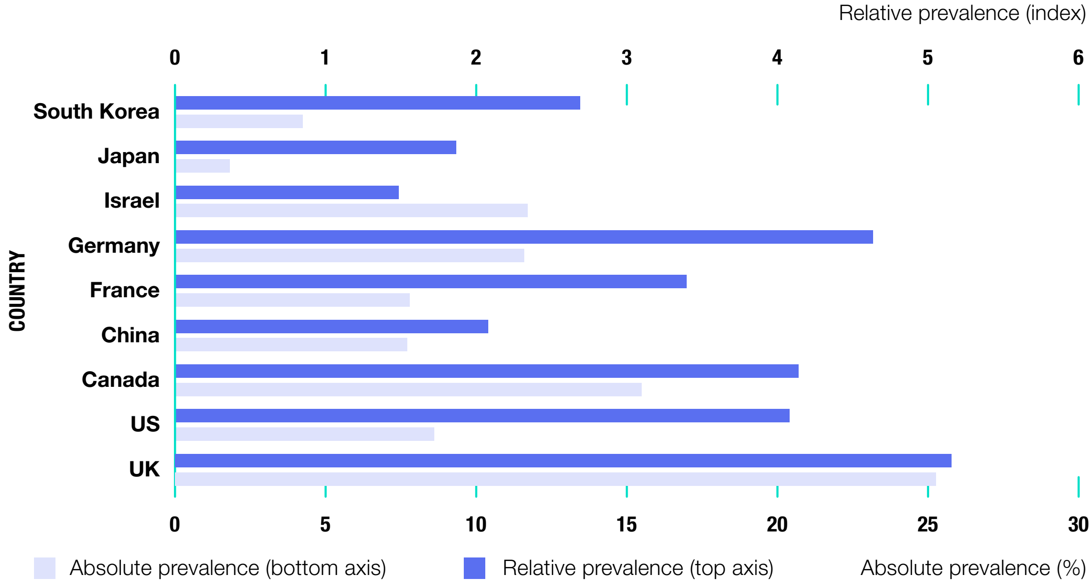
Innovate UK and other kinds of public grants drive a lot of early stage AI commercial projects. For example, The Hartree Centre (a public funding body that is part of the Science and Technology Facilities Council) has recently begun a new project aiming to introduce new communities to AI.

Grant funders were more likely to support longer term, deep tech-based AI projects compared to venture capital. This was particularly noticeable in sectors such as healthcare with the NHS Transformation Directorate getting access to increased funding for AI projects. Furthermore, venture capital is generally very hesitant to shoulder long term risk, with deeper, more speculative technologies providing less assurance about returns to investors. Data supported this finding, with public funding of AI firms having a much higher relative prevalence compared to private funding.

VCs can be more likely than public agencies to invest in Software as a Service (SaaS) AI startups, which tend to have at least a rudimentary business model in place with early market traction. Software-as-a-

27 As Ipsos Mori, (2021) suggests, Innovate UK funding in AI development is less concentrated in London and the South East than private sector investment

Figure 5. Prevalence of channel A3a, Development of new products/services using public funding (selected countries)



service will tend to be in areas that offer incremental technological improvements. Here, the marginal cost of scaling software is often minimal and can therefore offer significant returns.

The absolute prevalence of public funding (i.e. the proportion of AI companies that received public funding) is higher in the UK than for international competitors, including the US. There are several potential reasons for this.

One reason may be simply that countries such as the US spend more money on AI-related sectors such as defence in the form of contracts, as opposed to grants, meaning that this is not reflected in the public funding route.[28] Research has found that procurement contracts leading to patents are "primarily awarded to private companies by the Department of Defense, whereas grants leading to patents are primarily awarded to higher education institutions".[29]

A further potential reason is the size of the US private venture capital market. This is symptomatic of a more mature innovation ecosystem with higher value AI startups that have established themselves in the market. As a result, private funding of AI takes up a greater proportion of the market compared to public funding than in other countries[30].

Another reason may be due to the strength of UK universities and their strong relationships with public funding innovation agencies. Programmes like the Innovate UK Knowledge Transfer Partnerships are often organised around university clusters, enabling stronger networks to build in the commercial AI community.

Talent is another key driver. Investors interviewed were generally optimistic about the level of talent in the UK compared to the rest of the world. There is a relatively high number of researchers working on AI-related problems in Britain.

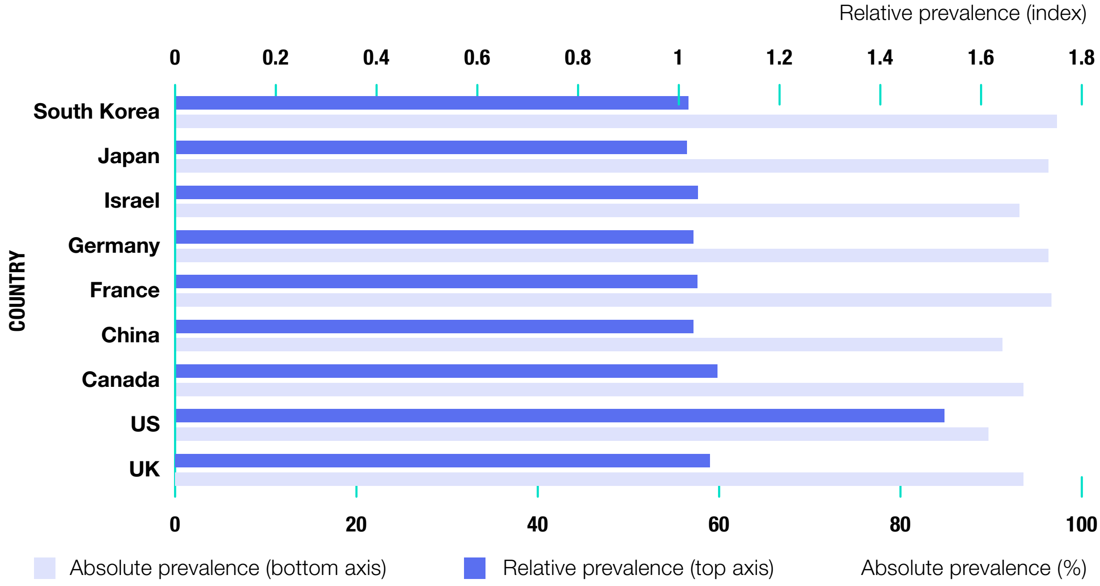
From an international perspective, private funding in particular is an incredibly popular route across all comparator nations. Reflected in both the quantitative data and interviews, the US appeared to have a higher relative prevalence for private funding of AI companies compared to other countries. Interviewees suggested that this may be due to the large size of the technology sector in the US.

28 Rassenfosse. G, Jaffe. A & Raeteri. E, (2019), The procurement of innovation by the U.S. government, PLOS One

29 *ibid*

30 According to analysis of Pitchbook data, Canada, Israel, Germany and the UK have a higher absolute prevalence of public funding in AI companies than the US

Figure 6. Prevalence of channel A3b, Development of new products/services using private funding (selected countries)



Barriers to Commercialisation

Public funding challenges

Concerning public funding, interviews raised several barriers to public funding successfully helping AI startups commercialise.

Grants often take a long time to apply for, with no guarantee of being awarded to the applicant. Moreover, when funding is provided, interviewees reported that grants do not tend to incentivise startups to align with market needs.

> *"And I think down the line, the more the risk that the government funding ends up taking you away from the concept of commercialisation by accident, because you have to swim to where the money is. The government is designing schemes that are not for the market."*
>
> *– Coadec, Startup Association*

By spending a lot of time writing business cases and grant proposals, researchers are spending less time doing actual research or scaling their company. An Innovate UK Smart Grant proposal is on average about 7,000 words in length and typically takes six-to-eight weeks to fill out[31].

This is compounded by the short term funding plans that UK innovation agencies deploy.

> *"So Innovate UK normally publishes a plan that runs for only a year, though it occasionally publishes plans that run for more than one year. But in Europe, three years in advance there will be a funding call stating the size of the pot and the problems being addressed"*
>
> *– Startup*

For a small company, a short funding horizon makes it very difficult to plan. Adapting larger parts of a business model to suit a funding application that may be unsuccessful is not an attractive prospect. Whilst scrutiny of public funding allocation is necessary to demonstrate a responsibility to taxpayers, there was broad consensus across those interviewed that reducing the burden that comes from the grant-making process is necessary.

Private funding challenges

Interviews noted that the UK has great availability of early seed funding for AI companies. However, at later stages, in particular series A and B, funding becomes increasingly more difficult to acquire. This is especially true for deep tech funding. Further, it is much more difficult to obtain funding for capital

31 https://datagardener.com/partners

intensive projects such as AI hardware. Interviewees explained that this was because hardware often requires much higher capital costs that can only receive a substantial return on investment over a longer term time horizon, a time frame that many private investors are often deterred from exploring.

