Enhancing knowledge spillover of innovation through artificial intelligence: an empirical investigation

The Journal of Technology Transfer
https://doi.org/10.1007/s10961-025-10217-7

RESEARCH

Enhancing knowledge spillover of innovation through artificial intelligence: an empirical investigation

Elettra D'Amico[1] · Maksim Belitski[2,3] · Alessandro Braga[3] · Robert Savoie[3]

Accepted: 2 May 2025

Abstract
Effective technological innovation relies on having ample knowledge resources to enhance firm performance and knowledge creation. Innovators seek both internal and external knowledge, actively engaging in a continuous search for these valuable resources. Knowledge collaboration is a specific strategy that innovative firms can follow during Artificial Intelligence (AI) adoption processes. This study investigates the role of AI and knowledge collaboration in firm innovation. Using data from 14,143 firms in the UK between 2004 and 2020, we explore how AI adoption impacts knowledge spillover of innovation. Our findings suggest that firms adopting AI can enhance their innovation performance if it complements firm's own investment in R&D. AI adoption can substitute knowledge collaboration with certain external partners. The results help us to rethink resource allocation for knowledge spillover of innovation in the era of AI and digital technologies.

Keywords Artificial intelligence · Innovation · Knowledge collaboration · Knowledge transfer · AI adoption

✉ Elettra D'Amico
elettra.damico@polito.it

Maksim Belitski
mbelitsk@loyno.edu

Alessandro Braga
abraga@loyno.edu

Robert Savoie
rsavoie@loyno.edu

1 Politecnico di Torino, Turin, Italy

2 University of Reading, Reading, UK

3 Loyola University New Orleans, New Orleans, USA

1 Introduction

The success of technological innovation depends on the availability of sufficient knowledge resources to support continuous discovery and knowledge creation (Acs et al., 2013; Audretsch et al., 2019). Innovators invest in R&D and new technologies to develop absorptive capacity (Cohen & Levinthal, 1990) and engage with external partners for knowledge transfer, engaging themselves in a process of continuous search for knowledge (Audretsch & Link, 2019). Knowledge emanating from the R&D and human capital of external firms spills over to generate innovative activity in partner organizations. Belderbos et al., (2004, 2015) and later Audretsch et al. (2022) extensively studied the topic of external knowledge sources and found that collaborations with different knowledge sources are important conduits of firm performance and innovation.

The extent literature on knowledge transfer and innovation (Cassiman & Valentini, 2016; Gassmann et al., 2010; Mudambi & Tallman, 2010) pointed out that sourcing knowledge via open innovation channels from external partners, including direct knowledge transfer and acquiring external knowledge via R&D and spillovers (Audretsch et al., 2024a, 2024b) shapes innovation outcomes. By choosing the type of knowledge collaboration partner and a type of internal knowledge investment, a firm chooses the type and extant of innovation it wants to produce.

Research on open innovation (Belderbos et al., 2004; Chesbrough, 2006) predates the development of highly-advanced digital technologies, such as Artificial Intelligence (AI), which could have significantly changed the scene of knowledge transfer (Benbya et al., 2020; Colombelli et al., 2023; Gama & Magistretti, 2023). Despite a massive and fundamental revolution in digital technology, along with a reduction in the cost of data collection and knowledge transfer using AI, the knowledge transfer literature still is unable to clearly evaluate the benefits that adoption of AI brings in addition to sourcing knowledge via spillovers and through collaboration with external partners for innovation (Audretsch et al., 2023, 2024a).

Despite a growing number of firms are using AI today to improve their performance, there is still a lack of theoretically grounded or empirically validated data to help innovators with their strategic choices (Perifanis & Kitsios, 2023; Yigit & Kanbach, 2021). Henceforward, there is a shortage of in-depth empirical evidence and theoretical argumentation on (a) the role of different types of collaboration partners for innovation and (b) the role that AI may play in facilitating the effect of knowledge spillovers on innovation.

Therefore, the purpose of this study is to advance our understanding of the role that AI plays in a firm's innovation along to what extent the use of AI moderates the effect of each specific type of knowledge collaboration partner for innovation. In particular, the main value of this study is in investigating how AI adoption by firms is connected with different types of knowledge collaborations. We ask our research question: How and to what extent AI adoption moderates the effect of variety of knowledge collaborations on firm's innovation performance? By answering this question, we can also test whether or not the adoption of AI by a firm serves as an important conduit to firm innovation itself (Chen et al., 2018; Haefner et al., 2021; Keding & Meissner, 2021; Link & Scott, 2019), as AI influences the context of innovation (Garbuio & Lin, 2021; Keding, 2021; Verganti et al., 2020). If it does not do so, the knowledge transfer literature will require a fundamental rethinking.

Using novel data on 14,143 firms with 24,017 firm-year observations over 2004–2020 in the United Kingdom from six Business Structure Databases (BSD) and UK Innovation Surveys (UKIS) matched to the Beauhurst database, our study examines the effect of different types of knowledge collaboration partners on firm innovation and the moderating role of AI extending prior research on the knowledge spillover of entrepreneurship and innovation (Acs et al., 2013; Audretsch & Belitski, 2022) and the role of AI in fostering firm performance directly and indirectly (Damioli et al., 2021). Our findings demonstrate a very different view of the role of AI in knowledge transfer and its complementarity with specific partnerships and knowledge types for firm innovation. The study is structured as follows. Section 2 discusses the literature and postulates the research hypothesis. Section 3 examines data and methods, Sect. 4 provides the main results, and Sect. 5 discusses and concludes.

2 Theoretical framework

2.1 The dynamics of knowledge collaboration

External partners are usually a relevant driver of innovation for firms (West & Bogers, 2014); however, the success of such initiatives relies on reciprocal knowledge sharing (Huang & Newell, 2003). Besides acquiring knowledge from other partners, resources can also be allocated externally with knowledge collaboration. The field of strategic management strongly highlights the significant positive impact of such collaboration on the formation of strategic partnerships and alliances (Belenzon & Schankerman, 2015), and it also encourages companies to make internal knowledge investments (Cohen & Levinthal, 1990). In this sense, the benefits of allocating external resources for knowledge collaboration are deeply rooted in the co-creation process and the economic worth of knowledge. This is further enhanced by understanding how to adapt existing knowledge (Bogers et al., 2017, 2019).

Knowledge collaboration is central within the different types of collaborative activities with partners. In general, it comprises getting access to similar or related knowledge (Teece et al., 1997) or a combination of specialized, differentiated, but complementary knowledge bases (Kogut & Zander, 1996; Tiwana & Mclean, 2005). It has numerous advantages that have been abundantly recognized by the literature. For instance, knowledge collaboration improves the added value of knowledge (Gao et al., 2016) and it achieves collaboration effects where the results of collaboration are greater than zero-sum games (Chen, 2010; Yu et al., 2023). Furthermore, it could provide an opportunity to tap into the intellectual property of partners for the purpose of learning and adopting new technologies (Bernal et al., 2022). External knowledge allocation can assist companies not only in their growth but also in accelerating the adoption of new technologies. This process involves a considerable degree of risk-taking, trust, and negotiation among the partners involved (Belitski et al., 2020; Hall et al., 2013).

Specifically, one of the main reasons for forming alliances on innovation is the sharing of costs between partners (Hagedoorn, 1993; Veugelers, 1997). This approach helps in reducing the average production costs per unit and leads to the creation of new combinations of knowledge (Antonelli & Colombelli, 2017; Nelson, 1982). However, an unbalanced distribution of knowledge led to a knowledge gap among firms (Haider, 2014; Liao & Cao, 2018). Considering the transmission of knowledge between different partners as a chain, the knowledge spillover effect is easily affected by internal and external factors and leads to a disorderly flow (Rodriguez-Enriquez et al., 2016). Thus, returns from knowledge collaboration may not be the same across institutional partners (consultants, university, government) and market partners (suppliers and customers) as well as competitors. Our contribution strongly supports this narrative and investigates each form of such relationships, by testing specific hypotheses below.

2.2 Collaboration with suppliers and customers: upstream and downstream

Knowledge collaborations provide unique benefits of learning from others but could also lead firms to appropriate other firms' innovations (Cohen et al., 2002; Nooteboom, 1999). The main literature on collaboration breadth (the variety of partners) and depth (the intensity of collaboration) (e.g., Brenk, 2020; Chapman et al., 2018; Kobarg et al., 2019; Lazzarotti et al., 2023) offers a valuable analysis of how innovation collaboration can start and how it develops.

Collaboration in innovation activities is positively linked to innovation performance, as noted by researchers like Belderbos et al. (2018) and Gilsing et al. (2008). Such partnerships facilitate better knowledge sharing and resource pooling. However, there is limited research on how a firm's innovation performance influences its likelihood to pursue future R&D collaborations (Phelps et al., 2012).

Moreover, firms exhibit diverse behaviors when it comes to innovation collaboration. Yet, firms that have achieved significant innovation may feel less inclined to collaborate, believing their internal capabilities are sufficient (Ahuja, 2000; Phelps et al., 2012). That is, these firms might worry that engaging in R&D partnerships could unintentionally lead to the loss of valuable knowledge to their partners, potentially jeopardizing their future innovation performance (Belderbos et al., 2018).

Increase in partner types may increase spillover of innovation (Audretsch & Belitski, 2022). However, partnering with too many organizations can dilute focus and create inefficiencies (Bengtsson et al., 2015). Firms often face resource limitations that hinder effective interactions during collaborations (Foss et al., 2013). As a result, having a diverse set of partners may reduce their ability to effectively capture and absorb knowledge from each one. Here, the challenge lies in the costs associated with coordinating collaborations with numerous partners, which can create a tension between costs and benefits (Mishra et al., 2015). This tension may ultimately outweigh the advantages of collaboration (Kobarg et al., 2019). In addition, Vivona et al. (2023) highlight that the key issue is identifying the optimal conditions for collaboration tailored to specific innovation challenges. Essentially, the focus should be on determining which collaborative arrangements can effectively address complex innovation problems while keeping collaboration costs to a minimum.

In terms of knowledge spillovers with upstream and downstream partners (Bernal et al., 2022; Isaksson et al., 2016 among others), firms gain significant advantages by strategically collaborating with partners who offer complementary knowledge (Antonelli, 2003; Fang, 2011; Un & Rodriguez, 2018). Antonelli (2003: 597) explains that "the opportunities to generate new knowledge are conditional on the identification and integration of the diverse bits of complementary knowledge that are inputs into the knowledge production process…".

This approach allows firms to effectively balance the exploration of innovative ideas while also leveraging their existing capabilities. By choosing partners that fill knowledge gaps (Haider & Mariotti, 2010), companies can enhance their overall innovation potential and ensure that they are not only developing new concepts but also maximizing the value of what they already possess.

