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The US university-industry link in the R&D of AI: Back to the origins?

Andrea Borsato[1*], Patrick Llerena[1]

Abstract

Contributing to the fast-growing Economics of Artificial Intelligence (AI), this paper examines the close relationship between university and industry for what concerns to the research and development of AI technologies in the USA. Recalling the history of the university-industry relationships in the several phases of the US national system of innovation (NSI), we argue that current collaborations resemble in some respects what happened during the prewar NSI. Yet, the AI R&D presents some peculiarities. Universities are changing their positioning in the innovation process and turning to a *research*-based training model in the domains concerned by AI. This could potentially change the trajectory of university-industry links, since it is very much in line with the typical Humboldtian perspective that was at work in some European institutes in XVIII century up to US early XX century. At the same time, if the way in which the production of knowledge and the training of the workforce envisages a return to the origins, differences arise in the definition of the main goals, e.g., Sustainable Development Goals, and in the role of stakeholders. The overall discussion also bears some implications for the link between division of knowledge and division of labour.

Keywords: Artificial Intelligence, AI research, University-industry relationship, US national innovation system.

JEL Classification: I2, L2, O31, O33.

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1) Introduction

Artificial Intelligence (AI) has experienced a surge in momentum since 2010 driven by breakthroughs in the development, diffusion, and application of machine learning and deep learning techniques (LeCun et al. 2015). These technologies are now being deployed across a range of scientific domains, such as protein synthesis (Callaway 2022), drug development (Lou and Wu 2021), flexible automation discoveries in chemistry and materials science (DeCost et al. 2020, Johnson 2021, MacLeod et al. 2022), and motion sensing research in computer science and electrical engineering (Furman and Teodoridis 2020). Beyond the ability to accelerate automation, AI is also bringing about profound changes in the structure of scientific systems. A growing body of literature highlights its ability to reshape the way knowledge is produced within and between many scientific domains (Agrawal et al. 2023, Bianchini et al. 2022). These remarkable advancements have stimulated an abundance of academic studies exploring the manifold relationships that AI weaves with economic systems. The debate on AI's nature as either a general-purpose technology (GPT) or a method of invention is enlivened by several scholars (Klinger et al. 2021, Vannuccini and Prytkova 2023).

Meanwhile, ethical concerns surrounding unequal access to AI resources are explored by Ahmed and Wahed (2020), Ahmed et al. (2023), Gibney (2022), Gundersen and Kjensmo (2018), Hagendorff and Meding (2021), Ho et al. (2021), Urbina et al. (2022), among the others. This strand of literature argues that large technological companies and prestigious universities are increasingly collaborating because of the complementary nature of their resources, namely companies provide access to hardware infrastructure and data whereas universities provide trained personnel. Beyond the crowding-out of scientists that do not belong to top-tier academic institutions and the potential narrowing in the thematic diversity (Klinger et al. 2020), the great concern is the growing interdependence between academia and industry in the domain of AI, which may direct university research towards a *third mission* that falls predominantly outside the scope of what a university is supposed to do, and which also undermines its research autonomy.

In this paper we challenge this broad concern by retracing the various stages that characterised the evolution of university in Europe and United States along with the history of the American National System of Innovation (NSI). Inspired by the literature on Martin (2003, 2012), Mowery and Rosenberg (1993), and Rosenberg and Nelson (1994), among the others, we assert that the current institutional setting around the research and development of AI resembles in several aspects the typical university-industry links of the prewar period. The prevalence of large firms in the innovation system, the increasing recruitment of PhDs by the private sector, the decentralised funding scheme of AI R&D, and the intellectual property rights (IPR) regime constitute an interesting change with what has occurred in the USA since the cessation of WWII hostilities. Moreover, it is our argument that AI does not encourage universities to pursue a third mission that is traditionally outside their primary engagement. Since the advent of modern science, research funding has been tied to the expectation of returns in the form of newly developed or improved weapons, more accurate instrumentations, better medicine, and other forms of technical progress (Martin 2003). It is challenging to find examples of scientific research where the expectation of economic or social gain did not influence the outcome, whatever the funding source, be it government, business, or a prince. Moreover, the historical account of the US NSI suggests that the third mission played a great role in the operation of universities in the XIX century, even in states where the imported Humboldt model was more effectively implemented.

Yet, the field of AI presents certain specificities. Based on the available empirical evidence, we argue that universities are changing and somehow tailoring their positioning in the innovation and diffusion process in the domains concerned by AI. They are increasingly engaged with the formation of skilled labour in this new field than in the development of scientific and technological knowledge – with the exception of very upstream and fundamental research. The role of universities is turning to a *research*-based training model. The workforce that will conduct research on AI at industry is not trained in coding skills and programming but rather on the fundamental understanding of science – e.g., physics, chemistry, mathematics. In other words, trained personnels are not technicians. Two main reasons explain this pattern. Firstly, this proves as a necessary condition to create good AI engineers. Secondly, firms are most interested in hiring scientists equipped with wide knowledge base that could be useful to a large range of tasks. They are not interested in engineers with very specific skills that could result in some mismatching. Scientists strongly equipped with fundamental science are also pivotal to (intrafirm) knowledge upgrade. Indeed, the scientific and technological knowledge is developed by firms and similar organisations but in collaboration with universities in order to have access to, and co-develop, the relevant skills. This could potentially change the trajectory of university-industry links, since it is very much in line with the typical Humboldtian perspective that was at work in some European institutes in XVIII century up to US early XX century. At the same time, there are notable discrepancies in the interpretation of the primary objectives, the characterisation of the knowledge being generated, and the intended applications. The research and development of AI is less *firm*-oriented than the innovative search that characterised the early stages of the US NSI. Significant resources are allocated to the pursuit of Sustainable Development Goals (Abbonato et al. 2024, Bianchini et al. 2023), which encompass a far broader scope and breadth of concerns than those previously associated with industrialisation. The number of stakeholders engaged in this field has increased, encompassing academic and private sector institutions, as well as governmental and supranational entities. All this may have implications for the nexus between division of labour and division of knowledge (Cohendet and Llerena 2010).

The paper is organised as follows: Section 2 is about AI and provides definition, some stylised facts that surround its potential GPT-ness and some patterns of research collaborations; Section 3 presents an outlook of university history in which academia is presented as an evolutionary entity that generates traits as to accommodate to the ever-changing institutional environment; Section 4 recaps the several stages of the US NSI since its industrial take-off. Both the third and the fourth Sections are pivotal to an overall assessment in Section 5 of the way university-industry links take place in the R&D of AI. Last Section concludes.

2) AI: definition, stylised facts, patterns of research and collaboration

A great deal of writing on the automation technologies that surround the so-called Fourth Industrial Revolution (Schwab 2016) has produced several definitions of AI (Boden 2016, OECD 2019, Russell 2019). For simplicity, we follow Vannuccini and Prytkova (2023, p. 2) that define AI as "a variety of systems each consisting of virtual machine(s) (algorithm(s)) performing statistical learning and inference, using data of different modalities (e.g. visual and audio) and types (e.g. text, cross-section and panel) and relying on dedicating computing capacity". In other words, we can conceive AI as a cloud infrastructure composed of three core elements: data, advanced algorithms, and the computational hardware to implement the algorithms for the analysis of data (Borsato and Lorentz 2023).

The dramatic increase in data availability, the recent achievements of machine learning and deep learning techniques, and the ongoing increase in computing power have prompted several scholars to argue that AI represents a further breakthrough in scientific and economic systems, as the steam engine and the electricity were in the past (Aghion et al. 2019, Agrawal et al. 2023, Bianchini et al. 2022, Brynjolfsson et al. 2018). The overall idea is that AI is a new GPT (Bresnahan and Trajtenberg 1995), characterized by the potential for pervasive use in a wide range of sectors and by its technological dynamism (Cockburn et al. 2018, Klinger et al. 2021). Moreover, as a GPT evolves and advances, it permeates the entire economy and leads to productivity increases.[1] GPTs typically act as *enabling technologies*, generating new possibilities as opposed to providing conclusive solutions. This process involves innovation complementarities, meaning that advances in GPT technology also leads to productivity gains in R&D in downstream sectors. These synergies thus amplify the impact of the innovation within the GPT and enhance its diffusion throughout the economy (Bresnahan and Trajtenberg 1995).

In this respect, AI has the potential to further accelerate the pace of automation and to reshape the way in which we produce knowledge in different domains (Agrawal et al. 2019, 2023). On the one hand, AI entails an explosion of data that researchers struggle to keep up with. Adopting the need-in-the-haystack metaphor, this impacts on *search* as AI multiplies the number of needles in a single haystack by predicting what knowledge should be most relevant to the researcher. On the other hand, the *discovery* process is also affected by the rise in combinable knowledge leading to new insights being gained. Therefore, AI potentially increases the number of haystacks by predicting “which combinations of existing knowledge will yield valuable new knowledge across a large number of domains” (Agrawal et al. 2019, p. 153).