Some interviews expressed concerns about UK venture capital investors' lack of ambition for funding AI startups as compared to far more aggressive appetite from investors in the US and China.

> *"I think the other issue I see is that there are a lot of conservative mindsets on the buying side. Whether that's with the government or big corporations that won't take a risk on smaller sovereign abilities versus just buying without risking their job… In the States this mindset is less prevalent. People spend much more time thinking about the potential upside than the doomsday downsides."*
>
> *– Startup*

Interviewees said that this cultural difference manifested in the UK in multiple ways. Accelerators would rather organise their programmes around technologies with a faster, but less fruitful path to profit. Startups and spinouts asked for smaller amounts of investment because their environment had not taught them to be more ambitious. This challenge echoes an additional problem, which is that the size of the UK's market is smaller than the US or Europe.

> *"Inevitably you're going to have to crack the international markets to make that a success. Your market in the UK is just not big enough to ultimately support a company that can survive on its own."*
>
> *– University*

Regulations

Navigating sector-specific regulation is a particular challenge in the commercialisation process. University-based networks and support appear to be effective in helping startups navigate highly regulated sectors such as healthcare with success. These support ecosystems have been able to leverage years of research excellence and research commercialisation in specific sectors (e.g. life sciences) and adapt the support for navigating emerging regulations related to the use of AI in these sectors.

> *"It takes absolutely ages for you to get your equipment in the hands of the clinician for regulated places, especially the health tech side. This is less so in insurance tech or fintech, they tend to do this much, much quicker."*
>
> *– RTO*

Procurement rules

Government procurement rules can also be an important determining factor in the likelihood of AI startup success. The UK government will often offer 'Smart Grants' to early stage companies. One respondent suggested that offering contracts instead would be an alternative that better supports commercialisation. A procurement contract indicates that the government is going to be a frequent consumer of a company's technology, which will drive up the value of that startup; a contractual commitment signals to the market that a major player is buying their product.

> *"The U.S. understands that when the government becomes a customer of a new tech company, it creates a unicorn. It doesn't take a very big contract to do so and can cost the same amount of money the UK typically invests into a smart grant – around half a million pounds.*
>
> *The UK Government could spend that same amount of money agreeing on a contract with a tech company, making that business worth 10 to 20 times the contract value – simply because someone is buying their product. That's a whole different set of unit economics."*
>
> *– Mind Foundry, Spinout*

Stanford Public and Private Funding Model

From the perspective of both public and private funding, the applied AI approach at Stanford University's Stanford Research Institute (SRI) has a proven track record of commercialising AI research. There are various research centres linked to the Stanford Research Institute, including the Stanford Institute for Human-Centred AI (HAI).

The SRI also has a corporate arm, called SRI Ventures, which has a specialist focus on AI startups. Recent startups funded include Vitrina AI, a SaaS platform for the film and television industry that tracks and facilitates international video content transactions. Under incubation at the SRI, Vitrina AI built a powerful search engine that uses NLP to connect video content buyers and sellers worldwide.

Risks, Consequences or Tradeoffs

One of the big risks to the UK's commercialisation of AI startups is a strategic one. Interviewees frequently mentioned that since late stage funding from UK venture capital dries up for AI firms, many startups may seek investment opportunities from abroad. Because many aspects of AI can have strategic, or dual-use capabilities (that can be used for both civic and military purposes), this generates a unique challenge for the critical infrastructure of the country if there is foreign ownership of UK AI startups[32].

Ethical and safety risks should also not be underplayed. Many startups in the UK operate within the high-stakes sectors that require a more precise and explainable process. Therefore, startups in these sectors have to trade off bringing a product to market and launching new features at speed with ethical and safety considerations, which could have important consequences for end-users and for the business itself.

Route A3 – Large firms that commercialise AI R&D

Description of route

This route refers to how large firms may commercialise AI R&D. Very often, the journey to AI commercialisation for these firms is markedly different from spinouts and startups. Large firms more often proceed with their own budget for AI-related projects, rather than depending on external funding from private or public sources.

Many of these firms operate across multiple sectors and as a result, develop technologies that have a broad set of applications across industries[33]. This partially explains why Natural Language Processing was a key subset of AI that is receiving a lot of attention by companies such as Google and Facebook.

Key enabling institutions

The enabling institutions for this route depends largely upon the area of AI that is being commercialised. 'Big tech' firms do not generally need to rely on public funding, due to the size of their R&D budgets. However, should they wish to commercialise AI in a public sector (for example health or judicial work), then they will engage with local government authorities and institutions, as well as universities for access to data.

Standards Development Organisations (SDOs) are another key institution that helps to foster AI commercialisation for large technology firms. All interviewees from large technology firms noted the importance of international AI standards development in achieving their commercial objectives. More details on standards and SDOs are provided in section 9 (p.46).

Enablers of commercialisation

AI R&D budget

Private AI R&D budget funding is the key driver of capital for large technology firms. Depending on the importance of AI to each company's offer, AI R&D can take up the majority of a firm's overall R&D budget. With large technology firms being

32 In 2022, the UK National Security and Investment (NS&I) Act passed, introducing standalone powers for the review of foreign direct investment into the UK. AI is one of the sectors covered.

33 These companies use and develop AI using a range of different actors: data scientists, user researchers, and public policy engagement officers; entrepreneurs with significant commercial experience in the data science sector; and industry AI researchers with university research backgrounds.

multinational corporations, their R&D budgets are generally global, and therefore do not have specific UK R&D budgets.

Many of the firms we spoke with mentioned that the level of investment in AI R&D for internal use has increased over time. This is because there is now an increased trend of developing AI for internal use before externally selling as product offerings. One interviewee said their approach is to 'learn by doing and applying internally first'. This respondent said they have created IT platforms for running AI applications at large scale that have first been used by their own research and product development groups, and later turned into product offerings.

One central driver of commercialisation for large technology firms is that they operate at multiple parts of the value chain. Because they are involved in building AI solutions across the value chain it means they can understand the technical and commercial problems that the market faces from top to bottom. Given that the barriers for so many other firms include having a clear understanding of the market and consumers' needs, this gives large technology firms a significant advantage.

Because of their very large R&D budgets, large technology firms can outcompete startups and spinouts when commercialising AI. This includes:

- access to better data and the computing resources necessary to train AI models;
- higher pay scales to attract talent;
- and a greater ability to build a diverse team.

Regarding diversity of team, large technology firms, compared to smaller firms, have the resources to do intensive recruitment that can find a diverse range of employees. Teams that come from a range of different backgrounds, academic disciplines and functionalities are essential when developing and deploying an AI system at scale. This helps to address issues such as algorithmic bias and usability.

Self-funding often means that there are less legal constraints and requirements that may slow the ability for AI to be commercialised. For example, when entering a collaborative R&D project with another organisation, such as a university or government service provider, the use of AI technology and data will have to be subject to the demands of those respective organisations. This is especially the case with publicly funded institutions in heavily regulated sectors.

Barriers to commercialisation

Non-functional requirements (NFRs)

Large technology firms are particularly likely to deploy AI at scale. As a result, a big barrier to commercialisation lies in what are known as non-functional requirements (NFRs). NFRs are attributes such as technical security, inclusivity (for example, does the user interface work for colour blind people?), and reliability. The challenges of catering for complex requirements, dealing with data breaches and surge capacity increase as the scale of deployment increases. Whilst large technology firms are able to build teams capable of dealing with these issues, they remain important challenges, especially if the requirement for different functionalities is sporadic.

> *"So the future of being able to, in my view, commercialise AI, on a small or large scale is going to be about multifunctional teams. So having data scientists is great, and they can do the data piece, but you need interpreters, translators, a product owner, someone that can understand the needs of users from the market and help translate the technical know-how to say; is this what's needed to give value?"*
>
> *– Large Technology Firm*

These NFR skills are really useful complements to the hard technical skills and are seen to be increasingly important as startups establish themselves and start to grow.

Risks, consequences or trade-offs

Interviewees from large technology firms were often particularly interested in what good regulation looks like, and in particular were wary of the risks to their commercial ambitions should they receive significant regulatory scrutiny. This is particularly pertinent for AI companies that operate in multiple jurisdictions, especially if there is an international movement towards greater regulatory oversight of larger technology firms that develop and deploy AI.

There are also concerns, especially amongst some startups, around an imbalance in how open source software benefits large technology firms. Many of the most popular open source platforms are managed by large technology firms. For example, Google Brain developed TensorFlow. Whilst that means that new data can become available to smaller firms, it also enables the owners of the open source platform to draw users to their platform, collect further data and therefore produce new, more personalised products in order to sustain market penetration.

