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Opening the black box of Artificial Intelligence technologies: Unveiling the influence exerted by type of organizations and collaborative dynamics

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Abstract

Until now, the management literature on Artificial Intelligence (AI) focuses mostly on the diverse applications of this technology, while its development has attracted only limited attention. To partially fill this research gap, the present paper analyses a large sample of AI patents and investigates the potential determinants of their technological impact. We show how University-Industry (UI) collaborations seem to be less able to develop high-impact AI patents, compared to other types of partnership based on the involvement of either universities or companies. This result contrasts with the previous literature on the inventing process of other general-purpose technologies (GPT), thus clarifying how the development of AI may be significantly affected by the peculiar characteristics of this technology. Thereby, our findings not only shed further light on the inventing process of AI solutions but may also stimulate the debate on the development of other GPTs strongly imbued with scientific knowledge.

1. Introduction

The term Artificial Intelligence (AI) was coined at the Dartmouth conference in 1956 by McCarthy et al., who defined AI as “the science and engineering of making intelligent machines” (McCarthy et al. 2006). During its evolution, which was characterized by several ups and downs (Haenlein and

Kaplan 2019), AI has been gradually extended to an increasing number of applications, thanks also to the development of new software techniques. The wide range of applications in different sectors, ranging from healthcare to finance, has led many scholars to consider AI as one of the most promising general-purpose technologies (GPT) of the near future (Borges et al. 2021; Brynjolfsson and McAfee 2017). The GPT nature of AI is confirmed not only by a high level of general applicability, but also by its technological dynamism and the large number of innovation complementarities (Bresnahan and Trajtenberg 1995). Nevertheless, most studies explore the implications of the GPT nature of AI from a macroeconomic perspective by analyzing its effect on productivity and economic development (Brynjolfsson, Rock, and Syverson 2018; Crafts 2021), while only a few qualitative works (Magistretti, Dell’Era, and Messeni Petruzzelli 2019; Yang, Chesbrough, and Hurmelinna-Laukkanen 2022), based on a single case study, instead discuss how the GPT nature may affect the process of development of AI solutions.

In the present paper, we try to fill this gap in the literature, shedding further light on the development of AI solutions through a large-scale quantitative analysis that investigates if this process is based on the same dynamics that characterize the development of other GPTs. In this sense, previous studies on GPTs have pointed out how the impact of these technologies, measured as the degree of reuse of the related knowledge spillovers (Jaffe, Trajtenberg, and Henderson 1993), may be enhanced by a wider variety of the knowledge base available for the inventing process (Hicks and Hegde 2005). Following a recombinant perspective (Fleming and Sorenson 2001; Savino, Messeni Petruzzelli, and Albino 2017), this knowledge base may be enriched by involving diverse organizations in the process of innovation development (Motohashi and Muramatsu 2012; Nikulainen and Palmberg 2010). In particular, the previous literature has largely discussed how innovation development can benefit from the combination of the different resources and knowledge provided by companies, and universities and research institutes (URIs) (Lavie and Drori 2011; Soh and Subramanian 2014). Indeed, the market-based expertise of companies can support the exploitation of inventions thanks to the definition of appropriate business models (Agarwal, Sarkar, and Echambadi 2002), while URIs may provide cutting-edge scientific knowledge (Lavie and Drori 2011; Soh and Subramanian 2014), which may enable knowledge exploration with a better selection of the potential search avenues (Fabrizio 2009). The combination of these different knowledge bases in University-Industry (UI) collaborations may lead to the development of more impacting technologies (Briggs 2015), especially in the case of GPTs strongly imbued with scientific knowledge (Motohashi and Muramatsu 2012; Nikulainen and Palmberg 2010). Nevertheless, the capability of UI collaborations to develop high-impact inventions may be hindered by the related costs and risks, which are increased by the high cognitive and institutional distance between the academic and the industrial partners (Khoury and Pleggenkuhle-Miles 2011; Veugelers and Cassiman 2005). Besides, to correctly evaluate the capability of UI collaborations in developing high-impact inventions in AI, it is necessary to point out how companies and URIs can provide some critical resources for this technology, such as a significant volume of data, advanced algorithms to analyse these data, a sufficient computational capacity to implement these algorithms, and deep knowledge of the possible application fields (Brynjolfsson & McAfee, 2017).

In the present paper, we try to investigate which type of applicants’ partnership may generate AI inventions characterized by a specific technological impact. In particular, we analyse the role of UI collaborations comparing them with more homogenous partnerships based on the involvement of only one kind of organizations, either companies or URIs.

To investigate the effect of different types of partnership, we collected data on all the AI patents as identified by the UK Intellectual Patent Office (2019) and we codified all the applicant organizations, classifying them into companies or URIs. To measure the technological impact of these patents, we collected and codified their forward citations, excluding self-citations, using them to compute our dependent variable in different negative binomial regression models. Our analyses show that AI patents developed by UI collaborations are characterized by a lower technological impact compared with those developed by other types of partnership. Besides, AI patents developed by only companies seem to have a higher technological impact than those developed by a URI.

Our study contributes to the management literature on AI through the exploration of the dynamics behind the development of successful inventions in this technological field, clarifying the possible impact of different types of applicant partnership. Moreover, our paper contributes also to GPT studies (Nikulainen and Palmberg 2010), by highlighting a peculiar characteristic of AI inventions, whose development may be more impacting if not based on R&D collaborations between companies and URIs.

From a practical point of view, our paper gives interesting suggestions to companies that want to develop impacting AI inventions. Our findings may indeed provide useful insights even to policymakers interested in supporting the development of AI, by supporting a better design of the related policies and strategic initiatives.

The rest of the paper is organized as follows. The next section presents a discussion of the literature on the development of AI inventions, while the third section illustrates our sample, variables, and method. After the description of the results of the regression models in the fourth section, in the last section, we discuss the main theoretical and practical contributions of the paper, as well as its limitations and future developments.