However, there has been criticism of the portrayal of AI-based technologies. Arguably, AI is not as ubiquitous as commonly believed (Bresnahan 2019, McElheran et al. 2023, Vannuccini and Prytkova 2023): it has only been deployed in a limited number of sectors, namely ICT, professional and scientific services, and finance and insurance, and even in the industries where the adoption of AI systems is most widespread, the technology appears to be an addition to existing systems, with the adoption process involving the replacement of capital for certain tasks. Furthermore, AI technologies are such a complex phenomenon that the description of them as a GPT may be reductive, somewhat paradoxically. Typically, a GPT consists of a single upstream source with many edges that extend to a host of downstream sectors, where it contributes to the introduction of complementary innovations. Whereas AI is undisputedly inducing further downstream innovations, this technology actively participates in the creation of new technologies, thereby steering the role of invention and innovation: this role goes beyond that of a typical GPT (Bianchini et al. 2022, Vannuccini and Prytkova 2023). At the same time, current developments in AI raise concerns on its application. To introduce these growing issues as in Ahmed and Wahed (2020), Ahmed et al. (2023), Hagendorff and Meding (2021),

[1] The issue of productivity dynamics in the USA and its observed growth slowdown since the 1970s make the impact of all digital technologies difficult to assess (Borsato 2024, Gordon 2015, Solow 1987). The same concern well extends to AI, whose actual deployment is smaller than what believed (McElheran et al. 2023).

Jurowetzki et al. (2021), Klinger et al. (2020, 2021), and Lohr (2019), we list in Table 1 a collection of stylised facts that map the dynamics of technological innovations in AI-related domains.

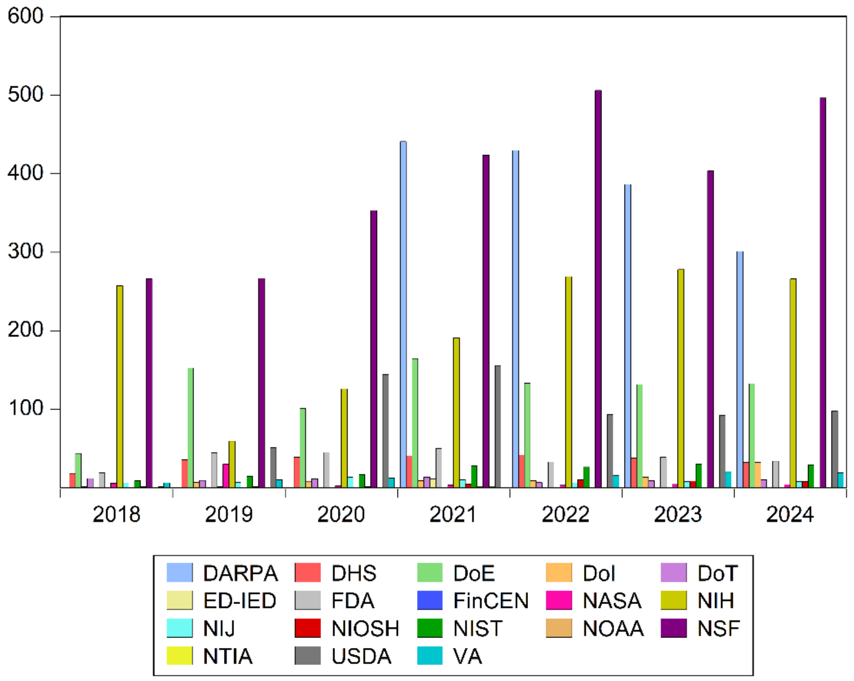
Potential	**References**
AI as GPT	Agrawal et al. (2019, 2023), Brynjolfsson et al. (2018), Cockburn et al. (2018) Klinger et al. (2021)
AI as IMI[a]	Bianchini et al. (2022)
AI as LTS[b]	Vannuccini and Prytkova (2023)
Empirical evidence	
Most research carried out by scientists with academic fellowship	Furman and Seamans (2019), Liu et al. (2021)
Rapid increase in AI patenting (1991 – 2020)	Liu et al. (2021)
Most AI patents are owned by large private companies	Holm et al. (2023), Liu et al. (2021), Petruzzelli et al. (2023)
Specialisation: USA in Life Sciences, China in Technology and Physical Sciences	Bianchini et al. (2022), Klinger et al. (2021)
Polarisation: USA maintain leadership, China is catching-up, Europe lags behind	Bianchini et al. (2022), Liu et al. (2021)
Balkanization of data	Cockburn et al. (2018)
Transition of PhDs to industry	Ahmed and Wahed (2018), Ahmed et al. (2023), Jurowetski et al. (2021), Lohr (2019)
Increasing involvement of industry in research	Ahmed et al. (2023), Ho et al. (2021)
Substitution of AI capital for ICT capital	Bresnahan (2019)
AI diffused in several sectors but not widely adopted	McElheran et al. (2023), Vannuccini and Prytkova (2023)

[a] *Invention of a Method of Invention;* [b] *Large Technical System.*

Table 1. Some broad beliefs and stylised facts on AI

The empirical evidence related to AI can be organised into three broad categories: worldwide patterns of research contributions, geographical distribution and specialisation, and cross-disciplinary relationships. In terms of general patterns, significant contributions to the subject are highlighted in Cockburn et al. (2018), Furman and Seamans (2019), and Liu et al. (2021). Their analyses reveal a steady increase in AI publications and AI patenting since 2009 at least relative to publications in other contiguous fields such as robotics and symbolic systems. Notable, the vast majority of these publications come from members with academic affiliations. These findings are consistent with the increase in student enrolment on AI and machine learning courses at USA, UK, and Chinese universities, as well as the significant proportion of jobs requiring AI skills and increased private sector investment in AI-related projects (Ahmed et al. 2023). For what concerns to patenting policies, the leading assignees of AI patent applications in the last thirty years are primarily corporations. Public organisations and universities seem less prominent in ownership, with China as potential exception. In other words, patenting activities overturn the (im)balance between public and private institutions (Liu et al. 2021). Additionally, co-patenting collaborations through joint ownership are not common (cf. Holm et al. 2023, Liu et al. 2021, Petruzzelli et al. 2023).

Examining the geographical distribution and patterns of specialisation, the literature suggests that the emergence of a new GPT – AI in this case – could change the geography of research, with the arrival of new entrants and the emergence of new patterns of consolidation once central hubs are in place (Bianchini et al. 2022, Klinger et al. 2021). The first indication is an international trend in AI and deep learning activities since 2012. This is accompanied by a geographical clustering, whose concentration is seemingly stronger than the broader domain of computer science research, supporting the hypothesis that knowledge spillovers in AI are highly localised. During the 1990s, indeed, the development of AI was primarily driven by theoretical contributions from the USA. In the following decades, China surpassed the USA becoming the most prolific country in AI research. The pattern of geographical concentration is confirmed by patent applications: even though the USA maintain a leading position, China grew most rapidly in recent years and now challenges US leadership (Liu et al. 2021).[2] Data on US federal budget in Fig. 1 tell about major investments in AI R&D by key agencies such as National Institute of Health (NIH), National Science Foundation (NSF), and DARPA. Starting from an expenditure between $600 million in 2018 with NIH and NSF as leading investors, AI R&D spending more than doubled in 2020-2021 to overcome $1800 in 2022. Though NIH and NSF still maintain the largest share of federal budget, it is interesting to note the increasing number of federal agencies – i.e., eighteen – currently involved in research and development activities for AI. This pattern suggests a growing decentralisation in the allocation of public funds to this domain.



Source: Authors' computations based on NITRD data.

Note: Values are in millions of constant 2022 US dollars. AI R&D aims at improving "the technical capabilities of computational systems to conduct, simulate, or extend the performance of tasks that have traditionally required human intelligence; this includes innovations in perception (to include spoken language and gestures), computer vision, natural language technologies, representation, learning, reasoning, recommendation, and action; novel and use-inspired application of these techniques to various domains; and examination of trustworthiness and the associated measurements, methods, and tools needed for designing, developing, and evaluating

[2] Although a number of advanced European and Asian countries have conducted research on related topics, their substantial presence in the system of innovation and in the university-industry link of AI is of low relative magnitude and relevance (Bianchini et al. 2022, Liu et al. 2021). Moreover, this can be connected with the general weakness of European countries in both scientific research and innovation outcomes with respected to counterparts as USA and Japan (Dosi et al. 2006).

such systems" (NITRD 2024). In accordance to NITRD, we excluded from AI R&D the federal investments in other Program Component Areas (PCAs) technologies, e.g., computing-enabled human interaction, communication and augmentation, cyber security and privacy, or large-scale data management and analysis. Acronyms refer to: Defense Advanced Research Projects Agency (DARPA), Department of Homeland Security (DHS), Department of Energy (DoE), Department of the Interior (DoI), Department of Transport (DoT), Institute of Education Sciences (ED-IES), Food and Drug Administration (FDA), Financial Crimes Enforcement Network (FinCEN), National Aeronautics and Space Administration (NASA), National Institute of Health (NIH), National Institute of Justice (NIJ), National Institute of Standards and Technology (NIST), National Oceanic and Atmospheric Administration (NOAA), National Science Foundation (NSF), National Telecommunications and Information Administration (NTIA), US Department of Agriculture (USDA), Department of Veteran Affairs (VA).

Figure 1. Federal Budget for AI R&D

For what concerns *specialisation*, there is significant variability in the geographic distribution of fields. In Asian countries, most in China, AI research and patenting activity concentrates primarily on "Technology" and "Physical Sciences", whereas in North America, a larger proportion of research is centred on life sciences and biomedicine.[3] All these specific domains have experienced a significant boost in terms of publications since 2010, and this surge has come at the expense of publications broadly categorized as "Computer Science". This pattern of specialisation is hence observed in what is commonly referred to as the *double-boom cycle* (Klinger et al. 2021). Initially, there is an abundance of theoretical contributions in the wider domain – e.g., Computer Science – which is later replaced by research articles that hold greater emphasis to practical issues – e.g., life sciences. The application-oriented contributions subsequently result in impressive advancements toward real-world tasks.