Respondents from large technology firms were sensitive to the risk of algorithmic bias in the development and deployment of their AI models. Many are increasingly placing importance on employing individuals with a background in ethics to work alongside developers.

Route B2 – Direct Hire/Joint Tenure

Description of route

The direct hire/joint tenure route (for brevity, referred to as 'direct hire') refers to the hiring of academics working in the field of AI to join firms that are aiming to commercialise AI. This can also take the form of joint tenure, where AI researchers hold joint posts with a university and a firm.

The actors most likely to pursue this route are large technology firms that commercialise AI. Most of the large technology firms that were interviewed for this project have hired several researchers from universities, either to work full time or whilst retaining joint tenure.

Researchers who have backgrounds in areas such as natural language processing (NLP) are in high demand. NLP knowledge, whilst in high demand across the industry, is particularly valuable to large technology firms compared to startups and spinouts owing to the importance of language models to many of their business goals, and scale at which they are deploying AI.

There is significant potential commercial value in the development of NLP, and in particular, Large Language Models (LLMs). LLMs can be used to make predictions about how a sentence might continue at scale, and as a result, have commercial potential in areas such as news reporting, personalised advertising, and voice assistants. To be effective, LLMs require billions of parameters. With the infrastructure, servers and Graphic Processing Unit (GPUs) clusters necessary to develop and maintain such a model, it is often only the largest of firms that have the resources to commercialise LLMs.

Drivers of commercialisation

Applying for grants as a university academic can also be time consuming. With direct hire, this is no longer an issue. Applying for grants and supervising PhD students are not normally requirements under joint tenure and direct hire, and can in many ways, free up time for academics to focus on their immediate work. A further driver includes the access to data and computing resources that are available at large technology firms.

Furthermore, pay is a crucial driver of this route. The salary of AI researchers at large technology firms is much larger than for similar roles at universities or startups. Various startup founders interviewed are worried that they cannot compete with larger firms in this respect. This is a differential that is particularly unique to AI. As a result, there is a pronounced monetary incentive for AI researchers to work for large technology firms.

Barriers/challenges for commercialisation

Whilst direct hire and joint tenure can provide time and opportunities, it is not without its constraints. Interviewees spoke of some of the legal requirements necessary when commercialising AI at a large technology firm. Academics with joint tenure positions spoke of extensive Non-Disclosure Agreements (NDAs) that needed to be signed to prevent data sharing between company and university. Furthermore, academics are often not allowed to be involved in other startups while employed by large companies.

Risks, consequences or trade-offs

If direct hire continues to be an increasingly prevalent route by which AI is commercialised, this will impact the kind of AI research completed and as a result the kind of AI being produced. Without the freedom for academic inquiry, critical scrutiny of transformative AI will not be undertaken. For example research that was critical of LLMs ability to discriminate by a Google AI research team culminated in the dismissal of a researcher[34]. This poses a risk to the independence

34 Bender. E, Gebru. T & McMillan-Major. A, (2021), On the dangers of stochastic parrots: can language models be

of corporate research, and with direct hire becoming an increasingly prevalent route of commercialisation, is a risk that will only heighten.

This means that there could be a narrowing of AI research, and a narrowing of AI commercialisation as a result.[35] The privatisation of such research may potentially result in the prioritisation of monetising short term AI capabilities, as is sometimes the case in private sector R&D more generally. In this sense, the 'wrong kind of AI' could be produced, which displaces workers without material impacts on productivity.[36]

Another risk could be the lack of university lecturers to help train the next set of AI scientists and leaders. There is significant academic literature that suggests this is also a trend in the United States. Here, there is a growing net flow of researchers from elite institutions into technology companies. In particular, those working in the field of deep learning are especially likely to make this transition.[37] Whilst there is not as much evidence of this route being prevalent in other nations, interviewees suggested that this was just as much of a trend, if not more of one, in the UK.

Brief notes on other routes

Route A2 – Exit through buyout or acquisition

6% of all UK AI firms have exited through buyout or acquisition. Additionally, the proportion of AI firms using this route is lower than the proportion of non-AI firms using this route.[38]

There is an increasing tendency for AI firms to be acquired (and exit the market) at each successive stage of evolution. This may reflect increasing certainty around their prospects and thus lower risk to any purchaser. Interviews pointed to the trend that investors and founders were beginning to receive more clarity about what AI could and couldn't do. Beginning to break away from what respondents described as a 'buzzword industry', more established AI firms were able to show a clearer product market fit, thereby demonstrating the functionality necessary for an effective acquisition.

Across most stages of evolution, this route is no more important for AI high-growth firms than for non-AI high-growth firms. At the 'established' stage, however, buyout/acquisition is much more prevalent for AI firms than non-AI firms. This could be because established AI firms have attractive growth prospects; or had reached their maximum potential, given their capacity and resources, and needed to sell to a company with greater resources to support further growth. From an international perspective, the exit through buyout or acquisition route is not more important for AI firms in any of the nations analysed.

Route B1 – Joint/collaborative R&D

At each successive stage of evolution, there is an increasing tendency for AI firms to have engaged in joint/collaborative R&D via receiving at least one collaborative grant. This likely reflects greater certainty around the contribution a firm can make to a joint/collaborative R&D project and, therefore, a greater likelihood of being involved in one. But it may also indicate that past involvement in a joint/collaborative R&D project increases the likelihood that the firm succeeds and grows.

Route B3 – Knowledge Exchange via conferences, publications etc.

The proportion of AI firms at the 'mature' stage that have published at least one academic research article is high but lower than the proportion of AI firms at the 'growth' stage that have published at least one academic research article.[39] This may reflect or indicate: differences in the need to publish between 'growth' and 'mature' companies due to differences in market conditions and domain knowledge over time, or behavioural differences, if 'mature' firms are less inclined to publish/share R&D.

too big? In: Conference on Fairness, Accountability, and Transparency

35 Mateos-Garcia. J, Klinger. J & Stathoulopoulos. K, (2020), A narrowing of AI research?

36 Acemoglu. D & Restrepo. P, (2019), Automation and New Tasks: How Technology Displaces and Reinstates Labor, Journal of Economic Perspectives

37 Hain. Daniel et al, (2021), The Privatisation of AI Research(-ers): Causes and Potential Consequences

38 This is based on Beauhurst, a database of high-growth businesses, rather than all businesses

39 As referred to more in the technical appendix, the 'mature', 'growth' and 'established' terms are being deployed because the data was acquired from the CSET PARAT database, as opposed to the Beauhurst database which refers to companies at levels of 'seed', 'venture', 'growth', etc

Overall, this channel is moderately more important for AI firms than non-AI firms. The channel is more important for UK AI firms at the ‘growth’ stage than non-AI firms at the ‘growth’ stage. But the channel is equally important for AI and non-AI firms at the ‘mature’ stage.

The Role of Technical Standards

We investigate the potential role of technical standards and Standards Development Organisations (SDOs) in supporting the commercialisation of AI R&D, owing to the significant impact technical standards have had on the commercialisation of other digital and emerging technologies.[40] Insights here are largely generated from ten interviews with stakeholders from SDOs such as BSI, ETSI, IEEE and UK's ISO/IEC mirror committee, ART/1- Artificial Intelligence (which mirrors the work of ISO/IEC JTC 1/SC 42).

Description of route

Technical standards set out requirements, specifications, guidelines or characteristics that can be consistently applied to ensure that AI products, materials, processes and services are safe, efficient and fit for purpose. SDOs act as a platform to bring together a range of stakeholders to develop technical standards that can impact how the technology will be designed, developed and implemented, and therefore, play a role in the commercialisation process.

Examples of SDO engagement include commenting on draft standards, and actively participating in SDOs' committee meetings. This can occur at both a national (through national standards bodies (NSBs) such as BSI) and international level (in international fora such as ISO, through NSBs representation). Individuals and companies cannot join ISO directly as members, with standards here being developed by technical committees, which are groups of experts appointed by the relevant NSBs.However, a direct membership model exists for other global SDOs relevant for AI, such as ETSI, IEEE SA, and ITU.

Whilst there is significant attention being paid to the role of technical standards, AI standards are in their infancy. AI technology itself is still nascent, and furthermore, has potential applications in a broad variety of sectors. Technical standards around, for example, computer vision would need to cover applications sectors as varied as transport, healthcare, manufacturing, and agriculture. The future journey of AI technical standards development has a lot of sectoral ground to cover.

Additionally, interviewees frequently spoke of the importance of technical AI standards to foster trust in AI systems, both from the perspective of businesses and the general public.