Prior literature has demonstrated that knowledge coming from upstream and downstream partners in the industry value chain is most valuable for innovation, collaborating with suppliers (upstream), and customers (downstream) will have a larger positive impact on innovation than other types of collaboration partners (Un et al., 2015; Chesbrough, 2003, 2006).

Although Un et al. (2015) argue that the upstream R&D collaborators such as suppliers dealing with the input side of firm operations are more important than clients or customers within the downstream chain dealing with the final products, we use a different approach here. Collaboration with clients and customers (downstream) is likely to promote co-creating new products as a proxy for innovation, therefore better addressing the need of a customers. Following Ries (2011), customer is not anymore, a consumer of the project but also a creator participating in the input side of firm operations and therefore improving the process innovation but also results in better product and service provision. Product and process innovation requires the improvement of inputs and material flow in the firm. Collaboration with suppliers and customers facilitates the transformation process of knowledge creation in a focal firm and improves both final innovation outcomes and speeds up a process which enables to achieve those outcomes. In addition, a closer relationship with suppliers and customers allows for the integration of company-specific tacit knowledge and external knowledge. This facilitates the adoption of best practices and accelerates the process of product creation and modification (Battisti & Stoneman, 2010; Battisti et al., 2015; Chesbrough, 2003).

Both suppliers and customers provide direct new inputs in terms of materials, knowledge (suppliers), feedback, advice and co-creation (customers) in the production using digital technologies and other forms of knowledge collaboration within the country and beyond (Ghobadian et al., 2014). Suppliers and customers work closely with the firm, independently on location as the firm needs to engage with customers and suppliers conditional on the marker it buys from or sells to, which is partner-specific and not spatial-specific. Thus, we hypothesize that:

H1a *Collaboration within upstream industries has a positive effect on firm innovation.*

H1b *Collaboration within downstream industries has a positive effect on firm innovation.*

2.3 Collaboration with competitors

After investigating the knowledge collaboration with upstream and downstream market partners, we now focus on the collaboration with competitors. Collaboration with competitors is relevant due to the close knowledge proximity and horizontal competitiveness in market segments. Close contextual knowledge distance within the knowledge chain (Un et al., 2015), or close technological proximity (Hall et al., 2009, 2013) is acknowledged as the proximity form most closely linked to innovation (Huber, 2012) and with positive effects on learning and innovativeness by the implications of absorptive capacity (Cohen & Levinthal, 1990). It enables better understanding of products and processes and therefore enhances the introduction of new modified products within the same industry, allowing the product to be more adjusted to market.

Best practices and new tacit knowledge developed by competitors may be relevant to other firms in a market to improve their processes and design new improved services and products (Tsai et al., 2017). A rapid growth of knowledge-intense industries (e.g. automotive eco-cars industry) enhances the importance of tacit knowledge, as well as knowledge exchange to find more efficient and faster solutions. Much of this knowledge is a human embodied tacit knowledge which is difficult to codify. The rapid pace of innovation challenges traditional and new industries making companies collaborate on new projects and ideas and support broad intra-industry collaboration build on trading with each other, supplying inputs and materials, joint R&D expenditure, and joint patenting (Hall et al., 2014).

Moreover, inter-personal connections and knowledge exchange is facilitated through intra-industry collaborative activity, driven by companies, industry consortia, and industrial/professional associations. This allows pushing the technologies and industry ahead. Therefore, it might take place when facing major technological challenges (Gnyawali & Park, 2011), and likely internationally (Vanyushyn et al., 2018). Collaboration between close competitors may happen due to customers specific needs, new markets, resources available from venture capitalists, local and national government.

Firms engaging in coopetition need to manage it carefully. Reverse engineering when collaboration with competitors is a common practice and may decrease innovation effort. Despite the known challenges related to intellectual property protection and appropriability collaboration with competitors (locally, nationally and internationally) may increase returns to market and technology, speed up the process of innovation and organizational learning. Therefore, we also hypothesize:

H2 *Collaboration with competitors increases firm innovation.*

2.4 Collaboration with institutional partners

Now we discuss the role of institutional partners (e.g. consultants, universities, governments and public organizations) and their role as knowledge collaborators for innovation. Institutional partners have long been recognized as central to national innovation systems (Chung, 2002; Krishna, 2019) while limited emphasis is dedicated on investigating how the location of various institutional partners can change the returns to R&D collaboration for a firm (Dimakopoulou et al., 2023; Lin & Yang, 2020). Several studies have shown a strong correlation between the degree of connectivity between different stakeholders and regional productivity (e.g. Iammarino & McCann, 2013), while studies investigating cross country—cross firm interplay has been very limited (e.g. see Han, 2021; Kukreja et al., 2024). Earlier studies, such as Fritsch and Aamoucke (2013) found that public research through universities has a strong positive impact on new business formation. This effect is limited to innovative industries, while results on industries classified as non-innovative are not significant, indicating "the importance of regional knowledge for the formation of innovative new businesses" (2013:875). Similar findings are presented by Korosteleva and Belitski (2015) who demonstrated that business education provided by the university had multi-facet effect on entrepreneurial dynamic.

While the initial appeal of universities as contributors to regional economic growth and innovation was linked to the rise of new organizational structures like research labs, university-industry research centers, incubators, and accelerators, the role of the university as a global innovator was credited to a handful of Ivy League Universities that excelled in creating and transferring technology to the industry on both a national and international scale. Despite being a vital source of knowledge, many universities and consultants (Fromhold-Eisebith et al., 2013) encounter challenges in transferring knowledge across national boundaries, and sometimes even regional ones (see Schofield, 2013). This positions universities as regional knowledge providers (Belitski & Sikorski, 2024).

Therefore, while a university's participation in a regional innovation ecosystem doesn't guarantee innovation itself, it is likely to draw emerging industries and SMEs, as well as lead to the development of high-tech clusters (e.g., Stanford University's high-tech cluster, Cambridge University's IT and engineering cluster– see also Breznitz, 2011). Other research in the fields of regional economics and entrepreneurship, summarized by Piergiovanni et al. (2012), has also observed a strong correlation between the presence of universities and other institutional collaborators (such as government entities, conferences, exhibitions, consultants) and local innovation and the establishment of new firms. Furthermore, universities, especially those offering business and entrepreneurship education, play a significant role in fostering an 'entrepreneurial climate' and nurturing the innovation ecosystem (Audretsch & Belitski, 2017; Isenberg, 2010). Finally, we should also consider the role of local and national governments issuing laws and performing regulatory interventions over their jurisdictions. Collaboration with government aims to fundraise for innovation and exploit market opportunities at the very development stage of a projects when venture capital for innovation is not yet available. Institutional partners become useful and often first-hand source of fundings to create a prototype and test new products. Knowledge and resources received from partners stimulates innovation activity (Audretsch & Belitski, 2022). Based on the above we hypothesize:

H3 *Collaboration with institutional partners has positive effect on firm innovation.*

2.5 The role of artificial intelligence in knowledge collaboration

In recent years, the intersection of AI and knowledge collaboration has become a focal point for organizations seeking to enhance innovation. For example, Mishra and Tripathi (2021) explore how AI technologies are integrated into business models by identifying archetypal business model patterns for AI startups and emphasizing the value propositions enabled by AI capabilities and the impact on overall business logic. Giuggioli and Pellegrini (2023) analyzed the impact of AI on entrepreneurship, considering AI's role within Industry 4.0 paradigms with Li et al. (2016) demonstrated that employees and leaders that are equipped with digital skills and know how to use digital technologies to analyze, collect and process data, demonstrated higher performance of their small and medium-size firms (Colombelli et al., 2023). This study highlights the role of data analytics and big data as well as AI's potential as an enabler for leaders seeking competitive advantage. Chen and Tajidini (2024) examine the organizational determinants of the adoption intensity of artificial intelligence (AI) and its effects on firms' performance, under the moderating effects of technological turbulence.

With specific regard to the relationship with the business environment upstream, downstream and horizontal, the literature shares crucial yet contrasting results. Research by Arias-Pérez et al. (2023) tackles the question from the perspective of pressures (positive or negative) and illustrates the effects of external pressures for AI adoption. The first supports the key role of external partners (universities, governments among others) for AI adoption, while the latter considers external pressures for AI adoption as a moderator between business analytics capability and co-innovation. Authors challenge the common belief that external pressures negatively impact AI adoption. Instead, it suggests that such pressure can be seen as an opportunity for companies to embrace advanced digital transformation practices.

In terms of knowledge collaboration, the literature identifies the role of partners as essential for AI adoption, with particular regard to the implementation phase. In AI adoption processes, being exposed to knowledge earlier can create positive feedback loops, leading to knowledge spillover through network effects (Sorenson et al., 2006). This, in turn, impacts the performance of specific companies (Dahlke et al., 2024). Petersson et al. (2022) analyze the relevance of partner collaboration for AI adoption in the healthcare sector, identifying a challenging balance between the capacity building of firms, legal framework, and ethical integrity; Chin et al. (2024) consider the moderated effect of knowledge spillover from ecosystem-based business models for AI adoption. In addition, Li et al. (2023) suggest that intense market competition driven by AI adoption has improved innovation efficiency. In particular, the authors clarify that AI facilitates knowledge sharing among firms, allowing them to benefit from each other's innovation efforts through knowledge spillover effects. As a result, innovation efficiency across the industry increases, and enterprises quickly absorb and apply innovation results. Therefore, we hypothesize the following:

H4 *The use of artificial intelligence positively moderates the relationship between knowledge collaboration with different types of external partners and firm innovation.*

3 Data and method

3.1 Data matching and sample description

We develop a quantitative analysis by testing the four hypotheses set above. In particular, we adopt a more exploratory approach by testing new hypotheses, compared to confirmatory hypothesis testing (Rubin & Donkin, 2022). To test our hypotheses, we combine the Business Structure database (known as the BSD) and the UK Innovation Survey (UKIS) over 2004–2020, and the Beauhurst database for every second year available. We use Beauhurst data to identify technologies and products where use of artificial intelligence including generative AI was a commonplace.

The total number of firms in our sample is 14,143 firms with 24,017 firm-year observations during 2004–2020 (see Appendix A). Most of the firms in our sample were in the South-East of England, London, the North-West and East England. Most of the firms in our sample are from the other manufacturing sector, wholesale and retail and professional and scientific services. The majority of businesses are small firms with 10 to 49 full-time employees (FTEs), followed by large firms (250 FTEs and more) which constitute 17.93% of the sample and medium-small firms.

3.2 Variables and measures

3.2.1 Dependent variables

Our dependent variable is radical innovation which is calculated as share of total sales over the last three years from goods and services that are new to the market. This definition was used in prior research by De Leeuw et al. (2014) and Audretsch and Belitski (2022). This measure may have both radical and incremental innovations, or local adaptations (e.g., customized versions of existing products) that could contribute significantly to sales without reflecting radical innovation. Radical innovations often require long development cycles before reaching market readiness (e.g., up to 5–10 years for biotech and life sciences), while we only have a 3-year window that may primarily capture short-term, market-driven innovations that prioritize commercialization rather than fundamental breakthroughs.