The second aspect worth to be mentioned is *polarisation*. If there is a progressive specialisation in North America and China, it is notable how this development has nearly halted in Europe (Bianchini et al. 2022). The worldwide polarisation in AI activity is consistent with the notion of volatility during the GPT's development early phases, with certain countries advancing – e.g., USA, China – whilst others lagging behind – Europe's (Klinger et al. 2021). This trend envisages a *Matthew effect* for focussing on a specific field of AI research leads to the development of industrial clusters populated by few organisations acting as high-impact technology disseminators and adopters (Liu et al. 2021). These regions have sufficient capacity to maintain the mix of research and industrial capabilities essential to the growth of AI as GPT. This element is pivotal due to the benefits that a country can gain from the co-location and collaborations of researchers-developers and adopters.

Taken for granted such broad stylised facts, what about the university-industry collaborations? The evidence is scanty and most concerns the United States. Ahmed and Wahed (2020) and Ahmed et al. (2023) show that industry increasingly dominates the three key ingredients of modern AI, namely data, computing power, and researchers. Albeit growing since early 2000s, the demand for AI experts rapidly increases since 2012 and such increase in demand has yet to be matched by an adequate level of supply, engendering a competition for AI talent. Additionally, the increasing amount of AI research conducted by private companies is evident in the number of academics transitioning to industry (Ahmed et al. 2023, Jurowetzki et al. 2021, Lohr 2019). This trend has led to a greater collaboration between big-tech firms and top-tier universities, due to the complementarity of resources, with companies providing access to hardware infrastructure and data, and universities providing trained

[3] We have referred to North America because Montreal in Canada hosts a leading AI ecosystem that has its core in the collaboration between universities and start-ups in healthcare (Sultana et al. 2023).

personnel. Moreover, the data hunger inherent to any AI system renders data and its associated hardware essential to generating predictions. Yet, access is contingent upon organisational boundaries and policies. Cockburn et al. (2018) refer to the *balkanisation* of data and hardware infrastructure as a consequence of this phenomenon. Although the algorithms to perform deep learning techniques are publicly available, the generation of predictions requires private data and technical infrastructure, access to which is dependent on organisational boundaries such as patents and intellectual property rights. As the performance of algorithms is critically dependent on the availability of data, control of the data could give a private or public entity in a particular field a permanent and significant advantage in innovation. This advantage is distinct but related to the traditional economies of scale of demand-side network effect (Cockburn et al. 2018).

Such a dynamics in data ownership is paired with an increasing monitoring of academics' career in industry. Ahmed et al. (2023) document that the percentage of scholars with a PhD in AI subjects jumped from a "modest" 20% in early 2000s to almost 70% nowadays, most from elite universities. Accordingly, the share of PhDs entering industry is greater than the corresponding share of other engineering disciplines. The authors contend that the heightened collaboration between university and industry in AI research may result in two critical outcomes. Firstly, it may exclude scientists from non-elite universities, creating a significant technological gap between them and their elite counterparts. Secondly, it can narrow the range of knowledge produced, as a small group of actors will dominate the panorama of AI research. Ahmed and Wahed (2020), Hagendorff and Meding (2021), Klinger et al. (2020) show that the thematic diversity in AI initially covered various topics but has since stagnated and even declined in recent years. Specifically, computer language, computer vision, and information retrieval – i.e., recommendation systems and ad-targeting – are the narrow focus of industrial AI research, with potential for short-term gains but neglecting long-terms impacts and externalities. In other terms, the peril is that industry commercial motives push them to focus on topics that are profit-oriented, with outcomes often, but not always, in line with the public interest.

Without denying or lessening the worrisome signals out of this literature, we contend that over the past decades there has been a transition in the way science and universities receive funding and interact with industry. The risk that this shift in perspective ultimately has a negative impact on social welfare is not circumscribed to AI and dates to the early 1990s. As Martin (2003, 2012) argues, the situation has become much more like that of the late XIX century in several respects. Many universities have now explicitly embraced the *third mission* of contributing to the development of technology, innovation, the economy and society more broadly. Science and universities have been able to withstand and flourish amidst challenges for centuries, and they should now adapt to their new and crucial role in the knowledge-based economy, taking advantage of opportunities it and AI both present, without a loss of autonomy. Similarly, as we are going to deepen in the following pages, application-oriented research has been a constant feature in universities, particularly within the US NSI (Martin 2003, Rosenberg and Nelson 1994). A relative recent example, i.e., the emergence of biotechnology as a fast-growing industry since the late 1970s, points to the high concentration in a relatively small number of universities and companies for systematic forms of interrelations (Orsenigo 1989). Large pharmaceutical firms were most interested in new techniques and frontier research, which were available in top-tier universities, whose know-how was believed of a high quality and had a long tradition of collaboration with research-intensive industries. Furthermore, institutional boundaries between university and the private sector have consistently been blurred.

Such fusion of institutional boundaries may be more frequent and widespread in sectors with a strong science base.

While focussing on the USA, the following Sections describe the characteristics of universities as *evolutionary entities* and a brief recap of the US early NSI. Both Sections are pivotal to an understanding of the commonalities that the current AI ecosystem shares with other present systems and the past.

3) An evolutionary outlook of university

3.1) University: from Middle Age to Humboldt

Universities emerged in the XII century with the main purpose of educating a selected group of individuals with the expertise and aptitudes necessary to serve in the fields of medicine and law, as well as in the top echelons of the church (Etzkowitz and Leydesdorff 1997, 2000; Geuna 1999; Martin 2012).[4] The roots of medieval universities stood in the *utilitarian soil* (Cobban 1992) for in that period already, universities were thought of as means to spur the status of a region in terms of economic development. Specifically, universities performed two main functions at the base of two *species*. The first function consisted of teaching for priests, lawyers, and public servants, namely what Martin (2012, p. 545-546; emphasis in original) calls "the *pure* or '*immaculate*' *conception"* of knowledge while the second concerned to the systematic study and re-interpretation of existing knowledge. Both functions were present in different doses in the two different and rival species of early universities, that is one emphasising the arts of canon law and theology with the pursuit of truth (*bios theoretikos*), and the other more focussed on the spread of useful knowledge and skills as in the *faculties* of law and medicine (*bios praktikos*).

This overall organisation persisted, with winters and summers and obvious (sometimes important) changes, until the XVIII-XIX centuries in which a new *social contract* came out in Germany. The *Humboldt social contract* joined teaching with research, with the assumption that both activities should be undertaken within the same institution. Still largely believed as the benchmark of what a university shall be, this model aimed also at training bureaucratic and professional elites with humanistic education and relied on conspicuous public funds. Moreover, students and professors benefitted, at least in principle and from an ideological viewpoint, from a substantial level of autonomy about teaching and research activities. The model of the XIX century German universities, which Cowan et al. (2010) and Readings (1996) call the *university of culture*, has been adopted by universities in Europe and North America, though not everywhere the same way. Readings argues that Humboldt and the German idealists who helped create the university of culture saw universities as the primary repositories of the culture of a country. In the university of culture, scholarly activity has expanded into new disciplines, including literature. The study, preservation, extension and even the creation of national culture is pursued. This model generates a distinct public good, since the promotion of national culture creates a national identity. All citizens can participate in this identity.

[4] Table 2 summarises the broad *species* of university since the Middle Age.

The future leaders of the country, trained by the university of culture, acquire a shared vision of the country, facilitating cooperation.

The concept of a university of culture, born in Germany with the Humboldt model and exported most in North America, represents a good description of the social contract characterising the majority of universities in the world in the first half of the XX century. It was a powerful rationale for central government in providing funds and facilitating co-ordination (Cowan et al. 2010). The natural evolution of this social contract ran for the first forty years of the postwar period as the result of Vannevar Bush report (1945). This social contract implied, firstly, a high degree of autonomy of science; secondly, decisions of how to spend public funds were taken by an agora of scientists; thirdly, basic research was thought of as best done in academy. Albeit it is a matter of debate whether Bush report contained it, that social contract embodied the so-called linear model of innovation: from basic research to applied research to development to innovation.

Evolutionary *species*	**Characteristics and functions**	**Third mission**
Early university (XII-XVII century): *bios theoretikos*, *bios pratkikos*	Teaching and scholarship (not research)	Prince's ambition and desire for prestige; economic development and status of a region
Humboldt model and utilitarian social contract (XVIII-XX century)	University of culture; teaching-*cum*-research	Study, preservation, extension, and creation of national culture
Vannevar Bush's model (1945-1980s)	Autonomy of scholars; peer-review allocation of resources; basic research in university; linear model of innovation (*debated*)	Contributing to wealth, health, national security
Revised social contract (1990s – today)	University of innovation; complex science-innovation nexus (*debated*)	Scientists and universities should be responsive to the needs of users in business and society

Table 2. Broad overview of university species over time

3.2) Origins of the US university system

The Humboldt model first and the Bush model later are often regarded as social contracts that involve knowledge production within individual disciplines, mainly in universities and other institutions. The direct link with societal needs is consubstantial and the results of the research are transferred to the users at the end of the project, who may or may not take up the results (Geuna 1999, Martin 2003). The figure of the university professor conferred on a social status that usually implied an engagement in society. For instance, the 1909 Nobel laureate in Physics Karl Ferdinand Braun was professor at the University of Strasbourg and his knowledge spreading on electrical engineering was fundamental to make Strasbourg one the first European cities with electrical lighting. Focussing on United States, the emphasis on professional education, namely the training of knowledge and skills towards *useful men* was already in place at the dawn of 1800 with the foundation of the Academy at West Point. The progressive industrialisation of the USA throughout the XIX century enormously increased the need of trained workers and engineers. The Morrill Act of 1862 was an important milestone in laying the foundation of land-grant colleges, which were established with the primary purpose of teaching subjects related to agriculture and mechanical arts, but not excluding other scientific and classical subjects, as well as military tactics. This aimed at encouraging practical education for the industrial classes in various trade and occupations (Cornell Law School, 7 US Code § 304).[5] For example, the establishment of the University of Akron, Ohio was designed to provide industry with the skills needed to support the continued expansion of the rubber industry, with the first chemistry course being established at the university in 1909. The shift from iron-rich ore mining to taconite-based throughput production in the Mesabi Range, Minnesota acted as a catalyst for the University of Minnesota's Mines Experiment Station to undertake an in-depth research programme focussed on engineering and processing challenges which required several years of rigorous experimentation.