Actors commercialising AI through SDOs

According to interviewees, actors that are engaging with SDOs in order to commercialise AI are predominantly large technology firms. They employ staff whose roles included attending SDO committees and engaging with standards development processes.

Startups and SMEs see standards development as an important enabling feature of commercialising AI, but often have to forgo participation due to time and resource constraints. Some staff at startups, as well as academic researchers, do have experience helping to develop niche standards[41], but most do not have much experience. Small businesses and universities do not employ people with the specific task of engaging with SDOs in the way that large technology firms do. Without full time employees dedicated to such a task, it is often difficult for smaller AI firms to make a difference in standards development, with SME and startups effectively having to volunteer resources and time.

Yet there is clearly an incentive for smaller firms to engage with SDOs. Once technical standards are published, firms will generally comply if the standard is highly relevant to them. Often, complying later can be more expensive than doing so earlier. For smaller firms and academics, if they are engaged in the standards development process, this enables them

40 Bock. W et al, (2015), The Mobile Revolution: How Mobile Technologies Drive a Trillion-Dollar Impact

41 For example, some startups spoken to for this project had experience in standards development for areas such as material science printing and the statistical interpretation of data

to get ahead of the curve when it comes to having to undergo significant, quick engineering implementations to conform to the new standard.

Interviewees noted that smaller stakeholders may benefit from guidance as to how technical standards can support their business. However, with a lack of SME representation, SDOs may fail to articulate the commercial benefits of engaging with the process of developing technical standards sufficiently,[42] i.e. avoiding the expense of later re-development of products to achieve compliance with an emergent technical standard.

Academic researchers that are interested in forming spinout companies are also interested in the role that standards development plays in the commercialisation of AI. However, several respondents claimed that there are not strong incentives for UK academics to engage in SDOs. Interviewees said they are largely guided by the Research Excellence Framework (REF), which rewards publication of new research, over commercial engagement in processes such as standards development.

Some SDOs are looking at ways to address these challenges. For example, ISO have recommended a series of solutions to involve smaller firms and researchers in standardisation, including: national SDOs developing case studies of SMEs and academics that have successfully participated in standardisation; proposals for new work items should be accompanied by a feasibility study including relevant stakeholders and their interests; and national SDOs stimulating representation of SME groups via trade associations.[43]

According to interviewees, governments do show interest in the commercial implications of technical standards development and how AI standards in different countries will affect the ability of UK AI businesses to trade internationally. Interview respondents suggested that large technology firms want to see global AI standards harmonisation, which supports international trade by reducing coordination costs.

SMEs and startups tend to have more specific, niche, and often domestic interests. Startups frequently stated they had to become world-class in a small area of AI to stand a chance of outcompeting larger competitors. This gives them less incentive to participate in global standards setting, as they are likely to be focused, at least at first, at a sector of application in just one market.

Standards development focused on horizontals (across sectors) versus verticals (organised around a sector) was mentioned as a key driver of commercialisation. AI is seen as a horizontal technology with multiple applications across sectors/industries, which is reflected in the current approach of SDOs to AI standards development.

This supports claims from interviewees. The current focus in the standards community is on agreeing a broad set of high-level principles which characterise AI, a fundamentally horizontal approach. This will then create the foundational elements which will enable the exploration of more specific applications. One interviewee said that around 80% of the work being conducted by SDOs on AI concerns horizontals. However, attention is being given to AI on existing verticals too, and it might be early to understand horizontal AI standards needs.

Concerning verticals, respondents noted that in future, important sectors for AI standards may include: medical devices; biometrics and data labelling; and robotics.

AI Technical standards as an **enabler** of commercialisation

Interviewees pointed to how important widespread, agreed upon technical standards may be for the commercialisation of AI R&D through many of the routes discussed so far in this report. Technical standards may come to function as an essential enabler for AI commercialisation quite generally. More specifically, the impact of technical standards has been mentioned in relation to the following topics:

42 Some SDOs have begun trying to offer solutions to broaden SMEs and startup participation in standards development. For example, ETSI charges smaller membership fees for micro-enterprises and SMEs than larger firms: https://www.etsi.org/membership/sme

43 https://www.iso.org/news/2013/02/Ref1711.html

Trust

Many saw AI trust *itself* as an industry that could be commercialised, in agreement with the view in the CDEI AI Assurance Roadmap that AI assurance could become a multi-billion pound market.[44] Businesses may emerge that commercialise by offering consultancy and auditing services that ensure compliance with trust focused technical standards.

Interviewees frequently spoke of how necessary technical standards may end up being to ensure the trustworthiness of AI systems, and build business and public confidence in the technology. Without trust, uptake in AI may dwindle and commercialisation attempts may fail as a result of low adoption. All stakeholder groups interviewed noted the importance of trust as an enabling factor for AI commercialisation, from both a business to business, and business to consumer perspective. SDOs are working on AI standards that account for privacy, security, and the removal of algorithmic bias.

Because some AI systems can lack transparency and explainability, extra efforts must be taken to foster public confidence that AI systems work as intended and do not cause unintended harm (compared to other emergent technologies). Interviewees indicated that achieving explainability is particularly important for AI trustworthiness, and all the more so given the potential wide impacts and applications of AI across multiple sectors and societal domains.

For example, ISO 42001 provides a set of requirements for organisations to implement management processes that allow for a risk-based approach that can be continuously monitored and approved45. Standards of this kind aim to demonstrate a responsible and trustworthy approach to the use of AI, reducing mistrust which can often be an adoption barrier.

Setting the market norms

As a firm, shaping standards early could mitigate long term risks to business viability. Once standards are in place, they can be difficult to change. Therefore, it can be costly if a firm does not meet the chosen standard early on. Many firms may have to face significant costs revising any AI systems they have developed if their product is not closely aligned with industry specifications, and risk missing out on market opportunities and interoperability if they do not conform. Accordingly, interviewees spoke to the commercial benefit for AI firms/developers to engage in AI standards development at an early stage.

Regulatory compliance

Technical standards may eventually support commercialisation by empowering stakeholders to demonstrate a presumption of conformity with regulatory requirements for AI. This rationale is evident within the EU AI Act[46], a risk-based approach to regulating AI which recognises the role of harmonised standards for meeting regulatory requirements and ensuring the safe development and deployment of high-risk AI products. As indicated by interviewees, technical standards can provide a common language to operate in, which filters down to the foundational design of AI systems, providing an inherent level of trust throughout the product cycle.

Market access

Interviewees mentioned that adopting technical standards may support commercialisation by avoiding businesses being ‘locked-out’ of a market. Additionally, certification against specific standards can be leveraged in business deals, acting as a set of boundaries for acceptable market conduct and compliance with established good practices.

Scalable AI technology

Technical standards may also support commercialisation by enabling the scaling of AI technologies. According to interviewees, having aligned standards that apply across multiple countries might reduce costs significantly for industry that can therefore scale AI systems in a much easier manner.

Control oversight

‘Control oversight’ refers to a cross-cutting industry assessment of the range of technical and social risks that may arise from the deployment of a general purpose technology such as AI. Interviewees noted that technical standards may come to play an important part in such assessments, and businesses that provide audits (as, for example Horiba Mira do for the automotive industry[47]), would be a potentially important avenue for commercialisation of technical standards knowledge.

44 Centre for Data Ethics and Innovation, (2021), The roadmap to an effective AI assurance ecosystem

45 https://www.iso.org/standard/81230.html

46 https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX%3A52021PC0206

47 https://www.horiba-mira.com/

AI Technical standards as a **barrier** to commercialisation

Industry capture

Some respondents noted that internationally harmonised technical standards could give large technology firms a disproportionate influence on the kinds of AI standards proposed, developed and implemented. In particular, this could occur in areas such as AI quality control and privacy requirements. However, it is important to note that this overall risk of capture isn't particularly higher in AI compared to other technologies.

> *"The standards with concerns regarding industry capture are things like 'Quality Control'. For instance, privacy by design. If it is captured by a particularly large firm, there is a risk that they are building AI in ways which could weaken the privacy requirements."*
>
> *– SDO*

Prematurely curtailing the development of new AI technologies

Technical standards may prematurely cut off the development of potentially valuable AI technologies. Some interviewees (though this was not the prevailing view) believed that, because AI development is still going through a rapid evolution, it could be too early to begin moving towards standardisation.

If the context and use case for that application changes drastically, the standard may become outdated. This is why being able to amend and update standards is so important, but once again, this presents issues around which actors have sufficient resources to keep up with engagement with ever-changing technical standards.