In addition a product might be "new to the market" in a specific region or market but already common internationally, with the measurement does not allowing to specify the international dimension of novelty.

3.2.2 Explanatory variables

Our key explanatory variable is adoption of artificial intelligence, which is a binary variable equal to one when the firm adopts AI, or zero otherwise which draws on identification of AI using Damioli et al., 2021). We used a sectoral approach to construct the measure as we matched the 5-digit Standard Industrial Classification (SIC Code) where AI is adopted to our innovation survey. Firm that have adopted AI are located in the following sectors by SIC 2007 3 digits: 182; 261; 262; 263; 264; 279; 283; 289; 293; 322; 325; 329; 351; 465; 512; 522; 582; 591; 592; 612; 631; 639; 642; 643; 649; 651; 702; 711; 712; 721; 731; 741; 742; 743; 774; 801;803; 823; 856; 869; 900; 960. To address the potential heterogeneity within sectors, we use 5-digit SIC codes, which provide a high level of granularity and help minimize the risk of misclassification. This approach ensures a more precise analysis of firm-level AI adoption.

To avoid assigning AI adoption in the industry to a firm that is digitally uncertain and does not use AI technology (Audretsch & Belitski, 2024; Belitski et al., 2022), we applied one additional filtering criteria which is a firm should spend any resources on buying or investing in-house in information technology and software. If a firm reports zero such expenses, the AI is replaced with zero (not adopted).

Other explanatory variables include various knowledge collaboration partners (Audretsch et al., 2024a; Roper et al., 2017; Van Beers & Zand, 2014). The binary variables represent six types of collaboration partners such as the government, universities, consultants, competitors, customers, and suppliers. In order to account for potential diminishing returns from investment in knowledge (Audretsch & Belitski, 2023; Roper et al., 2017). Each variable varies between zero– collaboration on knowledge not used to 3– high importance of knowledge collaboration for innovation with each specific partner.

The list of variables including control variables in this study is in Table 1. Correlation matrix of the variables used in this study is in Table 2.

3.3 Method

We use Tobit regression model (Audretsch et al., 2023; Laursen & Salter, 2006; Negassi, 2004) to estimate a knowledge production function as our dependent variable which is double censored, as firms can have none or all sales from new to the market products. Tobit estimation provides a finer understanding of the potential selection of firms that innovate and develop new products and those that do not. We note that the standard Tobit model is useful if the sample is randomly selected among the population (Office for National Statistics, 2023a, 2023b). The underlying assumption of the method is that the disturbances are normally distributed and the same data generating process that determines the censoring is the same process that determines the outcome variable. Our dependent variable is censored at zero, which allows us to apply a standard Tobit estimation (Wooldridge, 2003):

$$y_{it} = \beta_0 + \beta_1 K_{it} + \beta_2 \rho_{it} + \beta_3 K_{it} \rho_{it} + \beta_4 X_{it} + u_{it} \tag{1}$$

where y_{it} represents innovation sales for firm i that varies between zero and 100 at time t. K_{it} is a vector of knowledge collaboration with each type of partner (suppliers, customers, competitors, universities, consultants, local and national government) of firm i at time t; ρ_{it} is AI– a binary variable which equals one if firm i uses AI at time t, zero otherwise; $\rho_{it} K_{it}$ is an interaction term aimed to test our key hypothesis on how the effect of knowledge spillover from collaboration changes between a firm i that adopted AI and other firms which did not adopt AI at time t, X_{it} is a vector of control exogenous variables including year, industry and region fixed effects; u_{it} is the error term and is assumed to be identically and independently distributed with mean zero and constant variance σ^2.

4 Results

4.1 Main results

Table 3 shows the regression estimates of the model (1) using innovation sales as the dependent variable. Considering different partners for external collaboration, we tested our Hypothesis 1–3. We support H1a and H1b, which states that collaboration between suppliers (β=0.26, p<0.05) and customers (β=0.77, p<0.05) have a *positive effect on firm innovation* (spec. 2 and spec. 6, Table 3). Our findings demonstrate that knowledge collaborations with suppliers (H1a) and customers (H1b) increase the absorptive capacity of a firm extending prior research on the role of heterogeneity in partner's choice and the intensity of knowledge collaboration, including across industries (Audretsch et al., 2021, 2024a, 2024c; Cassiman & Veugelers, 2002). External knowledge collaboration eases learning within an organization and with external partners and enables faster recognition and creation of new knowledge. Our H2, which states that collaboration with competitors increases firm innovation with positive learning effects that can be replaced by competition effects, is supported as we find the canceled-out effects are insignificant due to the presence of both learning and

Table 1 Description of variables. Source: Office for National Statistics. (2023a, 2023b)

Variable	Definition	Mean	ST.dev	Min	Max
Innovation	Percentage of sales from goods and services that are new to the market over last 3 years	0.07	0.13	0.00	1.00
AI	Binary variable = 1 if firm adopts AI, zero otherwise	0.11	0.22	0.00	1.00
Internal R&D to sales ratio	Internal R&D expenditure to sales ratio in logs	1.39	7.01	0.00	54.00
ICT to sales ratio	Advanced equipment, ICT, soft and hardware expenditure to sales ratio in logs	1.39	5.03	0.00	31.00
Suppliers	Important to business's innovation activities (from zero– not important to 3– highly important) was the extent of the interactions between the focal firm and its suppliers of equipment, materials, services or software	1.60	1.09	0.00	1.00
Customers	Important to business's innovation activities (from zero– not important to 3– highly important) was the extent of the interactions between the focal firm and its clients or customers	1.79	1.21	0.00	1.00
Competitors	Important to business's innovation activities (from zero– not importance and not used to 1- low, 2- medium and 3 highly important) was the extent of the interactions between the focal firm and competitor in the industry	1.41	1.11	0.00	1.00
Consultants	Important to business's innovation activities (from zero– not important to 3– highly important) was the extent of the interactions between the focal firm and consultants, commercial labs or private R&D institutes	0.87	0.99	0.00	1.00
Universities	Important to business's innovation activities (from zero– not important to 3– highly important) was the extent of the interactions between the focal firm and universities or other higher education institutes	0.62	0.79	0.00	1.00
Government	Important to business's innovation activities (from zero– not important to 3– highly important) was the extent of the interactions between the focal firm and government or public research institutes	0.49	0.77	0.00	1.00
New firms	Firms with age between 0 and 7 years since the establishment	0.22	0.41	0.00	1.00
Established	Firms with age between 8 and 15 years since the establishment	0.27	0.48	0.00	1.00
Transitioned	Firms with age between 16 and 30 years since the establishment	0.31	0.46	0.00	1.00
Mature	Firms that are more than 30 years since the establishment	0.20	0.41	0.00	1.00
Employment	Number of full-time employees, in logarithms	3.67	1.82	0.00	10.98
Scientists	The proportion of employees that hold a degree or higher qualification in STEM	8.01	16.69	0.00	100.00
Foreign firm	Binary variable = 1 if a firm has headquarters abroad, 0 otherwise	0.41	0.55	0.00	1.00
Number of subsidiaries	Number of firm's subsidiaries and local units	1.72	4.11	0.00	98.00

Table 2 Correlation matrix. Source: Office for National Statistics. (2023a, 2023b)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)
Innovation	1																
AI	0.171*	1															
Internal R&D to sales ratio	0.323*	0.261*	1														
ICT to sales ratio	0.125*	0.134*	0.226*	1													
Suppliers	0.166*	0.127*	0.085*	0.153*	1												
Customers	0.196*	0.148*	0.124*	0.100*	0.633*	1											
Competitors	0.167*	0.127*	0.110*	0.075*	0.584*	0.714*	1										
Consultants	0.194*	0.159*	0.162*	0.083*	0.483*	0.433*	0.500*	1									
Universities	0.203*	0.173*	0.207*	0.064*	0.374*	0.354*	0.403*	0.584*	1								
Government	0.182*	0.159*	0.159*	0.055*	0.382*	0.371*	0.438*	0.570*	0.713*	1							
New firms	0.105*	0.035*	0.064*	0.043*	0.019*	0.008	0.018*	0.002	0.004	0.009	1						
Established	0.032*	0.055*	0.047*	0.006	0.006	0.018*	0.004	0.005	0.001	0.007	0.252*	1					
Transitioned	0.044*	0.017*	0.039*	0.022*	0.003	0.006	0.007	0.011	0.010	0.018*	0.301*	0.433*	1				
Employment	0.005	0.031*	0.011	0.001	0.208*	0.225*	0.224*	0.198*	0.139*	0.152*	0.181*	0.052*	0.037*	1			
Scientists	0.258*	0.445*	0.391*	0.072*	0.123*	0.174*	0.156*	0.226*	0.294*	0.240*	0.056*	0.055*	0.032*	0.031*	1		
Foreign firm	0.036	0.010	0.015*	0.037*	0.028*	0.047*	0.060*	0.060*	0.015*	0.031*	0.166*	0.007	0.043*	0.404*	0.041*	1	
Number of subsidiaries	0.011	0.016*	0.006	0.012	0.027*	0.032*	0.033*	0.038*	0.035*	0.034*	0.064*	0.062*	0.048*	0.166*	0.017	0.034	1

*Significant at 5% statistical significance level competition effects, making the some exclusive novel knowledge dissipating within the industry extending prior research on the localization and internationalization of coopetition (Vanyushyn et al., 2018). The value of the coefficient is not statistically significant ($\beta=0.001$, $p>0.10$) (spec. 2 and spec. 6, Table 3). At one hand, collaboration with competitors diminishes the effort undertaken by businesses to build new product or introduce new process should the resources be limited and markets are saturated or very small or should competitors provide them with resources (substitution effect) extending research on the extent and intensity of collaboration with competitors (Belitski et al., 2024). Second, competitors will tend to limit innovation as peers could be observed and knowledge sourced, in particular operational process and radical innovation. In this case, non-disclosure agreements and joint patent protection of innovation may prevent firms from independently going to market (Mariani & Belitski, 2023). Third, knowledge is difficult to substitute and copy because it is subject to complexity and firm-specific characteristics (Lippman & Rumelt, 1982). Hence, the effect may be indirect, and relatd to firm's further investment in R&D or educating their employees via collaboration with compatitors.

Our H3, which states that collaboration with institutional partners such as consultants, universities and government has a positive effect on firm innovation *is partly* supported. We found that consultants ($\beta=0.13$, $p<0.05$) and universities ($\beta=0.33$, $p<0.05$) (spec. 2 and spec. 6, Table 3) increase innovation sales, while the effect of collaboration with government is insignificant. Furthermore, in specifications 3–5 (Table 3) we test our H4 on the interaction effects between AI introduction and customers and suppliers (spec. 3), competitors and AI (spec. 4) and institutional partners (spec. 5, Table 3) one at a time in their effects on firm's innovation sales.