2. The role of collaboration in the development of AI inventions

While the wheel, the steam engine, the electricity, and the computer are well-established examples of GPTs with a radical impact on human history (Lipsey, Carlaw, and Bekar 2005), some scholars consider AI the GPT that will drive the ‘Fourth Industrial Revolution’ (Crafts 2021). Despite the previous winters in AI history suggest being cautious about its impact in the near future (Haenlein and Kaplan 2019), its classification as a GPT is largely recognized because it results from general applicability, technological dynamism, and innovation complementarities (Bresnahan and Trajtenberg 1995). First, AI’s general applicability is confirmed by its wide range of applications, which covers several tasks that can be augmented or automatized thanks to its predictive power (Agrawal, McHale, and Oettl 2018). In particular, AI may enable fast and efficient analysis of a large amount of data, which may support the automatization of business processes and relationships with customers and partners (Davenport and Ronanki 2018). For this reason, AI is currently largely applied in many sectors, such as computer and electronics, IT services, machinery, and transport equipment (Dernis et al. 2019). Differently from physical GPTs and similarly to other digital ones, the general applicability of AI is further enhanced by its non-rival nature, as well as by faster sharing with new users (Yang, Chesbrough, and Hurmelinna-Laukkanen 2022). Data shareability may also enable the transfer of skills already learnt by existing AI solutions, which may support an easier development of future incremental innovation (Pratt 2015). In fact, data shareability may enhance the cumulativeness of AI development, boosting the effect of future investments and guaranteeing a high degree of technological dynamism (Brynjolfsson, Rock, and Syverson 2018). The development of further

innovation is not limited to the AI field, but also to several application sectors, in which AI has stimulated the generation of several complementary processes and products. For example, AI solutions for image recognition have been crucial enablers for the development of self-driving cars (Brynjolfsson and McAfee 2017), but also of several complementary products in the security and military sectors (Kreutzer and Sirrenberg 2020).

The GPT nature of AI may have implications on its possible effect on productivity and economic development (Brynjolfsson, Rock, and Syverson 2018; Crafts 2021), but also on the dynamics related to its inventing process (Magistretti, Dell’Era, and Messeni Petruzzelli 2019; Yang, Chesbrough, and Hurmelinna-Laukkanen 2022). Indeed, the development of GPTs requires the availability of different knowledge bases (Appio, Martini, and Fantoni 2017; Kaplan and Vakili 2015), which may increase their general applicability, technological dynamism, and innovation complementarities. In fact, a wider diversity of the knowledge bases available for the inventing process may support the development of original combinations that may nurture the future advancements of a GPT, its adoption in different application fields, as well as its reuse for the generation of complementary innovation (Argyres and Silverman 2004; Rosenkopf and Nerkar 2001). Previous studies have investigated at least two possible ways to enlarge the knowledge bases available for the inventing process of a GPT. Indeed, some studies suggest adopting a broader search strategy in the inventing process by using knowledge from distant and various technological domains (Appio, Martini, and Fantoni 2017; Argyres and Silverman 2004; Kaplan and Vakili 2015; Rosenkopf and Nerkar 2001). Other studies focus their analysis on the possible contributions provided by diverse invention developers, either at the inventor (Ardito, Messeni Petruzzelli, and Albino 2016) or the organization level (Motohashi and Muramatsu 2012; Nikulainen and Palmberg 2010). These latter studies specifically consider how the development of GPTs may be improved when it is carried out by R&D collaborations.

In general, R&D collaborations can be vehicles for acquiring external knowledge to forge new capabilities and achieve performance improvements (Kale and Singh 2007; Mowery, Oxley, and Silverman 1996). R&D collaborations help indeed to combine the complementary assets and knowledge bases owned by different organizations (Gulati 2007; Hagedoorn 1993). This is especially true in the case of UI collaborations, in which market-based expertise owned by companies may be effectively combined with the scientific knowledge owned by URIs (Hall, Link, and Scott 2003; Soh and Subramanian 2014). Indeed, the market-based expertise of companies may support the definition of profitable business models for an innovative solution (Agarwal, Sarkar, and Echambadi 2002), but it may be not sufficient to carry out an extensive exploration of the possible search avenues in the inventing process. This limitation is more evident in science-based sectors, even because many large companies have progressively reduced their investments in basic research (Arora, Belenzon, and Patacconi 2018).

For this reason, the development of GPTs, especially if strongly imbued with scientific knowledge, may benefit from the participation of URIs (Motohashi and Muramatsu 2012; Nikulainen and Palmberg 2010). Indeed, URIs may provide scientific knowledge (Gittelman and Kogut 2003; Lavie and Drori 2011) and tend to act as explorative organizations (Adams 2005; Saxenian 1994). This role of URIs is enabled by their scientists, who not only continuously develop cutting-edge knowledge, but guarantee a constant connection to a worldwide scientific community (Fabrizio 2009; Jensen et al. 2007). Besides, in the last years, URIs have started to undertake an entrepreneurial “third mission”, which has significantly increased their interaction with the industrial environment by adopting

different arrangements, such as consultation, contract research, joint research projects, co-development and licensing of intellectual property rights, till to the establishments of academic spin-offs and incubators (Etzkowitz 2004; Rothaermel and Thursby 2005; Siegel, Wright, and Lockett 2007; Todorovic, McNaughton, and Guild 2011). This evolution has further improved the URIs' capability to collaborate with companies in the development of successful innovation, especially in high-tech sectors like biotechnology and ICT (Cockburn and Henderson 2000; Zucker, Darby, and Armstrong 1998). Indeed, the scientific knowledge provided by URIs may enable the experimentation of new departures from the existing technological paradigms, with the selection of original search avenues that lead to achieving technological opportunities in a more efficient way (Fabrizio 2009; Fleming and Sorenson 2004). The combination with the market expertise of companies allows for a better selection and prioritization of these avenues by also considering their potential market impact (Hall, Link, and Scott 2003; Lavie and Drori 2011; Soh and Subramanian 2014). In fact, several studies have pointed out how inventions developed by UI collaborations, compared to solutions originating from the effort of single organizations or by other types of collaborations, have a higher technological impact in the long term (Briggs 2015; Briggs and Wade 2014; Su, Lin, and Chen 2015). Nevertheless, several UI collaborations may be not able to develop high-impact inventions because of their inability to solve some inherent problems of these relationships in an efficient way. First, UI collaborations are characterized by a high degree of institutional diversity that may prevent a sufficient alignment in goals and incentive systems between the partners (Khoury and Pleggenkuhle-Miles 2011; Dasgupta and David 2004). Second, these collaborations are characterized by a high cognitive distance between partners, which requires the presence of absorptive capacity to guarantee adequate knowledge sharing (Veugelers and Cassiman 2005). At this aim, the partnering organizations should incur several costs that are sustainable only in presence of sufficient benefits from UI collaborations (Cohen 2010). Therefore, the evaluation of the pros and cons of UI collaborations should consider the specific characteristics of the GPT under analysis and, more specifically, how companies and URIs can provide the necessary resources for the development of high-impact AI solutions.