UK Government initiative to increase the UK's contribution to development of global AI technical standards

Addressing these issues, the UK government recently announced the Pilot of the AI Standards Hub which will aim to ensure that UK multi-stakeholder perspectives drive the development of global technical standards for AI.

What is the AI Standards Hub pilot and why is it needed?

The AI Standards Hub Pilot is a key deliverable set out in the National AI Strategy published in September 2021, as a ten-year plan to strengthen the country's position as a global science superpower and "harness AI to transform the economy and society while leading governance and standards to ensure everyone benefits".

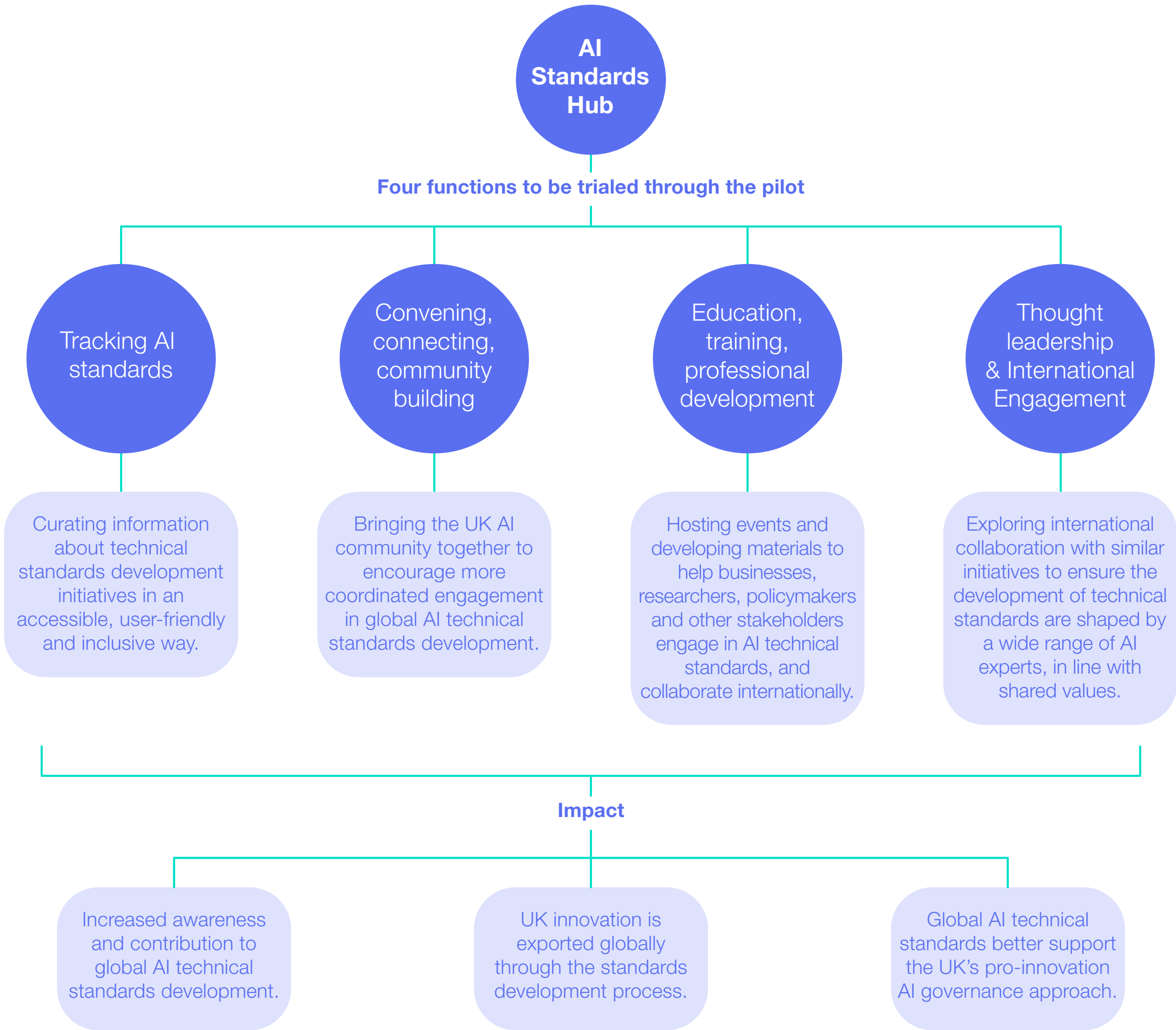
The AI standards Hub pilot will be led by the Alan Turing Institute, the national institute for data science and AI, supported by the British Standards Institution, the UK National Standards Body, and the National Physical Laboratory, the country's national metrology institute. The Hub Pilot is backed by the Department for Digital, Culture, Media and Sport (DCMS) and the Office for Artificial Intelligence (OAI).

How will the pilot support multi-stakeholder engagement in AI technical standards?

The AI Standards Hub aims to support multidisciplinary UK stakeholders to engage in the global AI standardisation landscape by creating practical tools for businesses to understand AI technical standards, bringing the UK's AI community together through a new online platform, and developing educational materials to help organisations develop and benefit from global standards.
In its pilot phase, the Hub will focus on:

- **Tracking AI Standards:** Growing UK engagement to develop global AI standards by bringing together information about technical standards and development initiatives in an accessible, user-friendly and inclusive way.
- **Convening, Connecting, and Community building:** Bringing the AI community together through workshops, events and a new online platform to encourage more coordinated engagement in the development of standards around the world.
- **Education, Training and Professional Development:** Creating tools and guidance for education, training and professional development to help businesses and other organisations engage with creating AI technical standards, and collaborate globally to develop these standards.
- **Thought Leadership and International Engagement:** Exploring international collaboration with similar initiatives to ensure the development of technical standards are shaped by a wide range of AI experts, in line with shared values.

Figure 7. AI Standards Hub pilot overview



Risks, consequences or trade-offs

Large firm dominance

Some respondents voiced concern that technical standards, and the resulting market harmonisation stands to directly benefit large multinational corporations who already operate across multiple regions and markets. One respondent suggested that more needs to be done to ensure engagement with SMEs – for instance an international innovation hub specifically intended to ensure the participation by SMEs in standards development.

Premature standard publication

As it can often be difficult to amend standards post implementation, there is a risk that rushing to develop a standard could lead to an ineffective one being implemented. This could cause a wide range of social and economic harm, and lock firms out of the realisation of potential commercial value. For an evolving technology such as AI , the time it takes to develop a standard may mean that cutting edge AI technology has rendered a yet-to-be-published standard out of date.

Practical challenges

Interviewees pointed to the fact that there has been a lack of joined-up thinking by stakeholders on how AI standards could work in practice. This manifested in insufficient expert engagement and market research, meaning that there was not a clear perception of where and how AI standards would be used.

Barriers need to be removed in order to help academics, SMEs and startups to engage in the standards developing process, to ensure that standards development caters to the needs of a diverse range of stakeholders. One way of doing this for academics would be to build in measurements of standards engagement work into the Research Excellence Framework (REF). For SMEs, a potential solution could be the establishment of **AI innovation hubs** growing engagement of SMEs and startups in the standards development process.

Support a more fluid relationship between academia and industry

Interviews noted that a principal difference between careers in AI in the US compared to the UK was the relative ease with which AI researchers move back and forth between industry and academia. In the UK, in contrast, pursuing industrial and business projects is not viewed as an accepted career path for academic success. A culture change would allow leading AI researchers to move into industry, direct companies, take secondments and sabbaticals, and interact more with private companies – without risking their academic career or credentials. At US universities like MIT or CalTech, industrial-focused labs (as opposed to theoretical ones) lead students to pursue a career in industry, and this does not prohibit their returning to university research at a later time.

Importantly, more career fluidity may also work to address some of the dynamics behind AI talent flows, making it much easier for AI researchers to return to academia in the UK after a spell in industry; for example, after a period with a technology business, a researcher might return to academia, bringing back valuable experience, knowledge and ideas – a two-way 'brain flow'.

Another aspect of academia-industry fluidity that would support commercialisation of AI R&D is creating a supportive context for 'entrepreneurial academics'. Here follow several considerations that would lessen some of the barriers faced by academic AI researchers in commercialising their research.

Commercial AI Fellowships

The research has identified a key challenge in connecting researchers with technical AI skills and who have developed novel AI techniques, to those with knowledge of specific sectoral areas and who properly understand the problems that need to be solved in their sector. This is a particularly important issue for AI, a largely general purpose technology that has applications in very many sectors.

Government could counter this issue by supporting the creation of a new type of commercial AI fellowship – networks of tech entrepreneurs that work with universities to find novel AI research, then connect the relevant researchers with relevant industry contacts. By paying grants to entrepreneurs who have already had successful careers in AI and similar fields, fellows could be partnered with universities across the country to seek out talent and capabilities with significant AI commercial potential. The fellows, with an eye for product-market fit, could help develop an idea with researchers, or even connect them to other people that could provide appropriate support. Fellows would have frequent opportunities to discuss their findings with other fellows at national events and using other networking channels.