Therefore, we can conceive the land-grant colleges as the response to the *pressures* of the environment, a response that took seriously a *third mission*, which in several instances was the transfer of agricultural knowledge to improving productivity in farms. But this does not represent an *ad hoc* example from the past of US history. The end of the XIX century and the early decades of the XX century witnessed the development of in-house R&D capabilities in high-tech sectors like chemicals. Although the evidence suggests that the knowledge scientists used to bring to firms was not at the frontier of science, nor that firms hired trained engineers with that purpose (Rosenberg 1985), we cannot deny that universities and engineering departments were pivotal to the birth of new science-based industries such as chemical and electric engineering sectors (Martin 2012).

In particular, this role for the education system and universities was determined by their reliance on state government funding (Mowery 1995). The limited amount of fundings from both state and federal sources pushed universities to establish formal linkages with the private sector, which found in universities an important ally for the monitoring of new technological opportunities. The formal relationships with business was visible in the curricula and programmes closely tailored to the needs of the private sector to a greater extent than what happened to European counterparts (Hounshell and Smith 1989, Swann 1988). The new programmes in engineering, mining and metallurgy financed by several state universities were accompanied by graduate and post-graduate fellowships sponsored by large firms, e.g. Du Pont with the University of Delaware's chemical engineering department and AT&T with MIT's electrical engineering department. Seemingly, the linkages between higher education and industrial research continued with post-graduate studies aimed at training the workforce to carry out research activities in the nascent industrial laboratories (Mowery 1995, Thackray 1982).[6]

To summarise, the foundations of universities and research departments across the large US landscape centred on research and teaching in diverse fields including agriculture, mining, accounting, finance, and engineering subjects. On the one hand, universities performed fundamental research to enhance the knowledge base. On the other hand, they used the results of research to train the workforce on

[5] The first Act of 1862 was subsequently shored up by a second Act in 1890 that provided land-grant colleges with federal funding.

[6] It is interesting to note that the foundation of new firms by university-based researchers did not often occur in the prewar period for reasons that spanned from general macroeconomic conditions to weak government policy in support of new firms. From this point of view, the typical small R&D-intensive start-ups represented a postwar phenomenon.

practical applications that could support the development of the *local* industry. This also explains why many institutes were land-grant *colleges* and not land-grant *technical* schools.

3.3) The US university postwar: from Bush to the revised social contract

A structural shift in policy occurred with the postwar through a greater involvement of federal agencies in research support. Data in Tabs. 3-4 and Fig. 2 are indicative of the expenditure provided for the conduct of basic and applied research. For instance, with respect to the former, federal funds doubled from an yearly average of $15 billion in the period 1976-1988 to the first decade of the XXI century. Similar arguments work for applied research, though funding is usually of greater average magnitude. Additionally, even if several agencies committed to research funding, the greater contributor has always been NIH. Its share in total funding gradually shifted from one third in late 1970s to almost one half in more recent years. Indeed, the largest discipline collector were the life sciences, which started with about $10 billion in the late 1970s – one third of total spending – to about $35 billion after 2007 – more than one half of the total. These values are remarkably higher than other disciplines taken both in isolation and in combination. The postwar increase in federal fundings represented a determinant of the changing role of the university within the US research system, which somewhat weakened some of the prewar links between corporate and university research (Leslie 1993). On the one hand, if industry increasingly relied on their internal R&D facilities for new technologies, on the other hand, universities no longer tried to established research partnerships with the private sector to secure funds in an aggressive way as they did before. In pharmaceuticals and chemicals, the analyses in Swann (1988) and Hounshell and Smith (1989) support the claim that the increase in federal research funding for academic research in life sciences significantly weakened the university-industry links that were typical before WWII. This was evident in the case of Du Pont, who could no longer rely on university research as much as before, whose public character made it available to its competitors.

Another aspect worth to be mentioned about the postwar was that much of research was in fact *mission oriented*, i.e., funded by government departments as DARPA, NIH, Department of Energy (DoE), with the specific aim of advancing the technological capabilities in some national-priority industry, be it aerospace, health, and the like. Universities were deeply involved in a form of utilitarian contract with government and industry, forming a *Triple Helix* (Eztkowitz and Leydesdorff 1997, 1998, 2000; Shinn 2002). Perhaps hidden, but the third mission was none the less in place.

				Basic research				
Year	**NIH**	**NSF**	**DoE**	**NASA**	**DoD**	**DoA**	**Other**	**Total**
1976-1988	5.57	2.53	1.92	1.81	1.62	0.87	0.89	15.22
1988-1996	9.71	3.18	2.92	3.16	2.01	1.03	0.83	22.83
1996-2007	17.35	4.29	3.72	3.24	1.90	1.12	1.02	32.65
2007-2022	19.92	5.54	5.13	3.68	2.45	1.21	1.39	39.32
				Applied research				
1976-1988	3.29	0.20	2.20	2.56	5.26	1.10	4.69	19.32

1988-1996	4.32	0.24	2.68	3.01	5.20	1.15	5.44	22.03
1996-2007	12.19	0.33	3.42	3.41	6.24	1.38	6.34	33.31
2007-2022	18.02	0.73	6.05	2.37	8.13	1.40	6.78	43.47

Source: Authors' computations based on AAAS data. Note: Values in billions of constant 2022 US dollars. Acronyms refer to: National Institute of Health (NIH), National Science Foundation (NSF), Department of Energy (DoE), National Aeronautics and Space Administration (NASA), Department of Defense (DoD), Department of Agriculture (DoA). We determined time intervals according to NBER's US major business cycles phases.

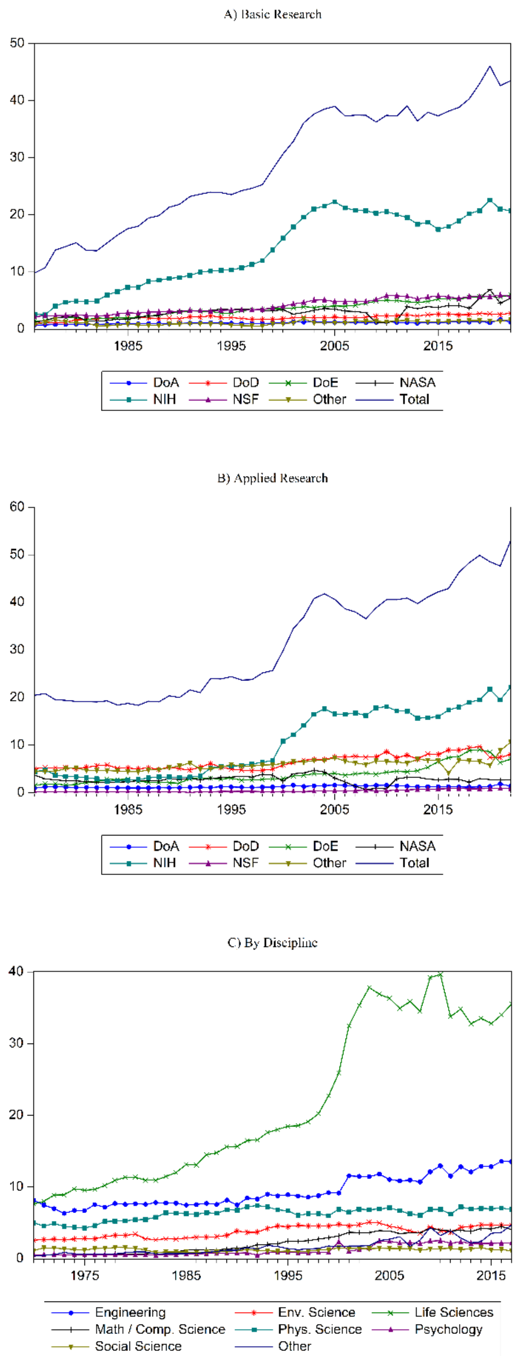
Table 3. Average trends in US basic and applied research by agency

Year	**Life Sciences**	**Psychology**	**Physical Science**	**Environmental Science**	**Math / Computer Science**	**Engineering**	**Social Science**	**Other**	**Total**
1970-1979	9.49	0.55	4.80	2.86	0.57	7.24	1.39	0.64	27.53
1979-1988	12.36	0.61	6.00	2.95	0.96	7.65	1.07	0.82	32.41
1988-1996	16.87	0.80	6.82	3.94	1.84	8.38	1.07	1.39	41.12
1996-2007	29.69	1.58	6.56	4.60	3.30	10.30	1.33	1.91	59.27
2007-2017	35.14	2.23	6.76	4.28	4.00	12.37	1.32	3.20	69.31

Source: Authors' computations based on AAAS data. Note: Values in billions of constant 2019 US dollars. We determined time intervals according to NBER's US major business cycles phases.