Our H4 which states that AI positively moderate the effect of knowledge collaboration with various types of external partners and firm innovation is partly supported. The interaction coefficients between AI and customers ($\beta=0.012$, $p<0.05$), suppliers ($\beta=0.019$, $p<0.05$) consultants ($\beta=0.007$, $p<0.05$) and university ($\beta=0.050$, $p<0.05$). Interactions between AI and knowledge collaboration with competitors and government are insignificant. Finally, specification 6 in Table 3 tests all the hypotheses simultaneously. We find that the effect of AI when collaborating with suppliers on innovation switches from positive (spec. 2, Table 3) to negative effect (spec. 6, Table 3). This means that by adopting AI, a firm may substitute information that it receives within its upstream supply chain. The positive effect of customers persists with the interaction effects of AI and customers positive and significant ($\beta=0.009$, $p<0.05$) (spec. 6, Table 3). Collaboration with universities when applying AI for innovation id also positive and significant ($\beta=0.050$, $p<0.05$) (spec. 5, Table 3), while the effect becomes insignificant when controlling for all collaboration partners.

Several interesting findings can be drawn from the control variables. For instance, the growth stage of a firm is a crucial factor influencing its innovation, with start-ups (0.059, $p<0.01$) and established firms (0.024, $p<0.05$) having a significantly larger impact on firm innovation than firms in transition and mature stages, broadening our understanding from Coad et al. (2016). The share of employees with STEM degrees is positively associated with firm innovation as well as investment in R&D and ICT.

4.2 Endogeneity correction

4.2.1 First stage estimation

As argued in the theoretical background section, the collaboration partner choice is not random. Therefore, we apply the following correction method to test the robustness of our results. In the first stage, we instrument φ_i with two exclusion restrictions (exogenous variables), assuming that we have six exogenous instruments that affect collaboration with suppliers, customers, competitors, consultants, universities, and government but do not affect the degree of every specific firm innovation. These instruments are 2 digit SIC 2007 classification industry-level of collaboration with every external partner such as suppliers (ϱ_1), customers (ϱ_2), competitors (ϱ_3), consultants (ϱ_4), universities (ϱ_5) and local or national government (ϱ_6). Each instrument is exogenous, i.e. it is uncorrelated with the error u_i but affects the decision of firms to collaborate first via a peer-pressure mechanism within the industry when an average likelihood of industry collaboration may directly signal to a focal firm the necessity to collaborate. In the reduced form our model is estimated as:

$$\varphi_i = \pi_0 + \beta_i x_i + \pi_1 \varrho_1 + \pi_2 \varrho_2 + \pi_3 \varrho_3 + \pi_3 \varrho_4 + \pi_3 \varrho_5 + \pi_3 \varrho_6 + v_i \tag{2}$$

where$E(v_i) = 0$,$cov(\varrho_1, v_i) = 0$,$cov(\varrho_2, v_i) = 0$. For this IV not to be perfectly correlated with ϱ_i we need that all $\pi_i \neq 0$ and not to be perfectly correlated with ϱ_i. The identification requires that $\sum_{i=1}^{6} \pi_i \neq 0$(Wooldridge, 2003).

We used six multivariate probit models to predict the fact of collaboration with the supplier (spec. 1),—with the customer (spec. 2), with the competitor (spec. 3), with the consultant (spec. 4) with the university (spec. 5) with the government (spec. 6, Appendix B). In addition toϱ_1, ϱ_2,ϱ_3,ϱ_4,ϱ_5, ϱ_6 which are exclusion restrictions, other explanatory exogenous variables x_i are included as well as a set of time fixed effects. Our dependent variable φ_i in model (2) is a collaboration (or not) with every specific partner type. The results of the first stage IV estimation across six types of collaborators are reported in Appendix B, including the post-estimation test (chi2) of a joint significance of chosen instruments. Table seven (specifications 1–4 for supplier collaboration across 4 regions) illustrates the evidence for the first condition being satisfied. The coefficients of the chosen instruments and significant and positively associated with endogenous variable φ_i and knowledge spillover, ceteris paribus. Appendix B illustrates the evidence for the first condition being satisfied. Firms located in the industry with a higher level of collaboration with suppliers, customers, competitors, consultants and universities will also have higher likelihood of collaboration with suppliers ($\beta=0.04$, $p<0.05$), customers ($\beta=0.17$, $p<0.05$), competitors ($\beta=0.05$, $p<0.01$), consultants ($\beta=0.13$, $p<0.01$), universities ($\beta=0.16$, $p<0.01$). An increase in industry collaboration with the government does not change the propensity of each firm to collaborate with the government.

Once we have predicted values for each of three collaboration partner and across four proximities, we estimate (1) using the two-stage procedure described in Wooldridge (2003) as two-stage least square estimation, applied to Tobit:

$$y_{it} = \beta_0 + \beta_1 \widehat{x_{it}} + \beta_2 z_{it} + \varepsilon_{it} \tag{3}$$

Table 3 Tobit regression results. Dependent variable: Innovation. Source: Office for National Statistics. (2023a, 2023b)

Specification	(1)	(2)	(3)	(4)	(5)	(6)
AI	−0.005	0.029	0.096**	0.120**	0.120**	0.120**
	(.02)	(.02)	(.04)	(.07)	(.07)	(.06)
Internal R&D to sales ratio	0.020***	0.016***	0.016***	0.015***	0.014***	0.015***
	(.00)	(.00)	(.00)	(.00)	(.00)	(.00)
Internal R&D to sales ratio squared	−0.002***	−0.001***	−0.002***	−0.001***	−0.002***	−0.001***
	(.00)	(.00)	(.00)	(.00)	(.00)	(.00)
ICT to sales ratio	0.011***	0.009***	0.008***	0.007***	0.010***	0.007***
	(.00)	(.00)	(.00)	(.00)	(.00)	(.00)
ICT to sales ratio squared	−0.001***	−0.001***	−0.001***	−0.001***	−0.001***	−0.001***
	(.00)	(.00)	(.00)	(.00)	(.00)	(.00)
Suppliers (H1a)		0.26***	0.37***	0.19***	0.22***	0.19***
		(.01)	(.07)	(.01)	(.02)	(.01)
Customers (H1b)		0.77***	0.84***	0.69***	0.70***	0.69***
		(.01)	(.01)	(.01)	(.02)	(.01)
Competitors (H2)		0.001	0.001	0.013	0.001	0.001
		(0.02)	(0.02)	(0.01)	(0.02)	(0.02)
Consultants (H3)		0.13***	0.11***	0.09***	0.20***	0.10***
		(.02)	(.02)	(.02)	(.04)	(.02)
Universities (H3)		0.33***	0.37***	0.30***	0.37***	0.32***
		(.01)	(.01)	(.05)	(.05)	(.01)
Government (H3)		−0.002	0.002	0.003	0.010	0.001
		(.01)	(.01)	(.01)	(.01)	(.01)
AI x Suppliers (H4)			0.019**			−0.032***
			(.00)			(.00)
AI x Customers (H4)			0.012**			−0.002
			(.01)			(.01)
AI x Competitors (H4)				−0.003		−0.001
				(.01)		(.01)
AI x Consultants (H4)					0.007*	0.005*
					(.00)	(.00)
AI x Universities (H4)					0.050**	−0.018
					(.02)	(.01)
AI x Government (H4)					0.018	−0.017
					(.01)	(.01)
New firms	0.064***	0.058***	0.056***	0.059***	0.053***	0.059***
	(.00)	(.00)	(.00)	(.00)	(.00)	(.00)
Established	0.011***	0.016***	0.011***	0.024***	0.010***	0.024***
	(.00)	(.00)	(.00)	(.00)	(.00)	(.00)
Transitioned	0.015***	0.016	0.011	0.016	0.015	0.016
	(.00)	(.01)	(.01)	(.01)	(.01)	(.01)
Employment	0.016**	0.017**	0.065	0.061	0.064	0.061
	(.00)	(.00)	(.01)	(.01)	(.01)	(.01)
Scientists	0.003***	0.002***	0.003***	0.002***	0.002***	0.002***
	(.00)	(.00)	(.00)	(.00)	(.00)	(.00)
Foreign	−0.073**	−0.049**	−0.048**	−0.043**	−0.052**	−0.043**
	(.00)	(.00)	(.00)	(.00)	(.00)	(.00)

Table 3 (continued)

Specification	(1)	(2)	(3)	(4)	(5)	(6)
Reporting units	0.001	0.002	0.002	0.002	0.001	0.002
	(.01)	(.01)	(.01)	(.01)	(.01)	(.01)
Constant	−0.35***	−0.51***	−0.51***	−0.52***	−0.54***	−0.52***
	(.08)	(.07)	(.07)	(.05)	(.05)	(.05)
Region, time and industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Left-censored	17,011	17,011	17,011	17,011	17,011	17,011
Uncensored	7006	7006	7006	7006	7006	7006
Number of obs	24,017	24,017	24,017	24,017	24,017	24,017
Chi2	3515.1	5067.2	5370.2	5230.2	5299.2	5323.5

Reference category for industry (financial services), city-region (Liverpool), year 2002–2004; growth stage (mature). Robust standard errors are in parenthesis. Significance level: *$p<0.05$; ** $p<0.01$, *** $p<0.001$

Our two-stage procedure involves using Eq. (2) where we obtain the predicted values of collaborations with suppliers, customers, competitors, consultants, universities and govenmrnt $\widehat{x_{it}}$. The second stage of the Tobit regression (3) is when $\widehat{x_{it}}$ is used instead of x_i, correcting for potential endogeneity in the relationship between knowledge collaboration x_i and innovation output y_i. Because we predicted values of collaborations $\widehat{x_{it}}$ in place of x_{it}, the IV tobit which serves as a robustness check for (1). Table 4 presents the result of IV Tobit estimation (second stage).

4.2.2 Second-stage estimation

Overall, the two-stage estimation (Table 4) supports our previous findings in Table 3, except of the positive moderation effect of AI adoption and an increase in collaboration with suppliers and customers which enhances innovation sales of the firms. We find collaboration with external partners (suppliers, customers, and consultants) has a positive and particularly conducive effect on a firm's product innovation, while collaboration with competitors has no effect. We were surprised to find no interaction between AI adoption and collaboration with universities and government. Collaboration with customers and suppliers adds more to product innovation in firms that adopted advanced AI technologies than in firms that do not adopt AI, supporting H4. Collaboration with customers and the adoption of AI facilitates innovation to a greater extent than collaboration with other partners.

5 Discussion and conclusion

5.1 Theoretical contribution

This study asks an important question– how knowledge spillovers through collaboration with external partners and adoption of Artificial Intelligence technology at a firm jointly enhance innovation activity?