The Turing Institute has recently announced The Turing AI Fellowships[48], wherein fellows will undertake innovative AI research working in collaboration with partners from other sectors to accelerate the impact of research. The Turing AI Fellowships are intended to support connections and collaborations between academia and industry and "cross-sector collaborations" and "two-way flow of knowledge and people". These and similar initiatives should specifically recognise the role of entrepreneurial skill and commercial experience in successful commercialisation.

Create greater incentives for university AI researchers to remain in Academia / the UK.

One of the biggest concerns that experts had around the future of commercial UK AI research was the potential impact of the AI brain drain, the potential narrowing AI research, and the potential for fewer startups being formed. A key response to this is the development of creative joint-tenure packages that make it easier for top AI talent to work in and alongside industry on applied AI projects;

There are several ways in which the 'AI talent drain' can be addressed and university AI researcher positions made more attractive. Some respondents

48 https://www.gov.uk/.../turing-artificial-intelligence-fellowships/turing-artificial-intelligence-fellowships

pointed to a need to compensate AI researchers with higher pay, involving an adjustment of pay scales and to the UCU Pay Framework[49] to reflect this wage disparity. However, it should be emphasised that a thorough exploration of the potential negative externalities of higher salaries for AI researchers would be necessary. Other possible incentives not related to pay, all of which would make staying in UK academia more attractive, and potentially lead to retention of researchers and involvement in spinouts and startups, are:

- Privileged or expedited access to public datasets;
- Access to significant compute resources;
- Favourable access to public sector stakeholders for important research;
- Joint academic-public sector research programmes;
- Permissive policies on forming new companies and time to pursue industrial projects.

Establish a National Research Cloud

As universities often do not have access to enough computing power to develop new AI applications, research institutes often hire extra capacity from private sector cloud providers. Taking inspiration from Stanford University[50] and the steps taken by the US government, the UK government could work towards implementing a National Research Cloud, providing universities with the the option to scale up their compute capacity with access to private cloud providers at a competitive rate.

The Machine Intelligence Garage programme was launched 3 years ago by Digital Catapult[51] to precisely address this lack of access to compute power for AI startups. The programme offers access to a range of computation resource. Startups can leverage up to £100,000 in cloud credits from Digital Catapult's partners, Amazon Web Services (AWS) and Google Cloud Platform (GCP), and access on-site NVIDIA DGX-1 deep learning servers. A National Research Cloud could make opportunities like this available for UK universities and more startups.

Relocating grant funding to procurement contracts, with government acting as the 'first customer' for AI businesses

AI is often viewed as a high-risk technology that takes longer to achieve a return on investment compared to other technologies. This creates some potential barriers for both public and private channels of funding. Public procurement can play an incredibly important role in providing further assurance to markets and lowering barriers to entry for prospective AI firms.

One way this could be achieved is by procuring AI through contracts, rather than providing grants. This would make AI startups that received contracts significantly more valuable than if they had received only the grant. Moreover, this would send a signal to the market that there is a government buying a given AI product, both potentially reducing the cost of the AI being purchased, and providing confidence to other potential buyers that there is a market that is here to stay.

Moving towards being the first customer for AI will require vision and an appetite for taking risks. However, the likes of the Small Business Research Initiative[52] shows that it is possible for the government to take these leaps of faith, something that will be particularly important for AI commercialisation.

Support spinout formation and success

Interviewees pointed to two issues in particular that disincentive spinout formation in the UK: high equity demands from TTOs, and an academic culture that sometimes lacks entrepreneurial spirit. Some possible responses to these problems are:

i. Create direct incentives. The UK government could opt to provide universities with a new Key Performance Indicator (KPI) which encourages spinout formation, committing TTO's to achieving a certain number of spinouts created in a given timeframe.
ii. Governments could also incentivise universities through subsidies to create commercial alumni ecosystems, in order to share best practice and channel the appropriate support necessary to commercialise AI technologies.

49 https://www.ucu.org.uk/framework
50 https://hai.stanford.edu/policy/national-research-cloud
51 https://www.digicatapult.org.uk/.../digital-catapult-launches-machine-intelligence-garage/
52 National Advisory Group, (2017), Encouraging Innovation in Local Government Procurement

iii. Specific grant programmes could provide AI researchers with time and resources necessary to pursue a spinout. This would be an important step in providing a path to seniority for academics who are more inclined to commercial ventures than theoretical research.

To maximise the success of university spinouts, as opposed to simply encouraging the frequency of their creation:

iv. Public funding awards should include criteria that favour teams demonstrating a mix of technical, commercial and sectoral-specific skills and experience.

v. Initiatives to link up research founders with commercial leadership through incubator and accelerator programmes should be continued, but should consider adopting a 'fail fast' approach – pulling funding and support from projects that fail to show the potential for commercialisation within a given timeframe.

- This said, it should be noted that this does not necessarily mean that longer term, speculative research should be curtailed. Commercialisation can only be a success by combining foundational, early-stage research with a commercialisation ecosystem that can shape and channel this research to meet market (and potential market) demand.

Regulatory sandboxes

Interviewees were generally critical of the NHS's approach to procuring and using AI technologies, apart from one exception: NHS Transformation Directorate's AI Lab. This innovative approach to buying AI[53] could also be reflected in experimenting with the application of AI to the health sector.

The Kalifa Review of UK FinTech recommended that the FCA sandbox be enhanced to provide more value to firms. By piloting regulatory sandboxes for AI technologies in the NHS, sandboxes could improve data sharing between different parts of the NHS and the wider healthcare ecosystem.

This could also be accompanied by a regulatory 'scalebox', as recommended in The Kalifa Review, introducing measures to support partnering between incumbents and regulators, and providing additional support for regulated firms within the growth phase.

53 NHS Transformation Directorate, (2020), National COVID-19 Chest Imaging Database (NCCID): https://www.nhsx.nhs.uk/covid-19-response/data-and-covid-19/national-covid-19-chest-imaging-database-nccid/

SDO relevant considerations

Use the Research Excellence Framework (REF) to improve academic engagement in SDOs

Explore the possibility of using the Research Excellence Framework (REF) to support engagement with Standards Developing Organisations for AI researchers and academics.

Interviews highlighted the need for growing SDOs engagement from stakeholders groups such as academia. As a result, new funding incentives should be designed to further improve the presence of academic researchers from universities in the standards development process.

The REF is a research impact evaluation of British higher education institutions, and aims to benchmark information to inform the selective allocation of funding for research. Much of the REF criteria refers to outputs specific to the university. However, since universities have the potential to be important players in standards development, embedding incentives to encourage academics to dedicate more time to SDO engagement would make this process more inclusive.

By setting targets for academic involvement in SDOs, such as through attending Joint Technical Committee meetings or recording the number of researchers that have relevant SDO membership, universities will be incentivised through the REF to push for greater academic involvement in standards development. As a result, wider industry will be more likely to play an important role in developing AI standards.

Establish innovation hubs to grow SMEs and startups engagement in standards development processes

SMEs can struggle to be heard when attempting to develop standards. They don't always have the time and monetary resources to partake in SDO committee meetings and consultations. A way of remedying this problem would be to establish hubs responsible for helping SMEs to engage in standards development.

These hubs could perform two main functions. Firstly, they could provide clear and practical information on issues such as: how to submit ideas and responses to standardisation initiatives; identify other firms with common interests so that collaboration and networking can take place; provide access to resources and training to identify relevant technical standards for their products/markets,and best practices from other parts of the world. Secondly, these hubs could subsidise the cost of engaging in this process, for example by paying for any paywall costs to access standards documents.

Such hubs could be national, or even transnational. Collaboration across borders is especially important when wanting to understand best practice in markets such as the EU. In this space, the new AI Standards Hub Pilot has been launched with the aim to address some of these needs.[54]

54 https://www.gov.uk/government/news/new-uk-initiative-to-shape-global-standards-for-artificial-intelligence

Considerations that warrant further study

As discussed above (p.24, p.29) and below (p.61), the difficulties of patenting software under the UK's IP regime can make it difficult to realise commercial value from AI software innovations. Respondents suggested that 'business process patents', as used in the US, might be an avenue that would help researchers and developers realise commercial value from software innovations. Although a thorough exploration of possible changes to the IP regime for AI software was beyond the scope of this project, we suggest it as an avenue for further research.