Table 4. Average trends in US federal basic and applied research funding by discipline

The 1990s experienced a shift in perspective in the way in which science and universities are funded and the emergence of a *revised social contract* (Cowan et al. 2010, Martin 2003). The scope *narrows* and the revised contract implies a clear expectation that, in return to public funding, scientists and universities should be focussed more on the industrial and economic impacts in their activities. In addition to this, they will be subject to an enhanced form of accountability for the resources that they have received. This revised social contract follows, or should follow, a more complex approach to the science-innovation nexus than the previous linear model. This change in perspective has raised several concerns about potential danger in long-term social welfare, with the welfare of future generation being challenged by current consumption (Martin 2003). As we will discuss later, the argument sounds like the previous discussion of the university-industry link mediated by AI technologies. Yet, once again, the empirical evidence that meeting societal needs through a great involvement of university in subjects that traditionally most interest industry may produce long-run negative effects on scientific research is rather weak. Nor this revised social contract represent a profound structural change with the very past. It is not just the first decades of XXI century that the third mission started characterizing university activity. The third mission had coexisted with teaching and research since the emergence of modern science. In this respect, it is the 1945-1980s period marked by Bush (1945) that could be thought of as a temporary deviation from the past. It was from an *ideological* point of view that "teaching *cum* research" was disentangled to the third mission in the postwar. Ideologically disentangled, but not actually. In fact, for what concerns the USA, be it both basic and applied, research was always directed to the pursuit of some *tangible* societal goals, with key changes in the role of stakeholders and about the *nature of societal goals* concerned notwithstanding (Rosenberg and Nelson 1994).



Source: Authors' computations based on AAAS data. Values are in billions of constant 2022 US dollars for basic and applied research by agency, while they are in billions of constant 2019 US dollars for funds by discipline. Data are from 1976 to 2022 for overall basic and applied research, while from 1970 to 2017 for funds by discipline. Acronyms refer to: Department of Agriculture (DoA), Department of Defense (DoD), Department of Energy (DoE), National Aeronautics and Space Administration (NASA), National Institute of Health (NIH), National Science Foundation (NSF).

Figure 2. Trends in US basic and applied research by discipline

Conceived as an evolutionary entity, academy keeps on developing new genetic traits as to adapt to an ever-changing economic and institutional environment. As Martin (2003) and Shinn (2002) have argued, one would expect a greater variety across higher education institutions, with hybrids of the traditional university *species*, fuelled by the development of digital technologies. This point of view does not want to underestimate the issues about competition within and between universities. As argued also by Cowan et al. (2010), university administrators and governments often have mis-interpreted the process of innovation and technical change. Such a misunderstanding caused universities to engage in unsuitable competition with both vocational schools and industrial labs, which often operate on much shorter time scales than the university of culture. Universities should be competing in a significantly different way than current public policy seems encouraging. We claim not that competition is opposed to university but rather that the distinct role of a university should hold is undermined when it is expected to *directly* provide industrial as well as vocational innovation.

Before turning back to the discussion on AI, we match this excursus on the history of universities to the changes in the US NSI. The following Section brings about some clues on the way university and industry did interact.

4) The US NSI and the relationship with university research: a historical overview

4.1) The prewar phases: origins and institutionalisation

Mowery (1992, 1995), Mowery and Rosenberg (1993, 1999), and Rosenberg and Nelson (1994), among the others, provide an accomplished representation of the development of the NSI in the USA, along with the links forged by the private sector with university over the last 150 years. The timeline in Fig. 3 splits the history of the American NSI in four main phases. At the *origins* of the system was the growth of the US economy in the XIX century, along with advances in transportation, information and production technologies with manufacturing operations of extraordinary scale. These operations expanded on a well-established pattern of technological innovation and adaptation, relying heavily on mechanical skill. Part of the growth in manufacturing productivity and output in the United States in the XIX century came from the development of production lines of light machinery and other mechanical equipment. Such a development did not depend much on scientific research to innovate. Mowery and Rosenberg (1993, p. 27) assert that “the coupling between science and technological innovation remained very loose during this period [the XIX century] because, in many industrial activities, innovations did not require scientific knowledge. This was true of the broad range of metal-using industries in the second half of the nineteenth century, in which the United States took a position of distinct technological leadership”.

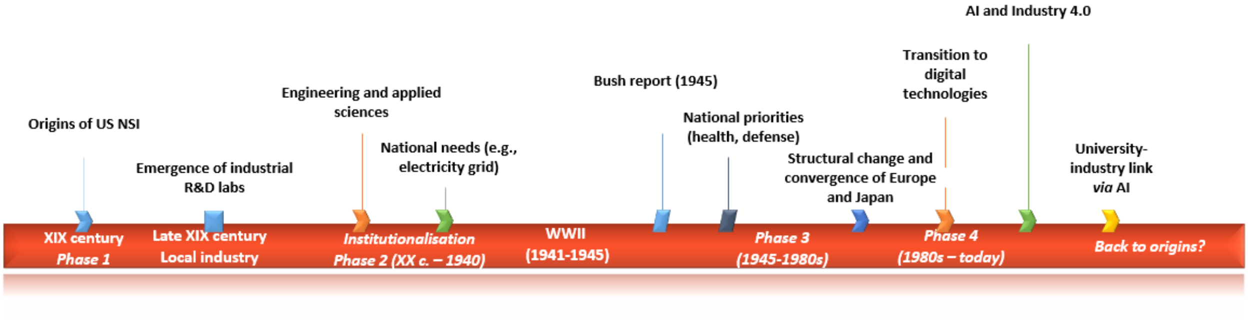


Figure 3. Timeline of US NSI

The literature considers the end of the XIX century as the starting point for the development of intrafirm R&D laboratories. The important advances in physics and chemistry increased the profitability associated with the application of scientific and technological knowledge in the economic system. However, as recognised by, e.g., Hounshell and Smith (1989) and Mowery (1992), the higher technological opportunities out of scientific achievements cannot be regarded as the only cause of the institutionalisation of R&D activity within the firm. The antitrust policy and the changing role of patents were equally determinant. Begun with the Sherman Act in 1890, the US antitrust policy made firms agreements for the control of prices and output suitable of prosecution. To preserve their market power, US firms followed two directions. On the one hand, they resorted to horizontal mergers that characterized the period between 1895 and 1904. On the other hand, since the antitrust policy responded to these mergers with further legislation, firms shifted from dominance of a single industry to diversify into other areas. The intrafirm R&D lab thus represented the means to support the commercialisation and exploitation of technological opportunities unveiled by scientific progress.

We should conceive the in-house R&D laboratory as *outward-oriented* (Mowery 1995) for it was not concerned with the creation of new technology only. Quite the contrary, in a period in which the US economic system was substantially borrower of technology developed elsewhere, e.g., Europe, R&D facilities and capabilities were pivotal to monitor new technological opportunities and advise management on which technologies could be acquired from abroad.

The changing role of patents in the early XX century reinforced the tendency to rely on internal R&D capabilities. Although several laws and Court's decisions strengthened the property rights regime to the benefit of the patentholders, any impending expiration fuelled the establishment of industrial labs. To avoid competitive pressure, large firms like General Electric and Du Pont strove to protect technological assets with patents and shifted away from price toward product competition.

At this time, much of the firm's core activity focussed on converting knowledge into marketable products rather than basic research. If this conversion resulted in a sufficiently tangible product, firms would seek to codify the corresponding knowledge and apply for a patent. What indeed was a characteristic of internal labs in major corporations like DuPont, Kodak, and General Electric was a fear of losing exclusivity of their core technologies and being imitated by competitors. In many instances, industrial research and development facilities were isolated and had minimal collaborations with university researchers. Universities were primarily viewed as a means of outsourcing talented individuals who could be employed full-time by the firms in their R&D labs (Mowery and Rosenberg 1993).

It is clear that the establishment of intrafirm research facilities was a peculiarity of large businesses operating mainly in chemicals, glass, rubber and related research-intensive industries. Small firms had to rely on independent firms selling R&D via contract (Stigler 1956, Mowery 1983). Albeit their employment records show interesting increases at least until WWII, their share in aggregate research employment significantly diminished as time went by for two main reasons. First, the knowledge employed in industrial processes is highly specific to the enterprise such that vertical integration of manufacturing, marketing, and R&D activities seemed often the only efficient organisation. Second, transaction-cost arguments left the sale of R&D services for a very limited class of activities, e.g., material testing. Moreover, independent research organisations were complementary rather than a substitute of in-house research (Mowery 1995).

Among the earliest industrial activities that required the hiring of scientists and engineers were the materials analysis and quality control performed by the laboratories established in new and large factories. Although a considerable amount of the initial testing and materials analysis research was a response to changes in the structure of production, the expansion and improvement of these activities reflected changes in the organisational structure of the company (Chandler 1990). Notwithstanding the idiosyncratic variations present in different sectors of the American economy, they shared commonalities with regards to a growing commitment to science. Firstly, the private industry exhibited a consistent increase in R&D expenditure, and most of research was conducted within firms rather than by sectoral associations of entrepreneurs (Rosenberg 1985). This feature distinguishes the US NSI from its European counterparts of the time. Additionally, firms performed innovative search through a growing number of engineers. However, although such engineers received training on the vast body of scientific knowledge and methodology, they were not taught to operate at the scientific frontier. Even well into the XX century, scientists and engineers were asked to carry out "elementary [tasks] from the point of view of the science content" (Rosenberg 1985, p. 26) and yet crucial to the progress of the industry.

These factory-level laboratories grew over time and were supplemented with the creation of central labs aimed at conducting more expansive research. Therefore, the panorama started changing in the first decades of the XX century with the *institutionalisation* of engineering and applied science (Rosenberg and Nelson 1994). The institutionalisation involved the systematic and cumulative linking of individuals and universities in intellectual pursuits. The fields of electrical engineering, aeronautical engineering, and computer science were the main beneficiaries of this linkage. Furthermore, this process enabled the development of disciplines such as chemical engineering, which would not have been achievable (yet) without a stronger connection between university and industry through professional associations, academic journals, and training programs.