Table 4 IV Tobit estimation of product innovation (second stage) with predicted values of knowledge collaboration partners. Source: Office for National Statistics. (2023a, 2023b)

Specification	(1)	(2)	(3)	(4)	(5)	(6)
AI	−0.004	−0.005	0.005	0.011*	0.102**	0.110**
	(.02)	(.02)	(.02)	(.02)	(.04)	(.06)
Suppliers ($\widehat{x_{it}}$) (H1a)			0.65***	0.45***	0.47***	0.49***
			(.02)	(.02)	(.02)	(.02)
Customers ($\widehat{x_{2t}}$) (H1b)			0.99***	0.87***	0.94***	0.99***
			(.01)	(.01)	(.01)	(.01)
Competitors ($\widehat{x_{3t}}$) (H2)			0.009	0.002	0.003	0.004
			(0.02)	(0.02)	(0.02)	(0.02)
Consultants ($\widehat{x_{4t}}$) (H3)			0.67***	0.19***	0.21***	0.24***
			(.02)	(.02)	(.02)	(.02)
Universities ($\widehat{x_{5t}}$) (H3)			0.60***	0.43***	0.38***	0.35***
			(.01)	(.01)	(.01)	(.01)
Government ($\widehat{x_{6t}}$) (H3)			0.005	0.003	0.004	0.002
			(.01)	(.01)	(.01)	(.01)
AI x Suppliers ($\widehat{x_{it}}$) (H4)			0.013**			0.010***
			(.00)			(.00)
AI x Customers ($\widehat{x_{2t}}$) (H4)			0.041**			0.022**
			(.01)			(.01)
AI x Competitors ($\widehat{x_{3t}}$) (H4)				0.003		0.001
				(.01)		(.01)
AI x Consultants ($\widehat{x_{4t}}$) (H4)					0.011**	0.004*
					(.00)	(.00)
AI x Universities ($\widehat{x_{5t}}$) (H4)					0.050*	0.018
					(.02)	(.01)
AI x Government ($\widehat{x_{6t}}$) (H4)					0.031	0.010
					(.01)	(.01)
Other controls	Yes	Yes	Yes	Yes	Yes	Yes
Constant	−0.43***	−0.45***	−0.42***	−0.49***	−0.52***	−0.56***
	(.03)	(.08)	(.08)	(.05)	(.04)	(.03)
Region, time and industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Left-censored	17,011	17,011	17,011	17,011	17,011	17,011
Uncensored	7006	7006	7006	7006	7006	7006
Number of obs	24,017	24,017	24,017	24,017	24,017	24,017
Log-likelihood	−4570.4	−4560.3	−4560.3	4637.3	−4544.2	4701.2

Reference category for industry (financial services), city-region (Liverpool), year 2002–2004; growth stage (mature). Robust standard errors are in parenthesis. Significance level: * $p<0.05$; ** $p<0.01$, *** $p<0.001$

Our results indicate a need for a significant reassessment of the importance of resource allocation for innovation. Specifically, the role of AI adoption and the recombination of internal and external knowledge resources seems to be more complex, as previous innovation studies have discovered (Antonelli & Colombelli, 2017; Audretsch et al., 2023; Paschen et al., 2020). Market partners such as suppliers and customers emerge as the most important sources of knowledge supporting prior research (Battisti & Stoneman, 2010; Ghobadian et al., 2014; Sydow, 1992). Interestingly, we found, as a result of dealing with the endogeneity of the relationship between collaboration for innovation and innovation outcomes, that the adoption of AI has been particularly conducive when a firm has increased its collaboration on knowledge with suppliers, customers and consultants.

The two-stage estimation largely corroborates the results from the earlier analysis, demonstrating the robustness of the findings. However, it highlights a noteworthy divergence: AI adoption positively moderates the relationship between collaboration with suppliers and customers, enhancing their contribution to firms' innovation sales. This emphasizes the critical role of AI in amplifying the value of these specific collaborations with upstream and downstream partners. This collaboration could (a) either reduce innovation or (b) significantly enhance it when adopting AI. While suppliers typically provide AI technologies or components that firms need to integrate into their existing systems, this type of collaboration often focuses on the technical and operational aspects of implementing AI, such as compatibility, installation, and maintenance. IN fact collaboration with suppliers and use of AI will go beyond integration and operational efficiency that will increase supply chain efficiency and increase creative problem-solving.

We found that collaboration with external partners—specifically suppliers, customers, and consultants—significantly fosters product innovation. The interaction between AI adoption and collaboration with universities and government is unexpectedly negligible, suggesting that these partnerships might operate independently of AI's transformative potential. Conversely, the combined effect of AI and collaboration with customers and suppliers is notably strong.

When collaboration with suppliers increases, AI can help suppliers move beyond offering standardized solutions. While suppliers often provide standardized options for product development, AI is designed to address a diverse range of client needs. By leveraging AI, suppliers can deliver highly effective, tailored solutions that meet the specific innovative requirements of individual firms. However, this reliance on AI-driven supplier solutions can create a dependency on the supplier's technology and expertise, potentially stifling a firm's internal innovation efforts. As firms increasingly rely on external support, their own capacity to innovate internally may diminish. At the same time, AI introduces complexity into the process, which can also foster more innovative outcomes by enabling unique and customized approaches. Thus, while AI enhances supplier collaboration, firms must balance external reliance with maintaining their internal innovation capabilities.

AI can expand the possibilities of knowledge transfer between suppliers and customers (Arias-Pérez & Huynh, 2023; Liu et al., 2017). The knowledge transfer from suppliers and customers due AI application may focus on functionality of supply chain and quick adjustment to customer needs. This can lead to a situation where the firm's internal team understand the underlying principles and capabilities of the AI technology, increasing their ability to innovate independently. AI adoption and collaboration with consultants and customers providing further strategic insights (Audretsch et al., 2023). External consultants through industry experience and customers through market experience bring specialized expertise and strategic insights into AI adoption and technology development overall in a firm. Their role often involves identifying innovative applications of AI, designing bespoke solutions, and providing strategic advice on leveraging AI for competitive advantage. Both working together with customers and consultants could be conducive in understanding unique challenges and opportunities of the market, fostering a more tailored and innovative approach to AI implementation.

Finally, AI adoption may facilitate and better integrate knowledge from customers through their experience with the product (Belitski et al., 2024) and with consultants that often engaged in-depth training and capacity-building activities with the firm's employees. This helps to develop a deeper understanding of AI technologies and their potential applications within the firm. By enhancing the internal team's capabilities and fostering a culture of innovation, consultants enable firms to continue innovating even after the consulting engagement has ended.

The individually testing moderation effects could uncover hidden relationships. For example, examining why AI adoption interacts positively with suppliers and customers but not with universities or governments could lead to deeper theoretical insights. For example, interaction with customers and suppliers and use of AI often involve immediate, practical, and feedback-driven interactions focused on improving products, processes, or services. AI can enhance these interactions by enabling real-time data analysis, predictive insights, and more efficient communication, directly contributing to innovation outcomes. We do not find the effects valid for collaboration with universities and government as these institutions for collaboration are often public and they focus on long-term, exploratory, or regulatory aspects of collaboration and innovation. AI's immediate, application-focused advantages may not align as closely with the strategic or policy-oriented nature of these partnerships, leading to less measurable innovation impact in the short term. This would help refine our understanding of how AI complements certain partnerships while being neutral or less effective with others.

The difference in innovation outcomes between partner types lies in the nature of the knowledge transfer and the partner's knowledge about the product, inputs and market.

5.2 Policy and practical implications

The results from this study provide actionable implications for innovation managers and policymakers. Policymakers could use our findings to promote collaboration networks that integrate suppliers, customers, and consultants within industries. Industry-specific innovation hubs could enable firms to access practical and immediately applicable knowledge, enhancing their innovation outcomes. Furthermore it is important for policymakers to encourage AI-enabled collaboration incentives and provide targeted grants or tax benefits to firms adopting AI while collaborating with customers and suppliers. This could incentivize practical, market-oriented innovations that yield higher returns. Finally, it is important to stimulate development policies to align university and government collaboration frameworks with AI's strengths, such as fostering applied research and real-world applications. This might include funding for translational research programs that emphasize short- to medium-term innovation impact.

Firm managers may learn from this study how and to what extent they should strategically invest in AI systems and what is the marginal value of enhancing collaboration with suppliers, customers and consultants when adopting AI for innovation. These partnerships allow real-time data exchange, predictive analytics, and process optimization, directly contributing to product innovation. We clearly demonstrate that engagement with consultants is important and it can offer real-life solutions and expertise facilitates tailored innovation approaches and enhances knowledge transfer, creating long-term competitive advantages. While suppliers may offer standardized AI solutions, managers should push for customization to meet specific innovation needs. Establishing co-creation agreements with suppliers can help ensure AI technologies align with the firm’s unique goals. Finally, managers may see suppliers and customers as inherently practical and feedback-driven partners, making them ideal co-creators of AI solutions for business. The lack of significant AI interactions with universities and governments suggests these partnerships may require a shift toward applied, shorter-term projects to align with AI's transformative potential. Our practical recommendations for the chief executive officers (CEOs), entrepreneurs and policymakers are summarized in Table 5.

5.3 Limitations and future research

Our study has an important limitation related to the measure of AI adoption. We developed a binary variable with a sectoral focus and adopted a couple of filtering criteria. While there is an element of strength here as we used SIC codes in a structured way to align industry classifications with AI adoption, and the exclusion of firms that neither invest in IT nor have STEM employees is a reasonable criterion to filter out companies that are unlikely to be actual AI adopters. However, this measure, while being an interesting attempt to evaluate AI adoption, still presents *a* limitation. Further research should offer more diverse and continuous measures of AI adoption and AI quality, including combining different forms of AI (Damioli et al., 2021).

Future research should focus on fundamental reevaluation of the importance of resource mobilization for innovation, understanding whether this is a knowledge collaboration or investing in its own knowledge and R&D (Audretsch, Belitski & Caiazza, 2024b), aligning with the ongoing digitization of managerial processes. It could be that, due to advancements in AI, reliance on such technologies will become a primary innovation strategy in the next generation of firms. Further research could focus on rethinking the role of absorptive capacity in a firm's innovation in particular in choosing between internal and external R&D investments and buying vs. making R&D. Adoption of digital technologies such as AI, e.g., ChatGPT, OpenAI, is capable of reducing transaction costs (Williamson, 1979), thus extending the firm's ability to invest further internally in absorptive capacity or acquire knowledge externally, including using knowledge spillovers and R&D collaborations (Audretsch & Belitski, 2022; Bernal et al., 2022).