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University of Oxford, (2021), Equity share policy for new spinouts: https://www.medsci.ox.ac.uk/divisional-services/opportunities-and-updates/equity-share-policy-for-new-spinouts

Appendix 1 – Literature Review

AI-specific commercialisation

Literature suggests several key reasons for why AI commercialisation should be considered as different to the commercialisation of other technologies.

The first concerns the matter of data. For most AI systems, to stand any chance of succeeding, require enormous amounts of data.[55] Access to such data poses a series of technical, economic, legal, and ethical challenges that place a series of constraints on the actors and institutions that play a role in bringing AI research to the market.[56] The same constraints do not often exist for other technologies that are less data-driven.[57]

Another reason for viewing AI commercialisation as different involves an understanding of how AI technology goes through iterative changes and continued development post-deployment. AI systems often have to be deployed with incomplete knowledge of the environment that they will operate in; and so AI technologies often require a period of 'on the job' learning. As a result, there will inevitably be errors post-deployment, which are then improved on iteratively through feedback loops within the AI system.[58] In other areas of technology commercialisation, such errors may not be tolerated in the same manner.

Gaining a further understanding of these differences was a theme in our research, interviews and analysis, with the aim of understanding the present (as well as absent) actors and institutions involved in the commercialisation of AI.

Public vs. Private R&D

There are differences in the routes to commercialisation for R&D that originate from private entities and public institutions. A report prepared for BEIS by Frontier Economics outlined several such conclusions about the difference between public and private R&D.[59] First, evidence shows that private investment in R&D proceeds relatively quickly to commercialisation, with little 'lag time', ranging from around one to three years. Public investment in R&D can take longer to reach commercialisation. There are several plausible explanations for this: differing incentives, and the relative scarcity of private investors that are willing to fund R&D at a low level of tech readiness, whereas public bodies have more 'patient' funding available.

Frontier Economics' report also posits that public funding channels have often differed to private investments. Examples of public funding may include research councils, government departments, and higher education, manifesting in policies such as grants and tax credits, whereas private R&D expenditure can emerge from internal company investment, venture capital, academic entrepreneurship, and other forms of angel investors.

There is insufficient attention in the available literature to the differences between public and private entities in the types of AI technologies being researched, developed, and then commercialised.

Routes of Commercialisation

The routes of commercialisation that emerged from the literature review are presented here. Note that, the final taxonomy (provided in p.20) reflects not just the results of literature review but also insights that arose in interviews with experts.

55 GPAI, (2020), The role of data in AI

56 Cath. C, (2018), Governing Artificial Intelligence: ethical, legal, and technical opportunities and challenges, Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences

57 GPAI, (2020), Innovation and Commercialisation Working Group Report

58 BaFin, (2018), Big data meets artificial intelligence: challenges and implications for the supervision and regulation of financial services

59 Frontier Economics, (2014), *Rates of return to investment in science and innovation*

Here follows an outline of the various commercialisation routes. For each route a general description is given, followed by an outline of the key stakeholders in facilitating this form of commercialisation, and whether the route is relevant to public R&D, private R&D, or both.

Route A – Direct Commercialisation

University spinouts

Technology Transfer Offices (TTOs) may be created with the specific objective of providing an intermediary platform to bridge universities and industry, enabling the 'spinout' of research completed by university students and academics into new firms that will enter the market. More specifically, a TTO is often tasked with the identification and management of academic intellectual property (IP), IP protection, IP commercialisation, and the licensing of contracts. Additionally, TTOs generally help to create and manage spinout organisations, and keep contact with key partners that help facilitate knowledge commercialisation.[60]

With respect to AI innovation, examples of the key stakeholders relevant to this route include: Nesta; Digital Catapult; UKRI; The Royal Academy of Engineering (RAEng); Venture Capital; and Universities themselves. Generally, this route is most relevant to public R&D, due to the nature of university funding.

Intellectual property

Intellectual property (IP) protects creations of the mind, enabling people and organisations to earn recognition or financial benefit from what they invent or create. Types of IP include: copyright; patents; trademarks; industrial designs; geographical indications; and trade secrets.[61] There is substantial economic literature which suggests that the external commercialisation of knowledge can be driven by having well-designed IP regimes.[62,63] OECD analysis of IP rights data notes that there has been a surge in the protection of AI developments since the mid 2010s,[64] driven primarily by patents and trademarks. The United States contributed the most patents and trademarks, followed by Japan, Korea, and China. Europe developed significantly less AI IP protection in this time. Overall, the OECD found that AI actors, in order to protect new AI-inventions internationally, rely most heavily on patents rather than trademarks. Previous consultations have found a difference in UK IP regimes compared to Europe and the US with respect to patenting software.[65]

Since AI is so software-dependent, and software can be difficult to patent under the UK IP regime, British AI technologies face unique commercialisation challenges compared to other technologies.

Relevant key stakeholders include the UK Intellectual Property Office (UK IPO); The Alan Turing Institute; and the Information Commissioner's Office (ICO). IP, as a route, is shaped significantly by both public and private R&D.

Private funding

Private funding of AI can take many forms, but venture equity funding is a central aspect of this route. Venture capital often fills a void between other sources of funds for innovation (such as government bodies, internal R&D funding from large technology firms, universities, etc). Investors funding venture capital funds are typically sizable institutions such as pension funds, insurance companies, and other financial firms. Here, funding can take place at numerous different stages, including:

- Seed funding – Often helps a company finance its first steps, including market research and product development;
- Series A – Where companies are aiming to optimise their user base and product offerings;
- Series B – Where investors help startups get beyond the development stage, expanding their market reach;
- Series C – These companies are looking for additional funding in order to help them develop new products, expand into new markets, or even acquire new companies.

60 OECD, (2011), OECD Innovation Policy Platform, Online Handbook

61 https://www.wipo.int/about-ip/en/

62 Teece. D, (1998), Capturing Value from Knowledge Assets: The New Economy, Markets for Know-How, and Intangible Assets, California Management Review

63 https://assets.publishing.service.gov.uk/government...Growing_the_artificial_intelligence_industry_in_the_UK.pdf

64 OECD, (2021), Who Develops AI-related Innovations, Goods and Services? A firm-level analysis

65 IPO, (2021), Government response to call for views on artificial intelligence and intellectual property

Examples of AI-focused VC firms with investments in the UK include Entrepreneur First, Air Street Capital, and Tech Nation.

The interviews and data analysis considered whether among private funding routes (bank loans, venture debt and venture equity, etc.) venture equity is particularly relevant for AI commercialisation compared with other more established commercialisation. This is plausible, given AI's relatively nascent stage and potential for disrupting established markets.

Public funding bodies

Public R&D funding bodies also play an integral role in the AI commercialisation ecosystem. In the innovation funding landscape, funding of this kind takes place at an early stage, including both the concept, development, and pre-commercial phase (with later funding stages including early commercial and scale)[66]. In the language of venture capital, public funding often takes place at a pre-Seed stage. Providing what is increasingly being described as 'patient capital',[67] funding programmes are designed to enable long-term investment in high growth potential companies across the UK. Many policy-makers claim that investment of this kind can only come from the public sector, due to the need for private companies to address shorter-term demands of shareholders and other stakeholders.[68]

Within the R&D funding ecosystem, there are a range of important stakeholders that drive public investment in the commercialisation of AI R&D. Examples include; Innovate UK; the Engineering and Physical Sciences Research Council (EPSRC); Research England; and the National Institute for Health Research.

Direct sell and revenue generation

This process involves the production of a product or offering of a service directly from the innovating organisation. For example, through a company selling an online course in machine learning for data scientists.

Buyouts from private companies

Commercialisation of this nature normally involves a company giving up their rights to IP, usually for a fee, shares or equity. Policy-makers sometimes express a preference for this route over commercialisation via university spinout, as it may be more productive for IP to be used by an existing company that already holds expertise and experience in commercialising such IP[69]. This is a route rarely used by public institutions and is more prominent in the private sector.

Route B – Knowledge Exchange

Consulting engagements

AI PhD students, post-doc researchers, and academics are known to engage in short-term consulting projects at private companies. Previous studies have shown that publications can be one of the most dominant channels to diffuse information from universities and other research institutions to businesses.[70]

The key stakeholders involved in this form of knowledge exchange include; the Knowledge Transfer Network (KTN); the Catapult Network; business engagement teams at universities; and the Alan Turing Institute.

Direct hire

This process refers to the case of an AI researcher (who may be at PhD, post-doc, or professorial level) being hired to work at a private company and leaving their research post at university. This, along with joint-tenure positions, is part of a theme unfolding in the academic sphere, known as the 'university AI brain drain'.[71] Essentially, large technology companies are now hiring tenured professors, or offering them joint-tenure roles at the company.