The key difference between this phase and the previous one was a shift in perspective: whereas earlier universities and research institutes had been established to support the development of local industry, institutionalisation was instead a response to a *national need*, as exemplified by the case of electrical engineering. The creation of a domestic electricity network by General Electric and Westinghouse led to an increased need for engineers with specialised skills. Universities established programs accordingly. These not only assisted in meeting the demand for skilled labour but also encouraged innovation through consulting and the foundation of academic-led spin-offs, which would become the norm in the following decades. Nevertheless, institutionalisation had a more profound effect on the expansion of national industries. Vincenti (1990) argues that modifications in scientific research practices in areas such as aeronautical engineering favoured the development of new methodologies that could not be derived directly from scientific principles. During the years between 1916 and 1926, Durand and Lesley conducted experiments to determine the most efficient design for propellers. This exercise was not solely a data-collection task; rather, it provided insight into the acquisition of data, thus generating novel knowledge in a field that was previously lacking a strong scientific basis.

4.2) The postwar period: federal intervention and national priorities

If the pre-WWII system of innovation was dominated by industry as both funder and performer of R&D, WWII significantly re-shaped this structure "as the federal government assumed a central role as a funder of research within both academia and industry" (Mowery 1992, p. 134). In other terms, WWII was a watershed in the role of academy in the American scientific landscape. The achievements of the Manhattan Project and the advancements in military medicine were crucial to victory and enhanced the university standing with the electorate and political arena. As aforementioned, Vannevar Bush seized the opportunity and formulated a proposal that significantly altered the nature of university research (Bush 1945). Firstly, it was important to acknowledge the considerable effort that had been devoted to military research and development during the war and that the federal government had a responsibility to support university research in engineering disciplines relevant to the military sector. Secondly, public funding to medical R&D was highly recommended. Thirdly, the government had a broad responsibility for facilitating research across universities. Even if the subsequent US administrations did not *literally* interpret Bush's report, the increasing role of federal government in funding R&D alongside the private industry was remarkable. Indeed, two features of post-WWII R&D were the size of the federal budget and the magnitude of national R&D which we report in Tabs. 5-6 and Fig. 4. The average federal investments grew from $44 billion of the 1950s to the current $166 billion, i.e., a four-fold increase. Moreover, if defense-related R&D have usually benefitted from a greater share, the share difference between defense and nondefense R&D expenditure was minimal between 1964 and 1979, reaching a peak in late 1980s. Likewise to the rise in federal funding, the private sector progressively enhanced R&D spending, from $4 billion in the 1950s to $18 billion in the 1970s toward $100 billion in the 1990s on average. In the last thirty years, industry average R&D expenditure grew from $180 billion to more than $330 billion. Albeit most research-intensive domains, such as energy, general sciences, and health took advantage from high average R&D increase, data in Fig. 4 suggest that before the moon landing most research was concentrated in space-related scientific domains while afterwards health became uncontested catalyst of research investments.

Year	Nondefense R&D	Defense R&D	Total
1953-1964	12.06	31.87	43.93
1964-1972	45.28	49.79	95.07
1972-1979	40.35	42.29	82.63
1979-1988	39.09	59.83	98.92
1988-1996	46.37	72.18	118.55
1996-2007	59.74	79.15	138.90
2007-2022	78.59	87.33	165.92

Source: Authors' computations based on AAAS data. Note: Values in billions of constant 2022 US dollars. We determined time intervals according to NBER's US major business cycles phases.

Table 5. The conduct of (average) US federal R&D

			By source			
Year	**Federal**	**Industry**	**University**	**Other**	**Total**	
1953-1964	7.39	3.96	0.06	0.20	11.61	
1964-1972	14.57	8.88	0.21	0.49	24.16	
1972-1979	20.31	17.70	0.50	0.94	39.45	
1979-1988	44.20	48.06	1.54	2.10	95.90	
1988-1996	61.29	93.86	3.53	4.65	163.32	
1996-2007	79.73	182.19	7.36	10.05	279.34	
2007-2020	123.22	333.05	16.15	22.75	495.16	
			By function			
Year	**Health**	**Space**	**General Science**	**Energy**	**Natural Resources**	**Other**
1953-1964	1.87	5.09	1.50	1.26	0.53	1.83
1964-1972	5.82	25.86	3.65	2.89	1.46	5.60
1972-1979	8.33	13.36	3.70	5.42	2.56	6.98
1979-1988	11.54	8.03	3.84	7.69	2.24	5.75
1988-1996	17.00	11.10	4.52	4.79	2.64	6.31
1996-2007	29.53	10.78	7.44	2.39	2.59	7.01
2007-2022	40.37	12.23	12.50	3.36	2.62	6.56

Source: Authors' computations based on AAAS data. Note: Values in billions of constant 2023 US dollars for funding by source, and in billions of constant 2022 dollars for funding by function. FFRDCs refer to Federally funded research and development centres. We determined time intervals according to NBER's US major business cycles phases.

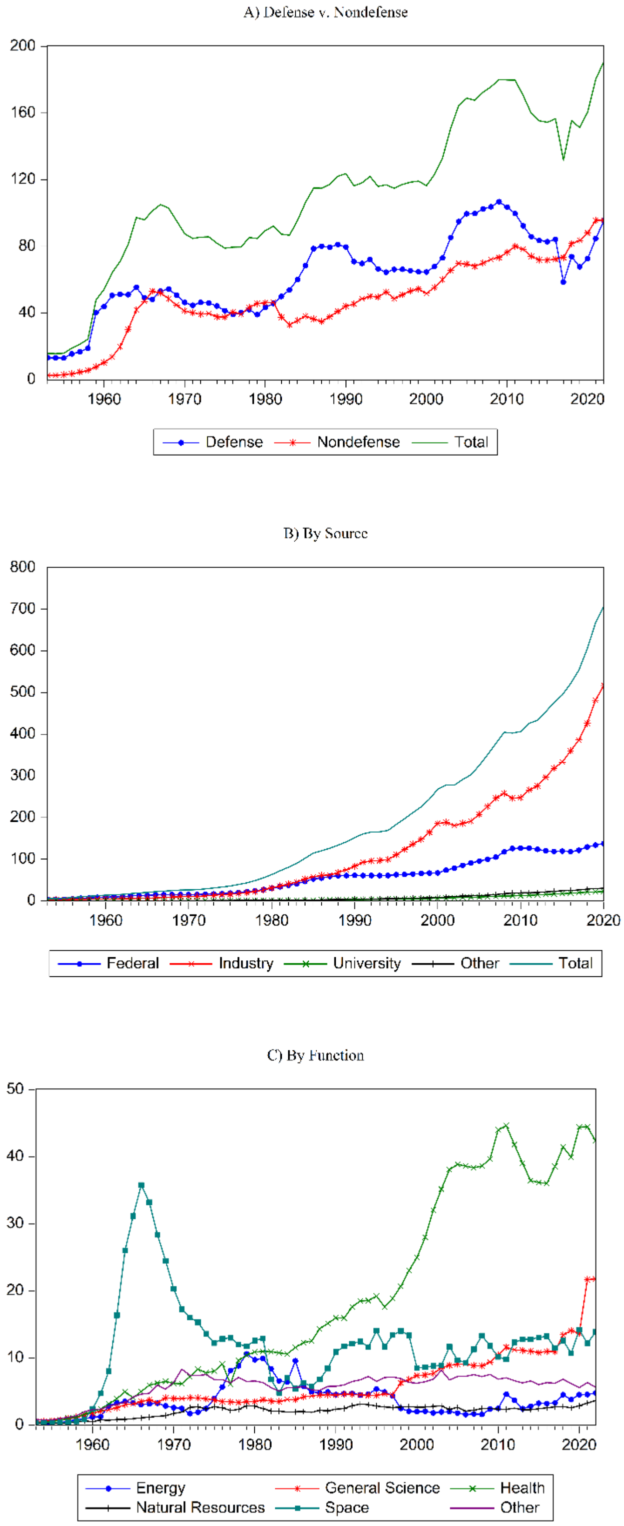
Table 6. Average trends in US federal R&D

There were two important implications out of these points. On the one hand, one key factor in the transformation of university research funding was the emergence of *national priorities* centred on health and defence. Rosenberg and Nelson (1994) emphasise that this shift in priorities was reflected in the foundations of organisations such as NIH and NASA. On the other hand, the second factor was a shift away from applied research, with universities increasingly focussed on basic research. As already said, this was based on the belief that basic research was best suited to the university environment. Yet, it is worth to be noted that although classified as fundamental, and thus somewhat removed from direct practical implications, the research recommended by Bush's report, and subsequently financed by several institutions, consistently sought to contribute to the understanding of significant issues and priorities. Universities mainly stimulated and improved the effectiveness of private sector R&D, while industry focussed on improving existing processes and products, and commercialising new ones. Essentially, the majority of R&D activity fell under *R* at universities with industry accounting for the remaining *D*.