3. Hypotheses development

Companies and URIs provide different resources that may improve the development of AI solutions, but the costs and risks deriving from their combination may reduce the impact of these solutions. To partially solve this open issue, we formulate and empirically test two competing hypotheses concerning the capability of UI collaborations to develop high-impact AI inventions.

To correctly frame this issue, it is necessary to consider how the successful recent evolution of AI has been enabled by the availability of a significant volume of data, the capability to develop advanced algorithms for the analysis of these data, and the computational hardware necessary to implement these algorithms in a limited time (Brynjolfsson and McAfee 2017). These three factors are sufficient for the development of original AI solutions but, in order to guarantee their profitability, it is also necessary a deep knowledge of the possible application fields, which allows for creating a sustainable business model for these solutions (Yang, Chesbrough, and Hurmelinna-Laukkanen 2022).

The market-based expertise of companies may support the identification of the most profitable possible application fields and business models for AI solutions (Agarwal, Sarkar, and Echambadi 2002). Besides, in the last years, the volume of business data collected by companies has been largely increased by the implementation of pervasive network technologies within the organization, in the

whole supply chain, and with the involvement of customers (Baesens et al. 2016; Martinelli, Mina, and Moggi 2021). Finally, the declining cost of computing power (Walton and Nayak 2021) and the advent of cloud computing (Nieuwenhuis, Ehrenhard, and Prause 2018) have allowed companies to implement ever more complex software for the analysis of the available business data.

Concerning the capability to develop advanced algorithms necessary for AI solutions, URIs still maintain a relative advantage over companies, thanks to their well-established teaching and research activities. Indeed, by promoting new lines of research and continuously training students and researchers, URIs may not only develop new AI techniques, but enable their diffusion and application in companies (Gherhes et al., 2022).

Hence, the complementary resources provided by URIs and companies may improve the innovative capability of UI collaborations, thus leading to the development of more valuable AI solutions. This leads us to formulate the following hypothesis:

H1a. UI collaborations are more able to develop high-impact AI inventions than other types of partnership.

On the other side the development of GPTs requires constant interaction among technology developers and potential users for the identification of the most promising business model to apply in each application field (Gambardella and McGahan 2010). This issue is even more urgent in some process-related GPTs, like AI, that call for more experimentation since, compared to product-based ones, they face greater uncertainty in their positioning in the value chain, market scope, degree of standardization, and switching costs required to their customers (Maine, Lubik, and Garnsey 2012). Magistretti, Dell’Era, and Messeni Petruzzelli (2019) and Yang, Chesbrough, and Hurmelinna-Laukkanen (2022) discuss how IBM has satisfied the need for large and even parallel experimentation with the adoption of an Open Innovation (OI) approach (Chesbrough, Vanhaverbeke, and West 2006). In particular, the development of its AI solution “Watson” has been boosted by the establishment of several R&D collaborations with other partners operating in the possible application fields (Magistretti, Dell’Era, and Messeni Petruzzelli 2019; Yang, Chesbrough, and Hurmelinna-Laukkanen 2022). The need for the experimentation of AI solutions may reduce the propensity to establish collaborations with URIs, which have limited knowledge of the specificities of several application fields, especially those closer to the market (Soh and Subramanian 2014). Indeed, URIs’ orientation toward pure science may reduce their capability, as well as their interest, to investigate the short-term and more applied problems faced by companies (Bruneel, d’Este, and Salter 2010).

Not by chance, some large companies have a leading role in the development of AI solutions, while the involvement of URIs is often limited to the provision of talents and the establishment of some flexible forms of collaborations (Lundvall and Rikap 2022). In this sense, the peculiar URIs’ orientation toward pure science may increase the cognitive and institutional barriers in UI collaborations, thus leading companies to avoid the joint ownership of the resulting inventions. No wonder, in AI several URIs and companies tend to collaborate not through joint patents but by arranging some specific challenges, in which multiple teams of researchers compete to solve a well-specified AI task proposed by a company (Amini et al. 2020). In other cases, several large companies have directly hired some of the most expert AI academics (Jurowetzki et al. 2021; Yu, Liang, and Wu 2021), or these scientists have created academic spin-offs, which directly collaborate with large companies, without any involvement of their parent university (Arenal et al. 2020). These new forms

of collaboration may reduce the cognitive and institutional barriers between the partners, giving companies greater control over the input and output of the innovation process (Teece 2018). For these reasons, the advantages of traditional UI collaborations in the development of AI solutions are more and more diminishing.

Hence, on the basis of the above reasoning, we formulate the following alternative hypothesis:

H1b. UI collaborations are less able to develop high-impact AI inventions than other types of partnership.

4. Methodology

4.1 Sample

During its evolution, scholars have proposed a multitude of definitions of AI (Baruffaldi et al. 2019), whose main difference concerns their focus on either the main techniques or the application fields (WIPO 2019). In line with the report developed by UK Intellectual Patent Office (2019), in the present paper, we adopt a narrow definition of AI, which is based on the selection of the inventions developed by using the main software techniques, which have been proposed by industrial and academic researchers in this scientific area. This choice is aligned with previous studies in the scientific literature (Fujii and Managi 2018; Tseng and Ting 2013), while other studies adopted a wider approach, which also includes the main application fields in which AI is commonly used (Cockburn, Henderson, and Stern 2018; Giczy, Pairolero, and Toole 2022). This latter approach extends the number of AI inventions but may also increase the risk of including many false positives, because some application fields usually associated with AI, such as robotics, speech recognition, and computer vision, may be characterized by the presence of inventions not based on AI solutions (Baruffaldi et al. 2019).