Thus, future research will extend the focus of management and knowledge transfer literature to the interplay between internal and external sources of innovation and the role of AI in leveraging the cost of knowledge adoption and complementarities with stakeholders (Freisinger et al., 2024). This comes with the understanding that traditional digital technologies and platforms have reduced the marginal cost of adding additional knowledge units to the firm's processes and that they can complement human skills and decision-making.

Table 5 Practical recommendations across stakeholders for use of AI and knowledge collaboration for innovation

Stakeholders	Practical recommendations for AI integration in knowledge collaboration
Entrepreneurs	**Leverage AI for market-driven innovation**: Use AI to analyze customer data and trends, enhancing product development and customization
	Engage in AI-driven co-creation: Collaborate with suppliers and customers using AI-enabled platforms for real-time feedback and iterative product design
	Utilize AI for knowledge spillovers: Participate in AI-powered networks and innovation hubs to access industry-specific expertise and best practices
	Prioritize strategic AI investment: Invest in AI systems that optimize collaboration efficiency, such as predictive analytics for supply chain and customer insights
CEO/Innovation managers	**Enhance supplier and customer collaboration through AI**: Implement AI-driven tools for real-time data exchange, predictive demand planning, and product innovation
	Customize AI solutions for firm-specific needs: Push suppliers for tailored AI applications rather than relying on standardized solutions
	Use AI-driven consultants for innovation strategy: AI-enabled consultancy services can offer specialized insights to refine R&D and market positioning
	Integrate AI with absorptive capacity: Use AI to streamline internal knowledge acquisition and decision-making, balancing internal R&D investment with external collaborations
Policy-makers	**Promote AI-enabled collaboration incentives**: Provide grants, tax benefits, or funding for firms adopting AI to enhance supplier-customer engagement
	Establish AI-driven industry hubs: Support innovation ecosystems where AI helps firms access real-time knowledge and industry expertise
	Align AI policies with applied research: Foster university-government-industry partnerships focused on AI's short- to medium-term economic impact
	Facilitate AI adoption in SMEs: Develop funding programs and training initiatives to ensure small firms can integrate AI into knowledge collaboration efforts

Appendix A

See Table 6.

Table 6 Sample distribution by industry (SIC 2007 ONS divisions), the UK regions and firm size. Source: Office for National Statistics. (2023a, 2023b)

Industry distribution	Obs	Share of obs.%
Other manufacturing	5,332	22.20
High-tech manufacturing	818	3.41
Construction	2,296	9.56
Wholesale and retail trade	3,837	15.98
Transport	1,139	5.62
Accomodation and food	1,334	5.55
ICT	1,776	7.39
Financial and insurance	847	3.53
Real estate	435	1.81
Professional and scientific	2,686	11.18
Admin services	2,370	9.87
Education	101	0.42
Other services	836	3.48
Regional distribution	**Obs**	**Share of obs.,%**
North East	1,349	5.62
North West	2,241	9.33
Yorkshire and the humber	1,954	8.14
East Midlands	1,952	8.13
West Midlands	2,115	8.81
Estern	2,119	8.82
London	2,328	9.69
South East	2,625	10.93
South West	2,013	8.38
Wales	1,588	6.61
Scotland	1,876	7.81
Northern Ireland	1,857	7.73
Firm size distribution	**Obs**	**Share of obs.,%**
Micro (< 10 FTEs)	2,927	12.19
Small (10–49 FTEs)	10,719	44.63
Medium small (50–99 FTEs)	3,478	14.48
Medium large (100–249 FTEs)	2,587	10.77
Large (250 + FTEs)	4,306	17.93
Total	24,017	100

Appendix B

See Table 7.

Table 7 Results of the first stage IV regression used for predicting values of collaboration across six types of knowledge collaboration partners. Source: Office for National Statistics. (2023a, 2023b)

Dependent variable: type of knowledge collaborator	Suppliers	Customers	Competitors	Consultants	Universities	Government
Specification	(1)	(2)	(3)	(4)	(5)	(6)
Collaboration with suppliers in industry	0.04** (.015)					
Collaboration with customers in industry		0.17** (.013)				
Collaboration with competitors in industry			0.05*** (.015)			
Collaboration with consultants in industry				0.13*** (.012)		
Collaboration with universities in industry					0.16*** (.019)	
Collaboration with government in industry						0.02 (.022)
Age	−0.01 (.00)	−0.01 (.00)	−0.01 (.00)	−0.01 (.00)	0.01* (.00)	0.01* (.00)
Age squared	−0.01 (.00)	−0.01 (.00)	−0.01 (.00)	−0.01 (.00)	−0.01 (.00)	−0.01 (.00)
Employment	−0.01 (.01)	−0.01** (.00)	−0.03*** (.01)	−0.02*** (.01)	−−0.01** (.00)	−0.01*** (.00)
SMEs	0.01** (.00)	0.01* (.00)	0.01*** (.00)	0.01*** (.00)	0.01* (.00)	0.01** (.00)
Scientist	0.01*** (.00)	0.01*** (.00)	0.01*** (.00)	0.01*** (.00)	0.01*** (.00)	0.01*** (.00)
Internal R&D to sales ratio	0.07 (.042	0.13** (.04)	0.15** (.04)	0.26*** (.04)	0.28*** (.04)	0.23*** (.03)
Foreign	−0.03*** (.00)	−0.02** (.00)	−0.09*** (.00)	−0.06*** (.00)	−0.03*** (.00)	0.01 (.00)
Reporting units	−0.01 (.00)	−0.01 (.00)	−0.01 (.00)	−0.01 (.00)	−0.02 (.00)	0.01 (.00)
Industry controls (2 digit SIC)	Yes	Yes	Yes	Yes	Yes	Yes
Year controls	Yes	Yes	Yes	Yes	Yes	Yes
City-regions controls	Yes	Yes	Yes	Yes	Yes	Yes

Table 7 (continued)

Dependent variable: type of knowledge collaborator	Suppliers	Customers	Competitors	Consultants	Universities	Government
Specification	(1)	(2)	(3)	(4)	(5)	(6)
Constant	0.08***	0.08***	0.12***	0.09***	0.05***	0.04**
	(.00)	(.01)	(.01)	(.01)	(.01)	(.01)
R2	.02	.03	.07	.06	.04	.05
F-stats first stage (joint significance of instruments)	34.84	53.30	58.19	65.39	42.20	16.67

Number of observations- total sample: 24,017. Reference category for legal status is Company (limited liability company). industry (mining), region (North East of England). Robust standard errors are in parenthesis. Significance level: * $p<0.05$; ** $p<0.01$, *** $p<0.001$

Acknowledgements This publication is part of the project NODES which has received funding from the MUR – M4C2 1.5 of PNRR funded by the European Union – NextGenerationEU (Grant agreement no. ECS00000036).

Author contributions Elettra D'Amico: Conceptualization, Methodology, Formal analysis, Data curation, Visualization, Writing. Maksim Belitski: Conceptualization, Methodology, Formal analysis, Data curation, Writing. Alessandro Braga: Theoretical contribution and Writing. Rober Savoie: Policy and managerial implications. All authors reviewed the manuscript.

Funding Open access funding provided by Politecnico di Torino within the CRUI-CARE Agreement.

Data availability No datasets were generated or analysed during the current study.

Declarations

Conflict of interest The authors declare no competing interests.

References

Acs, Z. J., Audretsch, D. B., & Lehmann, E. E. (2013). The knowledge spillover theory of entrepreneurship. *Small Business Economics,41*, 757–774.

Ahuja, G. (2000). The duality of collaboration: Inducements and opportunities in the formation of interfirm linkages. *Strategic Management Journal,21*(3), 317–343.

Antonelli, C. (2003). Knowledge complementarity and fungeability: Implications for regional strategy. *Regional Studies,37*(6–7), 595–606.

Antonelli, C., & Colombelli, A. (2017). The locus of knowledge externalities and the cost of knowledge. *Regional Studies,51*(8), 1151–1164.

Arias-Pérez, J., Chacón-Henao, J., & López-Zapata, E. (2023). Unlocking agility: Trapped in the antagonism between co-innovation in digital platforms, business analytics capability and external pressure for AI adoption? *Business Process Management Journal,29*(6), 1791–1809.

Arias-Pérez, J., & Huynh, T. (2023). Flipping the odds of AI-driven open innovation: The effectiveness of partner trustworthiness in counteracting interorganizational knowledge hiding. *Industrial Marketing Management,111*, 30–40.

Audretsch, D. B., & Belitski, M. (2017). Entrepreneurial ecosystems in cities: Establishing the framework conditions. *The Journal of Technology Transfer,42*, 1030–1051.

Audretsch, D. B., & Belitski, M. (2022). The knowledge spillover of innovation. *Industrial and Corporate Change,31*(6), 1329–1357.

Audretsch, D. B., & Belitski, M. (2023). Evaluating internal and external knowledge sources in firm innovation and productivity: An industry perspective. *R&D Management,53*(1), 168–192.

Audretsch, D. B., & Belitski, M. (2024). Digitalization, resource mobilization and firm growth in emerging industries. *British Journal of Management,35*(2), 613–628.

Audretsch, D. B., Belitski, M., & Caiazza, R. (2021). Start-ups, innovation and knowledge spillovers. *The Journal of Technology Transfer,46*(6), 1995–2016.

Audretsch, D. B., Belitski, M., & Caiazza, R. (2024b). Knowledge spillovers or R&D collaboration? Understanding the role of external knowledge for firm innovation. *R&D Management.,55*(2), 531–553.

Audretsch, D. B., Belitski, M., Caiazza, R., & Phan, P. (2023). Collaboration strategies and SME innovation performance. *Journal of Business Research,164*, Article 114018.

Audretsch, D. B., Belitski, M., & Chowdhury, F. (2024a). Knowledge investment and search for innovation: evidence from the UK firms. *The Journal of Technology Transfer,49*(4), 1387–1410.

Audretsch, D. B., Belitski, M., & Guerrero, M. (2022). The dynamic contribution of innovation ecosystems to schumpeterian firms: A multi-level analysis. *Journal of Business Research,144*, 975–986.

Audretsch, D. B., Belitski, M., Spadavecchia, A., & Zahra, S. A. (2024c). The more, the merrier or the less is more? The role of firm capabilities and industry in the knowledge spillover of innovation. *Technovation,138*, Article 103115.

Audretsch, D. B., & Link, A. N. (2019). The fountain of knowledge: An epistemological perspective on the growth of US SBIR-funded firms. *International Entrepreneurship and Management Journal,15*(4), 1103–1113.

Audretsch, D. B., Link, A. N., & van Hasselt, M. (2019). Knowledge begets knowledge: University knowledge spillovers and the output of scientific papers from US Small Business Innovation Research (SBIR) projects. *Scientometrics,121*, 1367–1383.

Battisti, G., Gallego, J., Rubalcaba, L., & Windrum, P. (2015). Open innovation in services: Knowledge sources, intellectual property rights and internationalization. *Economics of Innovation and New Technology,24*(3), 223–247.

