Department of Economics and Statistics "Cognetti de Martiis"
Campus Luigi Einaudi, Lungo Dora Siena 100/A, 10153 Torino (Italy)
www.est.unito.it

Dipartimento Economia e Statistica Cognetti de Martiis

Working Paper Series

15/23

EVALUATING INTERNAL AND EXTERNAL KNOWLEDGE SOURCES IN ADOPTING ARTIFICIAL INTELLIGENCE

ELETTRA D'AMICO, MAKSIM BELITSKI and ALESSANDRA COLOMBELLI

Bureau of Research on Innovation, Complexity and Knowledge

UNIVERSITÀ DEGLI STUDI DI TORINO

The Department of Economics and Statistics "Cognetti de Martiis" publishes research papers authored by members and guests of the Department and of its research centers. ISSN: 2039-4004

Evaluating Internal and External Knowledge Sources in Adopting Artificial Intelligence

Elettra D'Amico*
Department of Management and Production Engineering (DIGEP), Politecnico di Torino
C.so Duca degli Abruzzi 24, Turin, 10129, Italy
Email: elettra.damico@polito.it

Maksim Belitski
Henley Business School, University of Reading
Whiteknights campus, Reading, RG6 6UD, UK
Email: m.belitski@reading.ac.uk

Alessandra Colombelli
Department of Management and Production Engineering (DIGEP), Politecnico di Torino
C.so Duca degli Abruzzi 24, Turin, 10129, Italy
Email: alessandra.colombelli@polito.it

Abstract

Artificial intelligence has emerged as a key technology that individuals and businesses utilize to grow and innovate with the paucity of understanding what drives its adoption. This study examines how investments in internal R&D and Information and Communication Technologies (ICT), combined with open innovation through knowledge spillovers, R&D acquisitions, and collaborations with external partners, can encourage firms to embrace AI. Drawing from the Technology – Organizational and Environmental (TOE) context framework and integrating it with the recombinant knowledge perspective, we assess the interplay between a firm's organizational and technological contexts, as well as the impact of knowledge spillovers and collaborations. This assessment is based on micro-level data from UK firms spanning 2004-2020. Our findings highlight the distinct influence of investments in knowledge and capabilities, in conjunction with collaborative engagements on a firm's propensity to adopt AI.

Keywords: R&D; ICT; AI; knowledge collaboration, knowledge spillovers; innovation

JEL Classification: D24; O31; O33; H40

1. Introduction

The predicted rapid adoption of AI (World Economic Forum, 2018) made this technology a necessary strategy for business and development, prioritizing investment in AI research (Babina et al., 2020; Samoili et al., 2020; Van Roy, 2020). AI, as well as new emerging technologies such as blockchain and cloud computing, is an adaptive technology with broad applicability. This

characteristic of wide applicability makes different appropriability hypotheses compared to other discrete technologies with narrower applications. In the case of AI, the innovator's share of the benefits may be higher because innovators can enjoy the economies of scope resulting from the technology's broad applicability. Theoretically, the ability of AI technologies to enhance cross-location coordination procedures might result in further differentiation of global value chains as well as a rise in the production’s flexibility and efficiency in addition to the economies of scale and scope (Dachs et al., 2019; Kinkel et al., 2022). According to Kinkel et al. (2020), the percentage of organizations that have already adopted AI ranges from 16 to 23 percent, based on 309 German worldwide (Ransbotham et al., 2017) . Our data demonstrate that around 14% of the firms in the United Kingdom have made an attempt or have already adopted AI (ONS, 2020).
How companies can increase their AI adoption is still widely understudied (Kinkel et al., 2022). The actual tendency is to consider only the technical capabilities and competencies required to adopt AI technology (Chui & Malhotra, 2018; Daugherty & Wilson, 2018; Haefner et al., 2021; Razzaque, 2021) and almost ignores that adoption rates and uses by firms also depend on external and internal context (Grover et al., 2022; Rammer et al., 2022)Few explanations of how and why firms adopt AI - and what knowledge inputs are required for such technology adoption - have been offered by research to date.