Specifically, we adopt the approach proposed by the UK Intellectual Patent Office (2019), which is based on the selection of opportune technological classification codes, like the International Patent Classification (IPC) and the Cooperative Patent Classification (CPC) codes, and keywords contained in the patent title and abstract. These keywords are explicitly associated with the most diffused AI techniques, such as Fuzzy logic, Machine learning, Bio-inspired approaches, Classification and regression trees, Neural networks, Rule-based learning, Supervised learning, and Unsupervised learning. By using these selection criteria, we collected data on the population of AI inventions¹, including only patents that explicitly use AI techniques.

The focus on patents does not allow us to include in our analysis the AI inventions that are not patentable. In particular, similarly to other computer-related inventions (Webb et al. 2018), AI inventions that do not produce any technical result, but only carry out numbers and produce results in a numerical form, cannot be patented (Lankinen 2019). Nevertheless, as discussed in the previous sections, most AI inventions are based on real world data and are implemented into technical processes and/or physical products, thus producing some technical results that guarantee their patentability. For this reason, AI patents can be considered a reliable proxy for AI inventions (Zingg 2021).

¹ These data are validated thanks to the publication of the complete list of AI patents by the UK Intellectual Patent Office, which allows us to minimize the possible errors in the replication of this study.

In our study, by applying the approach proposed by the UK Intellectual Patent Office, from the PATSTAT database we collected data on 84,291 AI inventions filed in all the patent offices worldwide. The UK Intellectual Patent Office focused its analysis on patents filed from 1998 to 2017. After several cycles of winters and summers (Haenlein and Kaplan 2019), this period corresponds to the consolidation of AI, as confirmed by the establishment of a specific technological class for ‘Data Processing—Artificial Intelligence’ inventions by the USPTO in 1998. In particular, thanks also to the availability of larger datasets, like ImageNet, the period from 1998 to 2017 has been characterized by several advancements in AI, especially in Deep learning, which culminated in the historical victory of AlphaGo against the top world player in the ancient Chinese game of Go (Delipetrev, Tsinaraki, and Kostić 2020). The growth of AI in the period from 1998 to 2017 is confirmed by the data presented in the last column of Table 1, which shows that the AI patents filed before 1998 account for less than 5 percent of the total.

Table 1 also shows the number of AI patents developed each year by different types of applicant partnership. To compute these values, we codified the names of all the 16,768 organizations that filed AI patents and classified them into 14,141 companies and 2,627 universities and research institutes (URIs). This codification process leads us to exclude 5,910 AI patents that are filed only by physical persons, thus reducing our sample to 78,381 AI patents filed by at least one organization. These patents are classified into five different types of applicant partnership: only one company (*OneCompany*), only one URI (*OneURI*), several companies without any URI (*MultipleCompanies*), several URIs without any company (*MultipleURIs*), a collaboration between companies and URIs (*MixCompaniesURIs*).

As shown in Table 1, most AI patents have been developed by only one organization, and the share of collaborative patents has passed from about 15 percent in 1998, to about 6 percent in 2017. The limited number of AI patents jointly developed by more organizations has been rarely highlighted in previous literature (Van Roy, Vertesy, and Damioli 2019), while several studies have pointed out the prevailing role of companies in AI development (Cockburn, Henderson, and Stern 2018; Jurowetzki et al. 2021). Our data show that companies had a prevalent role in the development of AI patents till 2015. Specifically, till 2006, more than 70 percent of AI patents were developed by only one company and about 10 percent by firms in collaboration with other companies or URIs. These shares dropped to about 50 and 8 percent, respectively, in 2013, till to reach 31 and 5 percent in 2017. The decreasing role of companies in the development of AI patents has been counterbalanced by the growth of URIs, which has passed from about 10 percent before 1998, to more than 66 percent in 2017. The growing role played by URIs may be explained by considering their increasing effort in patenting (Geuna and Nesta 2006; Mowery et al. 2001), but also the large investments in AI approved by some governments, especially in China (Arenal et al. 2020; Lundvall and Rikap 2022). No wonder, all the top ten URI developers of AI patents are Chinese universities.

The disambiguation of the applicant organizations allows us to evaluate if the development of AI patents is concentrated in the hands of a few organizations and how this concentration has evolved over time. We computed the Herfindahl-Hirschman index to evaluate the concentration of AI patents developed in each year under analysis. In our data, this index varies from a minimum of 43 in 2012 to a maximum of 103 in 1998. These values of concentration appear to be extremely low, since the Herfindahl-Hirschman index can theoretically reach 10,000, if only one organization files all the AI patents developed in a certain year.

Table 1. Number of AI patents developed by different types of applicant partnership over time

	OneCompany	OneURI	MultipleCompanies	MultipleURIs	MixCompaniesURIs	Total
Before 1998	2,796	262	415	39	72	3,584
1998	797	96	132	8	20	1,053
1999	935	104	126	13	25	1,203
2000	1,004	135	128	12	37	1,316
2001	1,170	155	150	11	28	1,514
2002	1,099	189	136	19	31	1,474
2003	1,080	246	109	11	40	1,486
2004	1,212	238	111	15	59	1,635
2005	1,428	328	133	16	47	1,952
2006	1,536	396	140	24	65	2,161
2007	1,668	514	142	23	66	2,413
2008	1,945	764	127	30	96	2,962
2009	1,964	947	129	42	106	3,188
2010	1,897	1,080	129	39	90	3,235
2011	2,069	1,345	110	43	109	3,676
2012	2,487	1,808	176	44	170	4,685
2013	3,132	2,470	188	53	237	6,080
2014	3,787	2,979	242	65	268	7,341
2015	4,992	3,766	291	83	301	9,433
2016	5,002	5,262	331	118	321	11,034
2017	2,191	4,346	108	79	232	6,956
Total	44,191	27,430	3,553	787	2,420	78,381

4.2 Variables and method

The main aim of our analysis is to evaluate the effect of different types of applicant partnership on the impact of AI inventions.