Joint tenure / positions at university and large tech companies

Google, DeepMind, Amazon and Microsoft hired 52 tenured and tenure-track professors from US Universities between 2004 and 2018[72]. Whilst the university AI brain drain has been considered more extensively

66 **BEIS, (2021), UK Innovation Strategy**
67 **British Patient Capital, (2020), Annual Report and Accounts 2020**
68 **McKinsey Global Institute, (2017), Measuring the Economic Impact of Short-termism**
69 **Christopherson. S, Kitson. M & Michie. J, (2008), Innovation, networks and knowledge exchange, Cambridge Journal of Regions, Economy and Society**
70 **Cohen. W, Nelson. R & Walsh. J, (2002), Links and impacts: the influence of public research on industrial R&D, *Management science***
71 **Benaich. N & Hogarth. I, (2020), State of AI 2020 Report**
72 **Gofman. M & Jin. Z, (2020), Artificial Intelligence, Education, and Entrepreneurship**

in the US, this is a phenomena that is poorly understood in Britain. Studies of US universities found that 4-6 years after the departure of tenured professionals, the graduates that the professors would have taught are 4% less likely to start an AI company[73]. Further analysis of whether similar stories are underway in the UK is necessary to determine whether policy changes are required.

Knowledge exchange via conferences, seminars, etc.

Another way that knowledge can be disseminated, and commercialised, is through participation in conferences and seminars, where research and products can be presented and discussed. Immediate commercialisation can occur through either hosting the conference, or charging fees for showcasing organisational research.

Route C – Standards and SDOs

Standards and SDOs as a route to commercialisation

The International Standards Organisations defines standards as "a document that provides requirements, specifications, guidelines, or characteristics that can be used consistently to ensure that materials, products, processes and services are fit for their purpose"[74].

Standards Developing Organisations (SDOs) have the primary function of developing, coordinating, revising, amending, interpreting, and producing technical standards[75]. Here, SDOs aim to bring together a diverse group of stakeholders, including: large technology firms; SMEs; government; academics; and civil society groups. There are hundreds – perhaps thousands – of standards organisations around the world, and many of them are part of various larger standards organisations. There are numerous national, as well as international SDOs.

Some examples of the most integral SDOs, particularly with regards to AI, are:

- ETSI (European Technical Standards Institute)
- ISO (International Organisation for Standardisation)
- IEC (International Electrotechnical commission): ISO/IEC JTC 1 relevant for AI
- CEN-CENELEC (European Committee for Standardisation, and European Committee for Electrotechnical Standardisation)
- ITU (International Telecommunication Union)
- IETF (Internet Engineering Task Force)
- IEEE SA (Institute for of Electrical and electronic engineers Standards Association)
- BSI (British Standards Institution).

The development standards is a growing area of interest for governments around the world as an effective way to support AI development. Countries such as the US and China, whilst expressing the importance of international standards for AI, have also worked on how national standards can develop industry.[76,77] An overview of AI national and regional strategies highlights plans for national standards from Australia, the Nordic-Baltic region, and Singapore.[78]

Previous discussions of standards have broken them down into four key categories: [79]: Interoperability; Minimum quality/safety; Variety reduction; and Information quality.

There have also been attempts to create a clearer categorisation of AI-specific standards. The European Commission recently denoted that high-level AI technical standards include:

- data and data governance - which refer to best practices of how data can be stored, accessed and trusted;
- technical documentation - which emphasises how material referring to an AI system must be kept up-to-date;

73 *ibid*

74 ISO, https://www.iso.org/standards.html

75 Ping. W, (2011), A Brief History of Standards and Standardisation: A Chinese Perspective

76 National Science and Technology Council, (2016), The National Artificial Intelligence Research and Development Strategic Plan

77 Ding. J, (2018), "Deciphering China's AI Dream", Future of Humanity Institute

78 Dutton. T, (2018), An Overview of National AI Strategies, Medium: https://medium.com/politics-ai/an-overview-of-national-ai-strategies-2a70ec6edfd

79 Blind. K, (2013), The Impact of Standardization and standards on innovation

- record keeping - this denotes the extent to which AI systems possess the capability to automatically log events whilst an AI system is operating;
- transparent information - refers to whether an AI system's output can be interpreted sufficiently by users;
- human oversight - aims to ensure that AI systems be designed and developed in away that can be effectively overseen by natural persons during the period in which the AI system is in use;
- accuracy, robustness, and cybersecurity - refers to standards that ensure AI systems achieve an appropriate level of accuracy, robustness and cybersecurity, and perform consistently in those respects throughout their lifecycle;
- risk management system - this should be establishment, implemented, documented and maintained for AI systems to enable compliance; and
- quality management system - ensures the accomplishment of a required conformity assessment procedure, draws up the relevant documentation and establishes a robust post-market monitoring system.[80]

There is also a clear theoretical (albeit, not necessarily empirically proven) economic rationale for implementing standards in order to boost innovation and commercialisation. In theory, standardisation at the R&D phase; reduces costs; increases investment security; and gives providers of innovative solutions an information lead over future competitors.[81] However, economic theory also suggests standards can generate sunk costs (money that cannot be recovered), which could create a reluctance to innovate further; monopoly power; reduced choice; and higher rival costs.[82]

Standards can be aggregated in many different ways, including the distinction between open and formal standards.

Formal standards refer to standards that are normally approved by a standards setting organisation recognised under the WTO's agreements on international standards. On the other hand, open standards are a newer development in both the innovation and AI ecosystem. Open standards give users permission to copy, distribute and use technology freely or at low cost.[83] According the the Organisation for the Advancement of Structured Information Standards (OASIS), for a standard to be open, it must: be created by domain experts (not SDO staff); be open for public review and debate; be easy to access and adopt; not have hidden patents; allow anyone affected by the standard to contribute to the development of it; have the ability to implement the standard baked in; and be safe for government to endorse.

Open standards and their relationship to AI commercialisation have seldom been studied. For a fast-developing area of economic organisation, additional inquiry is necessary. Furthermore, the role in which open source communities, a tangential agent in the open standard ecosystem, shape the AI commercialisation process is another untapped area of study.

Additional questions that will be explored include whether and how standards interact with other routes of commercialisation, and whether standardisation *itself* could be a potential barrier to commercialisation.

80 Nativi, S & De Nigris, S. (2021). AI Watch: AI Standardisation Landscape, European Commission

81 BSI, (2015), The economic contribution of standards to the UK economy

82 Blind. K, (2004), The Economics of Standards

83 GOV.UK (2018), Open Standards Principles, https://www.gov.uk/government/publications/open-standards-principles/open-standards-principles

Appendix 2 – A framework for assessing AI businesses looking for Venture Capital funding[84]

A representative of a venture capital investment firm (VC) explained their approach to assessing AI commercialisation projects, startups and businesses, which is based on the '5Ps' given below.

The '5Ps' framework

PEOPLE – People who demonstrably understand the problem they are trying to solve and have the technical skills to build a solution. This pillar is also concerned with whether pitchers have connections with industry and a plan for the size of team that will be required.

PRODUCT – Defined as the value they are trying to create for the customer. Pitchers must demonstrate the value they are creating is greater than the expense of developing the AI solution, and also represent better value than other non-AI solutions. Pitches are often rejected because an alternative solution is available that doesn't require the development of an expensive machine learning algorithm.

PROCESSES – Different machine learning processes have quite different data requirements. Pitchers must demonstrate they understand the processes they will use, the compute resources the project will require, and the costs of accessing that resource.

PETABYTE (aka data) – Pitchers should have a firm idea on how much data is required to develop the machine learning process adequately, what kinds of data are required, where these will be acquired from, how it is to be structured and cleaned, and the costs involved in all of these. An investor is interested in whether a startup or small enterprise can feasibly meet the data requirements of the project, or whether the project belongs in 'big firm space'.

POSITIONING – Pitchers should be able to identify other businesses in the marketplace who are pursuing the same or similar problems or solutions. Demonstrating an advantage over potential competitors is important.

Key overall considerations for VC investors are:

- VC investors will be looking to see whether a business has a viable long term road map (c.18 years), and to assess where the business is in that timeline and whether they have a coherent plan to reach the goal of commercial success.
- Framing the overall business goal in terms of a 'David versus Goliath' type challenge to existing markets. VC is looking for businesses that can breach an established market by automating some elements and drastically reducing costs. Persuasive pitches understand this perspective and explain the businesses goals in similar terms.

84 Source: Matt Turck – https://mattturck.com/building-an-ai-startup – expanded on by John Spindler, AI Seed.

OXFORD INSIGHTS

cambridge econometrics
clarity from complexity

Department for Digital, Culture, Media & Sport

Office for Artificial Intelligence