Battisti, G., & Stoneman, P. (2010). How innovative are UK firms? Evidence from the fourth UK community innovation survey on synergies between technological and organizational innovations. *British Journal of Management,21*(1), 187–206.

Belderbos, R., Carree, M., & Lokshin, B. (2004). Cooperative R&D and firm performance. *Research Policy,33*(10), 1477–1492.

Belderbos, R., Carree, M., Lokshin, B., & Fernández Sastre, J. (2015). Inter-temporal patterns of R&D collaboration and innovative performance. *The Journal of Technology Transfer,40*, 123–137.

Belderbos, R., Gilsing, V., Lokshin, B., Carree, M., & Sastre, J. F. (2018). The antecedents of new R&D collaborations with different partner types: On the dynamics of past R&D collaboration and innovative performance. *Long Range Planning,51*(2), 285–302.

Belenzon, S., & Schankerman, M. (2015). Motivation and sorting of human capital in open innovation. *Strategic Management Journal,36*(6), 795–820.

Belitski, M., Caiazza, R., & Rodionova, Y. (2020). Investment in training and skills for innovation in entrepreneurial start-ups and incumbents: Evidence from the United Kingdom. *International Entrepreneurship and Management Journal,16*, 617–640.

Belitski, M., Delgado-Márquez, B. L., & Pedauga, L. E. (2024). Your innovation or mine? The effects of partner diversity on product and process innovation. *Journal of Product Innovation Management,41*(1), 112–137.

Belitski, M., Guenther, C., Kritikos, A. S., & Thurik, R. (2022). Economic effects of the COVID-19 pandemic on entrepreneurship and small businesses. *Small Business Economics,58*(2), 593–609.

Belitski, M., & Sikorski, J. (2024). Three steps for universities to become entrepreneurial: a case study of entrepreneurial process and dynamic capabilities. *The Journal of Technology Transfer,49*(6), 2035–2055.

Benbya, H., Davenport, T. H., & Pachidi, S. (2020). Artificial intelligence in organizations: Current state and future opportunities. *MIS Quarterly Executive*. https://doi.org/10.2139/ssrn.3741983

Bengtsson, L., Lakemond, N., Lazzarotti, V., Manzini, R., Pellegrini, L., & Tell, F. (2015). Matching Partners and Knowledge Content. *Creativity and Innovation Management,24*, 72–86. https://doi.org/10.1111/caim.12098

Bernal, P., Carree, M., & Lokshin, B. (2022). Knowledge spillovers, R&D partnerships and innovation performance. *Technovation,115*, Article 102456.

Bogers, M., Chesbrough, H., Heaton, S., & Teece, D. J. (2019). Strategic management of open innovation: A dynamic capabilities perspective. *California Management Review,62*(1), 77–94.

Bogers, M., Zobel, A.-K., Afuah, A., Almirall, E., Brunswicker, S., Dahlander, L., Frederiksen, L., Gawer, A., Gruber, M., & Haefliger, S. (2017). The open innovation research landscape: Established perspectives and emerging themes across different levels of analysis. *Industry and Innovation,24*(1), 8–40.

Brenk, S. (2020). Open business model innovation–The impact of breadth, depth, and freedom of collaboration. *Academy of Management Proceedings,1*, 21971.

Breznitz, S. M. (2011). Improving or impairing? Following technology transfer changes at the University of Cambridge. *Regional Studies,45*(4), 463–478.

Cassiman, B., & Valentini, G. (2016). Open innovation: Are inbound and outbound knowledge flows really complementary? *Strategic Management Journal,37*(6), 1034–1046.

Cassiman, B., & Veugelers, R. (2002). R&D cooperation and spillovers: Some empirical evidence from Belgium. *American Economic Review,92*(4), 1169–1184.

Chapman, G., Lucena, A., & Afcha, S. (2018). R&D subsidies & external collaborative breadth: Differential gains and the role of collaboration experience. *Research Policy,47*(3), 623–636.

Chen, J., Yin, X., & Mei, L. (2018). Holistic innovation: An emerging innovation paradigm. *International Journal of Innovation Studies,2*(1), 1–13.

Chen, Y. J. (2010). Development of a method for ontology-based empirical knowledge representation and reasoning. *Decision Support Systems,50*(1), 1–20.

Chesbrough, H. W. (2003). *Open innovation: The new imperative for creating and profiting from technology*. USA: Harvard Business Press.

Chesbrough, H. (2006). *Open business models: How to thrive in the new innovation landscape*. USA: Harvard Business Press.

Chin, T., Ghouri, M. W. A., Jin, J., & Deveci, M. (2024). AI technologies affording the orchestration of ecosystem-based business models: The moderating role of AI knowledge spillover. *Humanities and Social Sciences Communications,11*(1), 1–13.

Chung, S. (2002). Building a national innovation system through regional innovation systems. *Technovation,22*(8), 485–491.

Coad, A., Segarra, A., & Teruel, M. (2016). Innovation and firm growth: Does firm age play a role? *Research Policy,45*(2), 387–400.

Cohen, W. M., Goto, A., Nagata, A., Nelson, R. R., & Walsh, J. P. (2002). R&D spillovers, patents and the incentives to innovate in Japan and the United States. *Research Policy,31*(8–9), 1349–1367.

Cohen, W. M., & Levinthal, D. A. (1990). Absorptive capacity: A new perspective on learning and innovation. *Administrative Science Quarterly,35*, 128–152.

Colombelli, A., D'Amico, E., & Paolucci, E. (2023). When computer science is not enough: Universities knowledge specializations behind artificial intelligence startups in Italy. *The Journal of Technology Transfer, 48*(5), 1599–1627.

Dahlke, J., Beck, M., Kinne, J., Lenz, D., Dehghan, R., Wörter, M., & Ebersberger, B. (2024). Epidemic effects in the diffusion of emerging digital technologies: Evidence from artificial intelligence adoption. *Research Policy,53*(2), Article 104917.

Damioli, G., Van Roy, V., & Vertesy, D. (2021). The impact of artificial intelligence on labor productivity. *Eurasian Business Review,11*, 1–25.

De Leeuw, T., Lokshin, B., & Duysters, G. (2014). Returns to alliance portfolio diversity: The relative effects of partner diversity on firm's innovative performance and productivity. *Journal of Business Research,67*(9), 1839–1849.

Dimakopoulou, A. G., Chatzistamoulou, N., Kounetas, K., & Tsekouras, K. (2023). Environmental innovation and R&D collaborations: Firm decisions in the innovation efficiency context. *The Journal of Technology Transfer,48*(4), 1176–1205.

Fang, E. (2011). The effect of strategic alliance knowledge complementarity on new product innovativeness in China. *Organization Science,22*(1), 158–172.

Foss, N. J., Lyngsie, J., & Zahra, S. A. (2013). The role of external knowledge sources and organizational design in the process of opportunity exploitation. *Strategic Management Journal,34*, 1453–1471.

Freisinger, E., Unfried, M., & Schneider, S. (2024). The AI-augmented crowd: How human crowdvoters adopt AI (or not). *Journal of Product Innovation Management*. https://doi.org/10.1111/jpim.12708

Fritsch, M., & Aamoucke, R. (2013). Regional public research, higher education, and innovative start-ups: An empirical investigation. *Small Business Economics,41*, 865–885.

Fromhold-Eisebith, M., & Werker, C. (2013). Universities' functions in knowledge transfer: A geographical perspective. *The Annals of Regional Science,51*, 621–643.

Gama, F., & Magistretti, S. (2023). Artificial intelligence in innovation management: A review of innovation capabilities and a taxonomy of AI applications. *Journal of Product Innovation Management*. https://doi.org/10.1111/jpim.12698

Gao, S., Guo, Y., Chen, J., & Li, L. (2016). Factors affecting the performance of knowledge collaboration in virtual team based on capital appreciation. *Information Technology and Management,17*(2), 119–131.

Garbuio, M., & Lin, N. (2021). Innovative idea generation in problem finding: Abductive reasoning, cognitive impediments, and the promise of artificial intelligence. *Journal of Product Innovation Management,38*(6), 701–725. https://doi.org/10.1111/jpim.12602

Gassmann, O., Enkel, E., & Chesbrough, H. (2010). The future of open innovation. *R&d Management,40*(3), 213–221.

Ghobadian, A., Rugman, A. M., & Tung, R. L. (2014). Strategies for firm globalization and regionalization. *British Journal of Management,25*, S1–S5.

Gilsing, V., Nooteboom, B., Vanhaverbeke, W., Duysters, G., & Van Den Oord, A. (2008). Network embeddedness and the exploration of novel technologies: Technological distance, betweenness centrality and density. *Research Policy,37*(10), 1717–1731.

Giuggioli, G., & Pellegrini, M. M. (2023). Artificial intelligence as an enabler for entrepreneurs: A systematic literature review and an agenda for future research. *International Journal of Entrepreneurial Behavior & Research,29*(4), 816–837.

Gnyawali, D. R., & Park, B. J. R. (2011). Co-opetition between giants: Collaboration with competitors for technological innovation. *Research Policy,40*(5), 650–663.

Haefner, N., Wincent, J., Parida, V., & Gassmann, O. (2021). Artificial intelligence and innovation management: A review, framework, and research agenda☆. *Technological Forecasting and Social Change,162*, Article 120392.

Hagedoorn, J. (1993). Understanding the rationale of strategic technology partnering: Interorganizational modes of cooperation and sectoral differences. *Strategic Management Journal,14*(5), 371–385.

Haider, S. (2014). Identification, emergence and filling of organizational knowledge gaps: A retrospective processual analysis. *Journal of Knowledge Management,18*(2), 411–429.

Haider, S., & Mariotti, F. (2010). Filling knowledge gaps: Knowledge sharing across inter-firm boundaries and occupational communities. *International Journal of Knowledge Management Studies,4*(1), 1–17.

Hall, B., Helmers, C., Rogers, M., & Sena, V. (2014). The choice between formal and informal intellectual property: A review. *Journal of Economic Literature,52*(2), 375–423.

Hall, B. H., Lotti, F., & Mairesse, J. (2009). Innovation and productivity in SMEs: Empirical evidence for Italy. *Small Business Economics,33*, 13–33.

Hall, B. H., Lotti, F., & Mairesse, J. (2013). Evidence on the impact of R&D and ICT investments on innovation and productivity in Italian firms. *Economics of Innovation and New Technology,22*(3), 300–328.

Han, G. (2021). The Interplay between Network and Institution: Intergovernmental Network and Antitrust and Merger Laws on Cross-border Acquisitions, 1990–2012. Resourse available at https://nrs.harvard.edu/URN-3:HUL.INSTREPOS:37367327

Huang, J. C., & Newell, S. (2003). Knowledge integration processes and dynamics within the context of cross-functional projects. *International Journal of Project Management,21*(3), 167–176.