Following a large body of literature (Cohen 2010; Hall, Jaffe, and Trajtenberg 2005; Trajtenberg 1990), we measured the impact of AI inventions through the collection of all the forward citations of the patents in our sample. The use of forward citations allows measuring how the knowledge spillovers associated with each patent are reused in the development of successive inventions (Jaffe, Trajtenberg, and Henderson 1993), given the applicants' obligation to specify in the citations all the relevant prior art for these inventions (Almeida, Song, and Grant 2002). Thus, the number of forward citations can be considered a well-established proxy for the economic value, quality, and importance of inventions (Harhoff, Scherer, and Vopel 2003).

Nevertheless, the use of forward citations as a measure of patent impact may be affected by several biases. First, it may inflate the patent impact because of the presence of self-citations that cannot be unequivocally attributed to the knowledge search strategies adopted by the applicants in the invention development (Hohberger 2014). For this reason, we excluded self-citations, also excluding citations made by affiliates in the same corporate group (Messeni Petruzzelli and Murgia 2020).

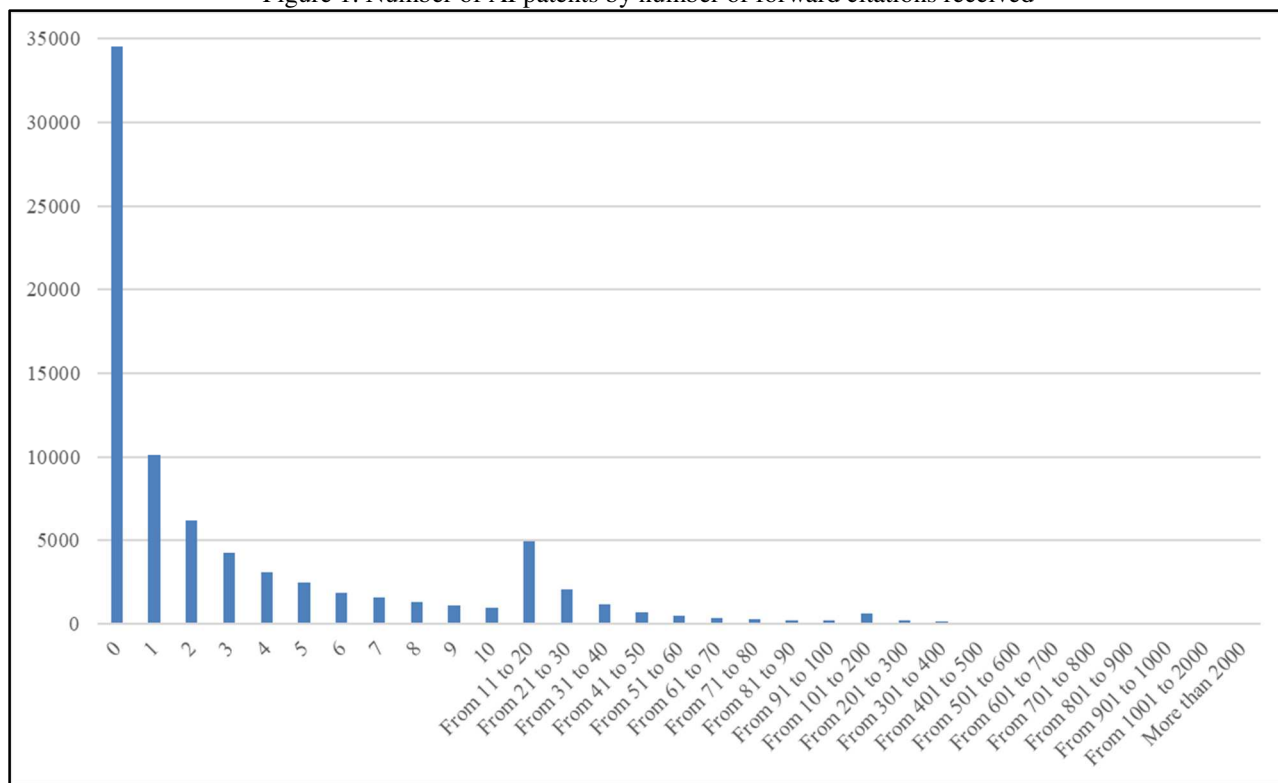
Second, several forward citations may be added by examiners and opponents, thus not resulting from knowledge search strategies adopted by the applicants in the invention development (Alcacer, Gittelman, and Sampat 2009). The number of forward citations not added by the applicants varies in accordance with the technological sector and the country of application. We will specifically address this issue in our robustness checks.

Hence, the technological impact of each AI patent (*TechImpact*), which is the dependent variable in the present study, is measured as the number of forward citations, excluding self-citations. As shown in Figure 1, this variable is highly skewed, with about 44 percent of patents with zero forward citations. This distribution leads us to select a negative binomial regression as the estimation method, as we discussed in detail at the end of this section. Besides, we will specifically address possible issues related to the large share of zero-impact AI patents in our robustness checks.

As independent variables, as discussed above, we considered five different binary variables associated with different types of applicant partnership, *OneCompany*, *OneURI*, *MultipleCompanies*, *MultipleURIs*, *MixCompaniesURIs*. Since all the AI patents in our sample are associated with one of these types of applicant partnership, we cannot include all these five variables in the same regression model, and we exclude *MixCompaniesURIs*, thus considering it as the baseline category for the evaluation of the effect of the other types of applicant partnership.