An important aspect of this phase was that, even though large oligopolistic firms in chemicals, semiconductors and pharmaceuticals greatly expanded internal R&D facilities, a prominent role in the introduction of novelty was performed by new entrants. Their leading role can be attributed to a number of factors. First, basic research facilities at universities and large firms were significant sources of frontier technological knowledge that was subsequent transferred from these entities to often-affiliated individuals that aimed at commercialising it. High labour mobility was a further vehicle for the transfer of basic science from university to industry (Mowery and Rosenberg 1993). Secondly, antitrust policy played again a pivotal role in shaping the market structure. Considering the semiconductors and the computer industries (Malerba 1985, Flamm 1988), consent decrees favoured a relatively unrestrictive IPR regime. This resulted in the common practice of low royalty rate patent licensing and a relaxed patent enforcement. Therefore, antitrust had adopted an approach in stark contrast to the early decades of industrial research, during which large firms employed patenting strategies to maintain market power and *evade* antitrust scrutiny. To sum up, one of the effects of increasing federal R&D funding and the changes in antitrust policy was the diminished relative importance of large businesses as sources of R&D outlets with respect to the prewar. Big firms heavily relied on their facilities as sources of new knowledge rendering their R&D boundaries less porous (Mowery 1995).

The last phase in the American NSI began in the 1980s with an important change in the international environment that has diminished the US economic leadership *vis-à-vis* other Western counterparts. The convergence in income per capita towards the US's by European countries is, however, not matched by a uniform pattern of decline in the relative strength of US firms in the core industrial sectors. Nelson (1988, 1990) and Mowery and Rosenberg (1993) point out the United States have preserved their technological leadership and dominance in crucial sectors such as scientific instruments, automobiles, steel, and consumers electronics, though their export share significantly reduced. In particular, both private and public sectors coped with faster technological transfers at international levels through new organisational approaches that include collaborations in R&D activity with consortia and alliances involving foreign partners. Moreover, these policies resemble somewhat the initiatives that were carried out before WWII. On the one hand, alliances and R&D consortia often occurred through mergers and acquisitions of small firms by large companies, as was the case in chemicals and pharmaceuticals in early XX century – DuPont is a leading example. On the other hand, state funds for applied research gained prominence and the research collaborations between university and industry "represent a partial revival of earlier relationships that were sundered by the dramatic changes in the structure of the US National research system during and after World War II" (Mowery 1992, p. 140).

This broad discussion on the evolution of university-industry links along the different stages of the US NSI was pivotal to the following interpretation of the R&D relationships in the domains concerned by AI. It is interesting to understand whether the way the R&D of AI is conducted constitutes a *symptom* of a more general phenomenon that concerns all digital technologies and potentially other industries too, or instead there are dynamics that are *technology*-specific and likely share some features with what happened in the prewar period. Though further research is needed, we offer some support to this second interpretation in the next Section.



Source: Authors' computations based on AAAS data. Values are in billions of constant 2022 US dollars for defense, nondefense and by-source R&D, while values are in billions of constant 2023 US dollars for funds by function. Data for defense, nondefense, and by-function R&D are available from 1953 to 2022, while data by source from 1970 to 2020.

Figure 4. Trends in US federal R&D in defense and nondefense, by source, and by function

5) Back to AI, back to origins?

5.1) Commonalities and specificities with respect to the prewar

We have drawn in Section 2 a picture of AI as the potential breakthrough technology emerging from Industry 4.0 for the alleged features that it shares with past GPTs. To summarise, AI impacts upon the *search* process through an explosion of data that researchers find hard to stay abreast of, and it also affects the *discovery* process with a rise in the potentially combinable knowledge as to elaborate new knowledge. With reference to the needle-in-the-haystack metaphor, AI is able to increase both the number of needles in each haystack as well as the number of haystacks (Agrawal et al. 2023, Borsato and Lorentz 2023). However, the distribution of elements that compose an AI technology – data, computing power, algorithms, and researchers – is asymmetrically allocated across the relevant institutional players, such that some scholars have envisaged a potential structural change in the university-industry link. More precisely, a body of empirical evidence suggests that the fuel of any AI technology – i.e., data – is increasingly an ownership of few big-tech companies which also have the greatest computing power (Cockburn et al. 2018). Seemingly, the rising involvement in AI research by the private sector looks evident in the number of academics that move to industry (Ahmed et al. 2023, Ho et al. 2021, Jurowetski et al. 2021). In other words, major technological companies and prestigious universities are increasingly collaborating because of the complementary nature of their resources: firms provide access to hardware infrastructure and data while universities educate trained personnel.

This strand of literature raises three main concerns. First, scientists from non-elite universities may find themselves crowded-out since they are not part of the mutual relationship that benefits top-tier academia and big-tech. Secondly, if only a small group of actors can fruitfully use and develop such breakthrough technologies, it is likely that the range and diversity of knowledge produced would be narrowed (Klinger et al. 2020). But more importantly, an increasing symbiosis between university and industry in the field of AI can divert university research towards a third mission that largely stands outside of what a university *should* do, also allegedly undermining its research autonomy. Therefore, the criticism runs that rising collaborations as such would shift academia away from *uninterested* studies for the long-term societal welfare toward profit-oriented and industry-driven short-term gains.

While we do not aim at denying the admissibility of these threats, nor we provide contrasting empirical evidence of the first two concerns, we instead move a criticism to the general argument on the diversion of university focus in the field of AI. AI is not conveying or pushing universities to pursue a third mission that traditionally lies outside a university's core commitment. Since the advent of modern science, the funding of research has tended to be tied to the expectation of returns in the form of new or improved weaponry, more precise almanacs due to improved astronomy, better medicine and agriculture, and other forms of progress (Martin 2003). In fact, it is difficult to find examples of scientific research where the expectation of economic or social gain has played no role, regardless the source of funds, be it a government, a firm, or some enlightened monarch.

More importantly, we believe there are some convergence points that make the current institutional environment similar to the prewar period (Tab. 7). Firstly, the increasing involvement of the private sector in the conduct of basic and applied research in AI-related domains is not very different from what happened prior to 1940. The institutional relationships between universities and firms that could be fruitful to the development of new products and technologies were very evident with respect to those universities that, by the way, promptly organised in accordance to the Humboldt model, e.g., Harvard and MIT. Indeed, engineering departments worked closely with their private counterparts "often effectively acting as research laboratories for new companies with their research results being directly applicable to innovative products" (Martin 2003, p. 12). In this respect, American universities constituted an important hub for external monitoring activities undertaken by numerous industrial research labs. At least some of these academic-industrial collaborations involved the development and commercialisation of novelties (Mowery and Rosenberg 1999, Etzkowitz and Leydesdorff 2000). Typical examples of agreements were the establishment of fellowships funded by key technological leaders with top-tier universities. Moreover, it was not unusual that colleges and universities funded by the firms asked them suggestions about future research endeavours (Hounshell and Smith 1988). Seemingly, fellowships were often conditional to the subsequent recruitment of PhDs, scientists and engineers by the businesses that paid their studies. As Thackray (1982) argued, PhDs became key figures behind the expansion of prewar industrial research. Therefore, the solution to practical problems through scientific means has usually been an important factor in scientific development (Etzkowitz and Leydesdorff 2000).[7]

Secondly, and in stark contrast with the postwar institutional setting, most AI R&D is carried out by very large companies holding key technological assets, with limited reliance, if any, on the small firms that were typical at the early stage of the, e.g., semiconductor and computer industries. This setting resembles the prewar period in which the bulk of industrial research was at hand of large enterprises, which established the required facilities to exploit technological knowledge at sufficient scale. Again, typical examples were firms in automobile, petrochemical, and electrical sectors. Furthermore, the very existence of independent research organisations was not pivotal to substitute the intrafirm lab in order to favour the diffusion of small but dynamic and innovative firms. Rather, they were complementary to the activities of in-house labs and provided ancillary services (Mowery 1983).

Thirdly, the IPR regime nowadays looks similar to prewar periods. As prior to 1940, in which firms used to accumulate patents to secure strategic assets, maintain market power, and evade antitrust scrutiny, today big firms increasingly rely on patent-holding. Though not circumscribed to AI, the increasing *monopolisation* of knowledge (Pagano 2014) since the 1990s has spurred the enterprises to undertake further investments in dynamic technological areas. The outcome of this process entailed a virtuous cycle for patentholders. For individuals owning the IPRs there is the incentive to develop new knowledge and skills and then new patents.[8]

[7] This often led to the juxtaposition between *Mode 1* and *Mode 2*. The first claims that new knowledge is most produced within individual disciplines at academic institutes and envisages little direct connection to societal need. Conversely, Mode 2 involves inter-disciplinary research carried out in a window of institutions also differing from universities: knowledge is therein produced in the context of application. Etzkowitz and Leydesdorff (2000) and Martin (2012) show that Mode 2 has represented the original format of science before its academic institutionalisation and for large part of the XX century, being Mode 1 a *parenthesis* in the 1945-1980s period. Moreover, Godin and Gingras (2000) present empirical evidence favourable to the view that collaboration of firms with academic teams is central to the operations of networks that transform the knowledge infrastructure.

[8] Yet, the cycle turns vicious for many others because their lack of IPRs discourages the acquisition of skills and the lack of skills discourages the acquisition of IPRs.

Fourthly, data accessibility represents a concern. Although the public sector has lots of data on several topics – e.g., health, demography – their limited accessibility to research institutes is often a barrier that pushes researchers to start collaborating with private firms, which also have data but of increased availability – e.g., out of social networks.

Last but not least, prewar university-industry collaborations were often necessary because of the decentralised and limited funding provided by state and federal governments. We have no empirical evidence to support the following hypothesis but perhaps the current federal investments in AI R&D that we plotted in Fig. 1 are still not enough for universities to pursue AI R&D without increasing reliance on private funds, let alone their critical assets. Potentially, the fixed costs of innovative search in AI is rather high such that huge private funds are a necessity for any institution wishing to take on the endeavour.