Huber, F. (2012). On the role and interrelationship of spatial, social and cognitive proximity: Personal knowledge relationships of R&D workers in the Cambridge Information Technology Cluster. *Regional Studies,46*(9), 1169–1182.

Iammarino, S., & McCann, P. (2013). *Multinationals and economic geography: Location, technology and innovation*. UK: Edward Elgar Publishing.

Isaksson, O. H., Simeth, M., & Seifert, R. W. (2016). Knowledge spillovers in the supply chain: Evidence from the high tech sectors. *Research Policy,45*(3), 699–706.

Isenberg, D. J. (2010). How to start an entrepreneurial revolution. *Harvard Business Review,88*(6), 40–50.

Keding, C. (2021). Understanding the interplay of artificial intelligence and strategic management: Four decades of research in review. *Management Review Quarterly,71*(1), 91–134.

Keding, C., & Meissner, P. (2021). Managerial overreliance on AI-augmented decision-making processes: How the use of AI-based advisory systems shapes choice behavior in R&D investment decisions. *Technological Forecasting and Social Change,171*, Article 120970.

Kobarg, S., Stumpf-Wollersheim, J., & Welpe, I. M. (2019). More is not always better: Effects of collaboration breadth and depth on radical and incremental innovation performance at the project level. *Research Policy,48*(1), 1–10.

Kogut, B., & Zander, U. (1996). What firms do? Coordination, identity, and learning. *Organization Science,7*(5), 502–518.

Korosteleva, J., & Belitski, M. (2015). Entrepreneurial dynamics and higher education institutions in the post-Communist world. *Regional Studies,51*(3), 439–453.

Krishna, V. V. (2019). Universities in the national innovation systems: Emerging innovation landscapes in Asia-Pacific. *Journal of Open Innovation: Technology, Market, and Complexity,5*(3), 43.

Kukreja, S., Maheshwari, G. C., & Singh, A. (2024). Interplay of cross-country distance with cross-border M&A performance: An institutional perspective. *Review of International Business and Strategy,34*(1), 24–39.

Laursen, K., & Salter, A. (2006). Open for innovation: The role of openness in explaining innovation performance among UK manufacturing firms. *Strategic Management Journal,27*(2), 131–150.

Lazzarotti, V., Puliga, G., Manzini, R., Tallarico, S., Pellegrini, L., Eslami, M. H., Ismail, M., & Boer, H. (2023). Collaboration with universities and innovation efficiency: Do relationship depth and organizational routines matter? *European Journal of Innovation Management, Ahead-of-Print.*https://doi.org/10.1108/EJIM-03-2023-0241

Li, C., Xu, Y., Zheng, H., Wang, Z., Han, H., & Zeng, L. (2023). Artificial intelligence, resource reallocation, and corporate innovation efficiency: Evidence from China's listed companies. *Resources Policy,81*, Article 103324.

Li, W., Liu, K., Belitski, M., Ghobadian, A., & O'Regan, N. (2016). e-Leadership through strategic alignment: An empirical study of small-and medium-sized enterprises in the digital age. *Journal of Information Technology,31*, 185–206.

Liao, M. Y., & Cao, X. (2018). The influence factors of knowledge potential difference and knowledge transfer in collaborative innovation enterprises. *Systems Engineering,36*(08), 51–60.

Lin, J. Y., & Yang, C. H. (2020). Heterogeneity in industry–university R&D collaboration and firm innovative performance. *Scientometrics,124*, 1–25. https://doi.org/10.1007/s11192-020-03436-2

Link, A. N., & Scott, J. T. (2019). The economic benefits of technology transfer from US federal laboratories. *The Journal of Technology Transfer,44*, 1416–1426.

Lippman, S. A., & Rumelt, R. P. (1982). Uncertain imitability: An analysis of interfirm differences in efficiency under competition. *The Bell Journal of Economics,13*, 418–438.

Liu, Y., Li, Y., Shi, L. H., & Liu, T. (2017). Knowledge transfer in buyer-supplier relationships: The role of transactional and relational governance mechanisms. *Journal of Business Research,78*, 285–293.

Mariani, M. M., & Belitski, M. (2023). The effect of coopetition intensity on first mover advantage and imitation in innovation related coopetition: Empirical evidence from UK firms. *European Management Journal,41*(5), 779–791.

Mishra, A., Chandrasekaran, A., & MacCormack, A. (2015). Collaboration in multi-partner R&D projects: The impact of partnering scale and scope. *Journal of Operations Management,33*, 1–14.

Mishra, S., & Tripathi, A. R. (2021). AI business model: An integrative business approach. *Journal of Innovation and Entrepreneurship,10*, 18. https://doi.org/10.1186/s13731-021-00157-5

Mudambi, S. M., & Tallman, S. (2010). Make, buy or ally? Theoretical perspectives on knowledge process outsourcing through alliances. *Journal of Management Studies,47*(8), 1434–1456.

Negassi, S. (2004). R&D co-operation and innovation a microeconometric study on French firms. *Research Policy,33*(3), 365–384.

Nelson, R. R. (1982). The role of knowledge in R&D efficiency. *The Quarterly Journal of Economics,97*(3), 453–470.

Nooteboom, B. (1999). Innovation and inter-firm linkages: New implications for policy. *Research Policy,28*(8), 793–805.

Office for National Statistics. (2023b). Business Structure Database, 1997-2022: Secure Access. [data collection]. 15th Edition. UK Data Service. SN: 6697, https://doi.org/10.5255/UKDA-SN-6697-15

Office for National Statistics. (2023a). UK Innovation Survey, 1994-2020: Secure Access. [data collection]. 8th Edition. UK Data Service. SN: 6699, https://doi.org/10.5255/UKDA-SN-6699-8

Paschen, U., Pitt, C., & Kietzmann, J. (2020). Artificial intelligence: Building blocks and an innovation typology. *Business Horizons,63*(2), 147–155.

Perifanis, N. A., & Kitsios, F. (2023). Investigating the influence of artificial intelligence on business value in the digital era of strategy: A literature review. *Information,14*(2), 85.

Petersson, L., Larsson, I., Nygren, J. M., Neher, M., Nilsen, P., Reed, J. E., Svedberg, P., & Tyskbo, D. (2022). Challenges to implementing artificial intelligence in healthcare: A qualitative interview study with healthcare leaders in Sweden. *BMC Health Services Research,22*(1), 850. https://doi.org/10.1186/s12913-022-08215-8

Phelps, C., Heidl, R., & Wadhwa, A. (2012). Knowledge, networks, and knowledge networks: A review and research agenda. *Journal of Management,38*(4), 1115–1166.

Piergiovanni, R., Carree, M. A., & Santarelli, E. (2012). Creative industries, new business formation, and regional economic growth. *Small Business Economics,39*, 539–560.

Ries, E. (2011). The lean startup: How today's entrepreneurs use continuous innovation to create radically successful businesses. Crown Currency.

Rodriguez-Enriquez, C. A., Alor-Hernandez, G., Mejia-Miranda, J., Sanchez-Cervantes, J. L., Rodriguez-Mazahua, L., & Sanchez-Ramirez, C. (2016). Supply chain knowledge management supported by a simple knowledge organization system. *Electronic Commerce Research and Applications,19*, 1–18. https://doi.org/10.1016/j.elerap.2016.06.004

Roper, S., Love, J. H., & Bonner, K. (2017). Firms' knowledge search and local knowledge externalities in innovation performance. *Research Policy,46*(1), 43–56.

Rubin, M., & Donkin, C. (2022). Exploratory hypothesis tests can be more compelling than confirmatory hypothesis tests. *Philosophical Psychology,37*(8), 2019–2047.

Schofield, T. (2013). Critical success factors for knowledge transfer collaborations between university and industry. *Journal of Research Administration,44*(2), 38–56.

Sorenson, O., Rivkin, J. W., & Fleming, L. (2006). Complexity, networks and knowledge flow. *Research Policy,35*(7), 994–1017. https://doi.org/10.1016/j.respol.2006.05.002

Sydow, J. (1992). *On the management of strategic networks*. USA: Belhaven Press.

Teece, D. J., Pisano, G., & Shuen, A. (1997). Dynamic capabilities and strategic management. *Strategic Management Journal,18*(7), 509–533.

Tiwana, A., & Mclean, E. R. (2005). Expertise integration and creativity in information systems development. *Journal of Management Information Systems,22*(1), 13–43.

Tsai, Y. H., Joe, S. W., Lin, C. P., Wu, P. H., & Cheng, Y. H. (2017). Modeling knowledge sharing among high-tech professionals in culturally diverse firms: Mediating mechanisms of social capital. *Knowledge Management Research & Practice, 15*(2), 225–237.

Un, C. A., & Asakawa, K. (2015). Types of R&D collaborations and process innovation: The benefit of collaborating upstream in the knowledge chain. *Journal of Product Innovation Management,32*(1), 138–153.

Un, C. A., & Rodríguez, A. (2018). Local and global knowledge complementarity: R&D collaborations and innovation of foreign and domestic firms. *Journal of International Management,24*(2), 137–152.

Van Beers, C., & Zand, F. (2014). R&D cooperation, partner diversity, and innovation performance: An empirical analysis. *Journal of Product Innovation Management,31*(2), 292–312.

Vanyushyn, V., Bengtsson, M., Näsholm, M. H., & Boter, H. (2018). International coopetition for innovation: Are the benefits worth the challenges? *Review of Managerial Science,12*, 535–557. https://doi.org/10.1007/s11846-017-0272-x

Verganti, R., Vendraminelli, L., & Iansiti, M. (2020). Innovation and Design in the Age of Artificial Intelligence. *Journal of Product Innovation Management,37*(3), 212–227. https://doi.org/10.1111/jpim.12523

Veugelers, R. (1997). Internal R & D expenditures and external technology sourcing. *Research Policy,26*(3), 303–315.

Vivona, R., Demircioglu, M. A., & Audretsch, D. B. (2023). The costs of collaborative innovation. *The Journal of Technology Transfer,48*(3), 873–899.

West, J., & Bogers, M. (2014). Leveraging external sources of innovation: A review of research on open innovation. *Journal of Product Innovation Management,31*(4), 814–831.

Williamson, O. E. (1979). Transaction-cost economics: The governance of contractual relations. *The Journal of Law and Economics,22*(2), 233–261.

Wooldridge, J. M. (2003). *Econometrics. A modern approach*. Thomson South-Western.

Yigit, A., & Kanbach, D. K. (2021). The importance of artificial intelligence in strategic management: A systematic literature review. *International journal of strategic management*: IJSM, 21(1 (March 2021)), 5–40.

Yu, X., Dai, Y., Xu, Q., & Ye, Q. (2023). Knowledge collaboration and benefits of standard implementation of enterprise in technology standard alliance. *Journal of the Knowledge Economy,15*(2), 8534–8562.