In our analysis, we included several control variables associated with several characteristics of the AI patents. First, we added a discrete variable (*FilingYear*) that measures the earliest filing year of the patent. By including this variable, we mitigated issues due to the variations of citing propensity in the last years, as well as the effect of different truncations of the forward citations of the patents in the

Figure 1. Number of AI patents by number of forward citations received



sample (Messeni Petruzzelli and Murgia 2021). Since the technological impact of a patent may be affected by its technological breadth, we added the number of three-digit IPC classes assigned to the patent (*Scope*) (Moser and Nicholas 2004). Besides, because of its impact on the visibility and reputation of patents, we evaluated their degree of legal protection by considering several variables, such as the number of patent applications belonging to the same family (*FamSize*) (Martinez 2011), the number of patent offices where the patent was applied (*Countries*) (Harhoff, Scherer, and Vopel 2003), the number of claims (*Claims*) (Tong and Frame 1994), and a binary variable (*Granted*), equal to 1 if the patent has been granted by at least a patent office, 0 otherwise (Yasukawa and Kano 2014). We also evaluated the breadth of the knowledge sources used in patent development by controlling for the number of backward citations (*BackCit*), the number of nonpatent references (*ScientRef*) (Harhoff, Scherer, and Vopel 2003), and the number of inventors (*TeamSize*) (Mariani 2004). Finally, we included a set of eight binary variables, *FuzzyLogic*, *MachineLearning*, *BioInspired*, *ClassificationBased*, *NeuralNetwork*, *RuleBased*, *SupervisedLearning*, and *UnsupervisedLearning*, that measure if each patent is developed by using specific AI techniques.

We also included a control variable associated with the technological capital developed by the applicants of the AI patents. The technological capital cumulated by applicants in the past development of AI inventions may improve their ability to generate high-impact patents in this field, thanks to the reuse of the related knowledge and expertise (Phene, Fladmoe-Lindquist, and Marsh 2006). For this reason, for each patent in our sample, we computed the number of AI patents developed by its applicant organizations in the previous five years (*AITechCap*).

Given the discrete nature of our dependent variable and potential issues due to overdispersion, we adopted a negative binomial regression as the estimation method. In particular, we computed robust standard errors to account for heteroskedasticity, while we checked if the variables have a variance inflation factor above the cut-off value of 10 to address possible issues related to multicollinearity (Neter et al. 1996).

5. Results

As presented in the Appendix (Table A), the variables included in our model show only a few cases of high correlation, and the value of the variance inflation factor is well below the cut-off value of 10.

Table 2 presents the results of two different negative binomial regression models that test the impact of our independent and control variables on *TechImpact*. Model 1 contains all the independent and control variables apart from the binary variables associated with the different AI techniques, which are included in Model 2.

Both these models show that *FilingYear* has a significant and negative effect on *TechImpact*, in line with the fact that the most recent patents have a lower probability to be cited. Conversely, *TechImpact* is positively affected by *Scope*, *Countries*, *Claims*, and *Granted*. These results suggest a positive effect of the technological breadth, as well as the legal coverage, on the technological impact of AI patents. Concerning the impact of the knowledge flows used for the development of AI patents, our results show a positive and significant effect of *BackCit* and *TeamSize*, while *ScientRef* has a significant and negative, even if minimal, effect on *TechImpact*. This latter result may be explained by assuming a difficulty in the reuse of scientific knowledge by the applicants of AI patents, but it should be further investigated with a more precise analysis of nonpatent references, which may include different forms of knowledge from heterogeneous sources (Brusoni, Criscuolo, and Geuna

2005). Concerning the control variable associated with the applicant, *AITechCap* has a significant and negative, even if minimal, effect. This result suggests that applicants with higher experience in AI are less able to develop high-impact patents. In Model 2, the inclusion of the binary variables associated with the different AI techniques adopted for the development of the patents in our sample shows that patents that used Classification and regression trees and Supervised learning have a higher impact. Conversely, the use of Fuzzy logic, Bio-inspired approaches, and Neural networks shows a negative and significant impact on the related AI patents.

Compared to the baseline category (*MixCompaniesURIs*), all four independent variables explicitly investigated in our models show a positive and significant effect on the impact of AI patents. These results suggest that the AI patents developed by an applicant partnership made up of both companies and URIs have a lower impact than those developed by only one company (*OneCompany*), only one URI (*OneURI*), several companies without any URI (*MultipleCompanies*), or several URIs without any company (*MultipleURIs*). This result supports *H1b*. In particular, the most impacting type of applicant partnership is the collaboration between several companies ($\beta = 0.268, p < 0.001$), followed by only one company ($\beta = 0.212, p < 0.001$), the collaboration between several URIs ($\beta = 0.161, p < 0.05$), and only one URI ($\beta = 0.116, p < 0.01$). The differences between the impact of the

Table 2. Results of negative binomial regression models

	Model 1	Model 2
OneCompany	0.237*** (0.037) [0.575]	0.212*** (0.037) [0.509]
OneURI	0.113** (0.037) [0.275]	0.116** (0.037) [0.279]
MultipleCompanies	0.284*** (0.049) [0.690]	0.268*** (0.049) [0.645]
MultipleURIs	0.189* (0.084) [0.459]	0.161* (0.080) [0.388]
FilingYear	-0.163*** (0.002) [-0.395]	-0.164*** (0.002) [-0.394]
Scope	0.094*** (0.009) [0.228]	0.097*** (0.009) [0.234]
FamSize	-0.002 (0.003) [-0.004]	-0.002 (0.003) [-0.005]
Countries	0.045*** (0.006) [0.108]	0.044*** (0.006) [0.107]
Claims	0.023*** (0.001) [0.056]	0.023*** (0.001) [0.055]
Granted	0.623*** (0.016) [1.513]	0.624*** (0.016) [1.500]
BackCit	0.012*** (0.001) [0.030]	0.012*** (0.001) [0.029]
ScientRef	-0.001*** (0.000) [-0.002]	-0.001*** (0.000) [-0.002]
TeamSize	0.055*** (0.003) [0.133]	0.056*** (0.003) [0.134]
AITechCap	-0.001*** (0.000) [-0.002]	-0.001*** (0.000) [-0.002]
FuzzyLogic		-0.187*** (0.033) [-0.450]
MachineLearning		0.023 (0.026) [0.056]
BioInspired		-0.151*** (0.028) [-0.363]
ClassificationBased		0.114*** (0.026) [0.274]
NeuralNetwork		-0.228*** (0.025) [-0.547]
RuleBased		-0.019 (0.066) [-0.047]
SupervisedLearning		0.136*** (0.023) [0.327]
UnsupervisedLearning		0.093 (0.076) [0.224]
Intercept	326.74*** (3.321)	329.563*** (3.278)
Alpha	1.726 (0.017)	1.704 (0.016)
Pseudo R-squared	0.156	0.157
Wald chi-squared	46,325.57***	47,323.73***
Log pseudo-likelihood	-168,043.49	-167,770.52
Observations	78,381	78,381

Baseline category: *MixCompaniesURIs*. Robust standard errors in parentheses, marginal effects in square brackets.