However, the domains concerned by AI present some peculiarities. In light of the available empirical evidence, we suggest that universities may be changing and adjusting their positioning in the process of innovation and diffusion in the areas affected by AI. They are increasingly involved in the training of professionals in this new field, rather than in the development of scientific and technological knowledge, with the exception of very upstream and basic research. The role of universities is shifting towards a training model *rooted into research*. The workforce that will conduct AI research in industry is not trained to code and program (only) but rather to understand basic science - e.g. physics, chemistry, mathematics. Trained people are not technicians. This pattern is explained by two main reasons. Firstly, this is an essential prerequisite for producing good AI engineers. Secondly, firms are primarily interested in hiring scientists who possess a broad knowledge base that can be applied to a multitude of tasks. Such engineers are sought after by industry, as their expertise is often broad enough to be of use in a variety of contexts. Scientists with a strong foundation in fundamental science are also crucial for facilitating intrafirm knowledge advancement. Indeed, scientific and technological knowledge is developed by firms and similar organisations, but in collaboration with universities to access and co-develop the relevant skills. This could potentially change the trajectory of university-industry relations, since it is very much in line with the typical Humboldtian perspective that was at work in some European institutes in the XVIII century up to the US early XX century.

We witness the emergence of a new organisational field that combines traditional academic research and the knowledge-based economy, reflecting appreciation, entrepreneurship, and social accountability. This *trans-institutional model* (Benner and Sandström 2000, Etzkowitz and Leydesdorff 2000) that seems to characterise AI has been in progress since the 1980s and it is based on academic independence and aspirations of university researchers, but at the same time measures are taken to guide researchers toward modes of operation that are adapted to the needs of industry. With respect to AI, we should circumscribe the evidence of a *back to origins* to the way university and industry interact in the production of knowledge. Differences emerge with respect to the definition of the main goals, on the nature of knowledge is being produced, and for what purposes. The R&D of AI is much less *firm*-oriented than innovative search at the dawn of US NSI. Much effort is devoted to the pursuit of SDGs, whose achievement is very much broader in scope and breadth than earlier concerns about industrialisation. Indeed, the combination of SDGs and AI in scientific research has surfaced over the past ten years and is rapidly expanding (Bianchini et al. 2023). As expected, the USA are major players in publications and hold a significant share of global research output. In addition, research teams and collaborations are often interdisciplinary (Abbonato et al.

2024). The number of stakeholders involved is greater than before and spans from university and private firms, to associationism, governments and supranational institutions.

AI R&D and prewar innovation system	
Commonalities	**AI R&D peculiarities**
- Tight collaborations between university and industry via (PhD) fellowships and recruitment	- Universities move to a *research-based* training model
- Great relevance of large rather than small companies in the innovation system	- Knowledge taught at university is *useful* as intended in XVIII-XIX century Europe
- IPR regime with monopolisation of knowledge by key firms	- Process *à la* Babbage at work: division of knowledge may precede division of labour
- Decentralised funding structure? (Fig.1)	

Table 7. Back to origins?

5.2) Implications for the division of knowledge and the division of labour

This consideration opens up the further issue about the relationship between the *division of labour* – i.e., the distribution of tasks amongst agents – and the *distribution of knowledge* – i.e., the distribution of interpretative capabilities across agents. The argument was first introduced by Smith (1776). The classical Smithian interpretation restricts the relationship between the division of labour, which distributes tasks amongst the agents, and the division of knowledge, which distributes interpretative capabilities between agents, to a mere causal relationship: the division of work *causes* the division of specialised knowledge. Then, the nature of competences and routines are *vertically* and *homothetically* determined accordingly. However, this does not seem the mechanism in place in the relationship between university and industry for AI-based technologies. Quite the opposite, the formation of skills at university seems a pre-requisite for finding a research job in the private sector. Stated differently, entrepreneurial decisions include elements of uncertainty, opportunities, creation of knowledge, and the vision of the role of the division of labour as in Smith can be complemented by the point of view that Charles Babbage (1832) presented in his description of England's transition from an agricultural to an industrial economy. The notion of division of labour was applied to both physical and cognitive activities for, while technical change had played a key role in the industrial take-off, manufacturing entrepreneurs had to spend a lot of effort in organisation and management issues. Babbage had emphasised the priority on skills in the sequence of steps that links division of labour to learning to further division of labour, based on the higher degrees of specialisation and knowledge. Furthermore, *skills* represent the means to decide how to divide labour, thus presuming that the division of labour should itself be founded on differences in skills. Hence, the causality link is reversed: the division of labour *is caused* by the characteristics of the human resources, rather than the other way around (Cohendet and Llerena 2010), and there is not a vertical deterministic process like in the Smithian argument. The lack of homotheticity implies a *horizontal* portfolio of different configurations of divisions of labour for any given division of knowledge.

Instead of determining which comes first between division of labour and division of knowledge in the R&D of AI, it is our assertion that they are intertwined in a co-evolutionary process where one mechanism may dominate based on the institutional setting. The innovation system around AI enables researchers to invest in their human capital early on their careers, allowing them to reap the benefits through research-job opportunities and collaborations across porous organisational boundaries with those possessing complementary skills. Moreover, we believe that the inherent uncertainty of the environments forces firms to gather new knowledge either *from within* or *from outside*. University provides companies with the skilled labour that is needed to advance technological progress in the industry: in this case, cognitive processes *à la* Babbage may come first since they drive the subsequent division of labour at firm level.

6) Conclusions

The aim of this article was to contribute to the nascent and fast-growing Economics of AI and to investigate the close relation between the private sector and academia concerning the research, development, and diffusion of AI technologies by integrating it into its relevant historical perspective. Besides its potential to further speed up automation, a growing body of research claims that AI embodies the several features that constitute a GPT (Bianchini et al. 2022), although its actual implementation regards a niche of the economic system (Bresnahan 2019, Vannuccini and Prytkova 2023). At the same time, there are concerns about the limitations (Gibney 2022, Johnson 2021), and likely misuses (Urbina et al. 2022) of its potential. Additionally, some authors suggest that AI research is becoming less democratised and more concentrated due to the growing presence of industry and lack of access to key resources – data and computing power *in primis* (Cockburn et al. 2018, Mazzucato et al. 2022). There is also significant evidence to support that the majority of AI research is shifting from academia to industry, contributing to a decrease in the breadth of thematic diversity (Ahmed et al. 2023, Klinger et al. 2020).

In this paper we reflected on these contemporary issues by comparing AI evolution with the development of university-industry relations in the United States since its industrial take-off. Although it is undeniable that industry and academia are working ever closer in AI, we argue that the increasing commitment to university to this *third mission* is neither something new under the sun nor it threatens university autonomy, as somewhat alleged by the afore-mentioned literature. We instead think that with a long-term historical perspective we would see that these patterns of collaborations are neither new nor damaging *by default*, but rather a return to a social arrangement like that which prevailed for much of the period before WWII. For a large part of the history of modern science, resources have been in fact allocated with the expectations of some benefits. It was only during the 1945-1980s period that this *social contract* was somehow loosened, with governments that kept some vision about the challenges ahead – e.g., fight against Communism and cancer – but also invested in science without the immediate expectation of payoffs. But this period came to an end in the 1990s and hence largely antecedent to the current surge of AI. Furthermore, Benner and Sandström (2000) and Martin (2003, 2012) suggest that a decreased dependence on government funds is not bad *per se*; quite the opposite, it might turn out that university autonomy strengthens. The key point to understand is that academia can be conceived as an evolutionary entity that persistently transform as to adapt to the surrounding, ever-changing environment. Amongst the current *variants* of university, a new model "is based on academic autonomy and initiative taken by university researchers, but at the same time efforts are made to direct academics to modes of operation that address the needs of industry" (Martin 2003, p. 18).

With reference to AI development, the argument is put forth that universities are undergoing a transformation in their positioning within the innovation and diffusion process in domains pertaining to AI. There is a growing emphasis on the training of skilled personnel in this emerging field, with less focus on the advancement of scientific and technological knowledge, except in the context of very fundamental research. The role of universities is evolving towards a *research*-based training model. The personnel who will conduct research on AI at industry are not trained in coding skills and programming; rather, they are trained in the fundamental understanding of science, including physics, chemistry, and mathematics. In contrast to the pioneering pursuit of knowledge characteristic of the early phases of US NSI, the advancement of AI is less oriented towards the specific objectives of individual firms. Significant resources are allocated to the pursuit of SDGs which encompass a far broader scope and breadth of concerns than those previously associated with industrialisation. A greater number of stakeholders are engaged in this field, including academic and private sector institutions, as well as governmental and supranational entities.

This has implications for the linkage between division of knowledge and division of labour. The AI innovation system offers researchers the opportunity to invest in their human capital early in their career, leading to payoffs like research-job opportunities and inter-organisational cooperation with those owning complementary skills. There is also a need for firms to acquire new knowledge either internally or externally due to the inherent uncertainty of their environment. Universities provide firms with skilled manpower necessary to drive technological progress in industry, in which case cognitive processes *à la* Babbage (1832) take the lead in driving the subsequent division of labour at firm level (Cohendet and Llerena 2010).

Finally, the paper did not consider the further potential role other than funding source for the other element that composes the Triple Helix together with university and industry, that is government (Etzkowitz and Leydesdorff 2000). The fruitful triple helix that characterizes AI technologies as well as other sectors may be compromised without the improvement of government skills and capabilities: last decades have witnessed an increasing outsourcing – i.e., the excessive reliance on markets to deliver government policies. While not bad *per se*, exacerbating this trend would impoverish public-sector capabilities to lead and guide the economy to societal and national security objectives. Investments in technical literacy, organisational overhaul, and mechanisms to attract talents are key to improve government value creation (Mazzucato et al. 2022). These issues provide avenues for further research.

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Data availability

The data that support the findings of this study are available from the Authors upon request.

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