[†] $p < 0.10$; * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.

four types of applicant partnership are partially confirmed by the Wald test, which shows that the coefficients associated with the collaboration between several companies, only one company, and only one URI are statistically different from each other. Conversely, the Wald test highlights how the differences between the coefficient of the collaboration between several URIs and the other types of applicant partnership are not statistically significant.

To test the robustness of these results, we made several checks based on the use of different regression models, different operationalizations of the existing variables, and the inclusion of further control variables. First, since our dependent variable contains a large share of zeros, we tested our models by using zero-inflated negative binomial regression (Appendix – Table B). The results are consistent with those presented in Table 2. Second, to control for the effect of forward citations added by patent examiners and opponents, we computed our regression models by considering only the forward citations explicitly added by the applicants (Appendix – Table C). The results of these models are consistent with those obtained in our main models, apart from the coefficient associated with *OneURI* that becomes significant but negative ($\beta = -0.309, p < 0.001$). Third, we evaluated the possible effect of blocking patents by checking the forward citations received by each focal AI patent, evaluating if it has been marked as “blocking”, thereby showing that the novelty or inventive step of the citing patents is challenged by the cited focal AI patent (Czarnitzki, Hussinger, and Leten 2020) (Appendix – Table D). We added this variable among the control variables, finding a positive and significant effect ($\beta = 0.140, p < 0.001$). In any case, the coefficients of the other independent variables are consistent with those presented in Table 2. Fourth, we tested the effect of the co-occurrence in patents references, by computing for each AI patent the number of backward citations to patents already cited by previous AI patents included in our sample (Appendix – Table E). We added this variable among the control variables, finding a positive and significant effect ($\beta = 0.027, p < 0.001$). In any case, the coefficients of the other independent variables are consistent with those presented in Table 2. Fifth, we tested the effect of possible hierarchies between the AI patents, by computing for each AI patent the number of backward citations to other AI patents included in our sample (Appendix – Table F). We added this variable among the control variables, finding a positive and significant effect ($\beta = 0.060, p < 0.001$). Even in this case, the coefficients of the other independent variables are consistent with those presented in Table 2. Finally, to evaluate the impact of Chinese universities, which are the top URI developers of AI patents, we added a binary variable that is equal to 1 if the focal patent is filed only at the China National Intellectual Property Administration (CNIPA), 0 otherwise (Appendix – Table G). This variable shows a negative and significant coefficient ($\beta = -0.111, p < 0.001$), while those of the other independent variables are consistent with the results presented in Table 2.

6. Discussion and Conclusion

The results of our regression models provide several insights concerning the development of high-impact AI solutions, thus contributing not only to the management literature focused on this specific technology, but also to the larger debate on the inventing process of GPTs. A large body of studies has previously investigated the determinants of the impact of patents (Cohen 2010; Hall, Jaffe, and Trajtenberg 2005; Trajtenberg 1990), even in the case of GPTs (Appio, Martini, and Fantoni 2017; Ardito, Messeni Petruzzelli, and Albino 2016), but the present paper shows that the results obtained in this literature are only partially confirmed in the analysis of the AI field.

The main result of the present study concerns the lower capability of UI collaborations to generate

high-impacting AI solutions, compared to all the other types of applicant partnership. In particular, the establishment of UI collaborations based on the joint development of innovations seems to be less effective in AI, for several reasons. First, most URIs have limited knowledge of several application fields of AI solutions, especially those closer to the market (Soh and Subramanian 2014). This knowledge is crucial for the definition of a profitable business model for these solutions, as shown in the development of the AI solution “Watson” by IBM (Magistretti, Dell’Era, and Messeni Petruzzelli 2019; Yang, Chesbrough, and Hurmelinna-Laukkanen 2022). URIs’ limited knowledge of several application fields of AI solutions is due to their orientation toward pure science (Bruneel, d’Este, and Salter 2010), which may increase the institutional and cognitive distance experienced in UI collaborations (Khoury and Pleggenkuhle-Miles 2011; Veugelers and Cassiman 2005). Second, companies can obtain most of the benefits of URIs’ involvement by using different organizational arrangements from UI collaborations based on the joint development of AI solutions. Indeed, in this field, many companies prefer to directly hire some AI academics (Jurowetzki et al. 2021; Yu, Liang, and Wu 2021), collaborate with academic spin-offs (Arenal et al. 2020), or create joint research laboratories and some specific challenges (Amini et al. 2020). All these organizational arrangements give companies access to expert human resources trained by universities, reducing the costs and risks associated with UI collaborations based on the joint development of innovations.

The analysis of the coefficients associated with the four types of partnership that are alternative to UI collaborations shows that those that involve only companies represent the most effective applicant partnership in the development of high-impact AI inventions. This finding is aligned with the previous results (Magistretti, Dell’Era, and Messeni Petruzzelli 2019; Yang, Chesbrough, and Hurmelinna-Laukkanen 2022), which show how a company may boost the effectiveness of an AI solution by establishing several R&D collaborations with other partners operating in the possible application fields. These partners, which are more often companies than URIs because of their presence in the final market, may support the AI developer company in the experimentation and definition of the most promising business model to apply in each application field (Gambardella and McGahan 2010). In any case, the coefficients associated with the different types of partnership should be interpreted with caution, because the differences between the coefficient of the collaboration between several URIs and the other types of applicant partnership are not statistically significant.

In any case, even our descriptive results show that companies had a prevalent role in the development of AI inventions, while our regression models point out that they are more able than URIs to develop high-impact AI solutions². Indeed, companies may have easier access to some resources, such as large amounts of business data, high-speed computational capacity, and deep knowledge of the possible application fields, which are critical for the development of AI solutions (Brynjolfsson and McAfee 2017; Yang, Chesbrough, and Hurmelinna-Laukkanen 2022).

Comparing our results with studies on others GPTs, the main difference concerns the scarce capability of more diverse types of partnerships, i.e. UI collaborations, to develop high-impact solutions, but even the coefficients associated with some control variables suggest peculiar dynamics of the inventing process in the AI field. In particular, while the result associated with the level of scientific knowledge needs further investigation because of the high heterogeneity that affects this variable

² This result is further confirmed by an alternative regression model, not reported in the text, in which we tested how the technological impact of AI inventions is affected by the number of firm applicants and URI ones. Only this last variable has a significant and negative effect, thus further confirming the cons of having URIs among the applicants of AI patents.

(Brusoni, Criscuolo, and Geuna 2005), the negative effect of the technological capital cumulated by the applicants specifically in AI may be explained by considering the fast pace of innovation that characterizes this field (Tang et al. 2020), which may favour the emergence of several radical innovations and, consequently, high speed of obsolescence (Goktan and Miles 2011). In such a field, the level of knowledge cumulated through past inventions may increase technological inertia and reduce the ability to develop cutting-edge inventions (Tripsas and Gavetti 2000). This result contrasts with several previous studies (Messeni Petruzzelli and Murgia 2021; Phene, Fladmoe-Lindquist, and Marsh 2006), which show how the technological capital of the applicants may enhance their capability to develop high-impact inventions.

6.1 Implications and contributions

Our paper gives an important contribution to AI studies because our results provide a coherent framework to explore the dynamics behind the development of inventions in this field, which has been almost neglected in the management literature. Indeed, most of the management literature has discussed the possible advantages and issues related to the adoption of AI solutions by organizations operating in different sectors (Borges et al. 2021; Davenport and Ronanki 2018), while only a few studies, based on a qualitative approach, have explored the dynamics in the development of these solutions (Magistretti, Dell’Era, and Messeni Petruzzelli 2019; Yang, Chesbrough, and Hurmelinna-Laukkanen 2022). The large-scale and quantitative nature of the present study may improve the generalizability of the resulting insights, also allowing a comparison of the inventing process of AI solutions with other GPTs.

Our analysis provides indeed a relevant contribution even to the GPT literature, as briefly summarized in Table 3. In particular, the results concerning the role of URIs and the effectiveness of UI collaborations seem to contrast with findings presented in previous GPT studies (Motohashi and Muramatsu 2012; Nikulainen and Palmberg 2010). In fact, differently from other GPTs strongly imbued with scientific knowledge, like nanotechnology (Nikulainen and Palmberg 2010), in the AI field the combination of the different knowledge bases provided by companies and URIs seems to be scarcely beneficial in terms of the impact of the resulting inventions. This result suggests that there is not one “fit-for-all” solution for the development of GPTs, but it is necessary to evaluate the peculiarities of each technology and the possible contribution that each partner can specifically provide in the related inventing process. In particular, like other GPTs, AI solutions may take advantage of the knowledge provided by different partners, but, unlike other GPTs, they need more

Table 3. Development of AI versus other science based GPTs solutions

	AI	Other science based GPTs
Scientific knowledge provided by URIs	Replaceable by knowledge independently developed by companies and/or acquired through the hiring of talents	Essential to enable effective experimentation of new departures from the current technological paradigms
Market knowledge provided by companies	Essential to effectively experiment the possible business models for an AI solution	Necessary to improve the effectiveness of the business model centred on a GPT
UI collaborations based on joint patenting	Development of solutions with a lower technological impact	Development of solutions with a technological higher impact

knowledge of the possible application fields than scientific knowledge.

From a practical point of view, our paper gives interesting suggestions to managers about the right strategy to generate relevant AI inventions. Specifically, the higher impact of AI inventions developed by R&D collaborations between different companies may stimulate managers to increase their relationships with external partners, especially those operating in the possible application fields. Besides, the lower effectiveness of UI collaborations suggests that the costs and risks of these relationships seem to be higher than the related benefits, even because of the companies' growing capabilities to obtain all the critical resources for AI development even without the direct involvement of a URI.

This latter result may be extremely useful even to policymakers interested in supporting the development of AI. Indeed, the transfer of AI technologies from URIs to companies seems to be less effective, if based on direct R&D collaborations between these different organizations. Thus, to stimulate the development of AI inventions, policymakers may design policies and strategic initiatives based on different technology transfer tools, like joint laboratories and AI challenges. In any case, the effectiveness of these alternative technology transfer tools deserves further evaluation in future studies, which should also consider the possible impact on the development of AI solutions that cannot be patented. More in general, the identification of the most effective types of applicant partnership may stimulate the evolution of national and local innovation systems, thus combining the current surge of patenting (Fink, Khan, and Zhou 2016; Kim and Marschke 2004) with the development of more impacting inventions.

6.2. Limitations and future research

The present paper has some limitations that may suggest potential areas for further research. First, it does not investigate several characteristics of the applicants, such as their size, nationality, industry, and previous technological experience beyond the AI field. As shown by the literature on innovation management (Hohberger 2014; Messeni Petruzzelli and Murgia 2021; Phene, Fladmoe-Lindquist, and Marsh 2006), all these characteristics may affect the capability to develop high-impact inventions. Hence, scholars may add these variables in future studies to overcome this limitation. Second, the present study measures the impact of AI solutions by considering only a single variable. In future studies, it is thus possible to include even other variables typically used in the GPT literature, like the patent generality (Martinelli, Mina, and Moggi 2021; Squicciarini, Dernis, and Criscuolo 2013), to better investigate the impact of an AI solution on a broad variety of sectors. Third, our analysis is focused on the investigation of partnerships resulting from the list of patent applicants. Therefore, it is not able to detect some possible "hidden" collaborations between inventors that participate in the development of an AI solution without the official involvement of their organizations. The large use of alternative forms of collaborations in the AI field, especially between companies and URIs, asks for future analysis of these "hidden" collaborations, even if they will require effortful disambiguation of the patent inventors. Finally, being focused on patents, the present study is not able to analyse innovative solutions in AI that are not patentable. Future studies may investigate if and how the dynamics pointed out in the present study can be generalized even to the development of these solutions.

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