As far as we know, few studies investigate the influence of the organizational, technological and external contexts and the role of knowledge recombination in increasing AI adoption rates. In fact, the availability of various digital skills, R&D and ICT intensity, the strategic direction of spillovers, collaboration with external partners or acquiring external knowledge may influence the adoption of new technologies, such as AI. Because of this research gap, there are still no empirical results on whether the technological, organisational and external contexts (Kinkel et al., 2022) in terms of recombining of existing internal and external knowledge (Antonelli & Colombelli, 2017) can facilitate AI adoption.

This study aims at filling this gap and answers the following research question: what technological, organizational and external knowledge contexts are more likely to increase AI adoption in innovative firms? We based our research model combining for the first time the Technology- Organization-Environment with the recombinant knowledge approach (Antonelli and Colombelli, 2017) to analyze company-level adoption of AI technology as the outcome.

In this work we analyze how changes in technological, organizational and external contexts affect the adoption of new technology. The TOE framework we have chosen has proven to be an applicable concept for explaining cross-industry new technology adoption (Bhattacharya & Wamba, 2018; Tornatzky et al., 1990), such as AI (Kinkel et al., 2022). In our work, internal (i.e. organizational and technological) and external environmental contexts provide a higher descriptive contribution to the adoption of AI technologies.

Second, we apply the TOE framework to examine the relationships between three contexts of knowledge sourcing (Technological – Organizational – Environmental) and their influence on the adoption of AI. The aim is to understand which factors in the TOE framework favour the adoption of AI only at the level of internal firm investment in knowledge and which external knowledge sources (Chesbrough & Brunswicker, 2013; Schroll & Mild, 2011) become a channel for AI adoption.

The rest of the paper is structured as follows. Section 2 reviews the micro-foundations on the TOE and recombinant knowledge approach. This is followed by section 3 with the model and data and section 4 with interviews. Estimation results are presented in section 5. Section 6 discusses and concludes.

2. Theoretical framework

2.1. Recombinant knowledge approach and TOE framework for AI adoption

The TOE framework was developed in 1990 (Tornatzky & Fleischer, 1990) with the aim of outlining the three dimensions of a company's context—technological, organizational, and environmental contexts—that affect the process of adopting a technological innovation (Kinkel et al., 2022). The technological context refers to the technological characteristics available in the organization for technology adoption. It includes both the structural aspects and the specialized human resources (Oliveira et al., 2014). The organizational context refers to the resources available internally within the company that can be used to facilitate the adoption of an innovation (Lippert & Govindarajulu, 2006). The environmental context encompasses a larger area within which the firm interacts and conducts its business; it is influenced by the company's competitors, access to resources offered by others, and interactions with government (Tornatzky & Fleischer, 1990).

Due to limited resources available in the firms, the recombinant knowledge approach (RKA) should be applied to explain new technology adoption (Ciarli et al., 2021; Xiao & Boschma, 2022). By adapting the recombinant knowledge approach (Antonelli & Colombelli, 2015, 2017) to the TOE framework, we can examine the role of internal and external characteristics of knowledge independently and the mechanism that allows for the recombination of knowledge internally (technological and organizational context) and externally (environmental context). In this perspective, the technological context of knowledge represents the firm's technological resources, such as advanced equipment, ICT, software and hardware expenditure (Aboelmaged, 2014; Hall et al., 2013). The organizational context of knowledge represents investments in internal sources of knowledge (e.g., R&D) (Berchicci, 2013; Kinkel et al., 2022). Environmental context represents various sources of external knowledge such as active knowledge collaboration with suppliers, customers, competitors, consultants, universities and government (Audretsch et al., 2021; Cappelli et al., 2014), knowledge spillovers (Cassiman & Veugelers, 2002; Iammarino & McCann, 2006; Jaffe & Lerner, 2001) and buying R&D (Cassiman & Valentini, 2016; Ebersberger et al., 2021). While it may not be obvious technological and organizational knowledge contexts are often connected and aligned (Antonelli & Colombelli, 2017; Audretsch & Belitski, 2023). In fact, new knowledge is a result of a portfolio of various existing knowledge within a firm (Antonelli, 1999): such as training, internal R&D, search for technology and outside the firms, such as knowledge spillovers, knowledge collaborations and other (Audretsch & Belitski, 2023; Chesbrough, 2003, 2006; West & Bogers, 2017).

In particular, the TOE framework assumes that new technologies are adopted by changes in organizational, technological, and external context with the theory not explicitly acknowledging the interactions within the context. At the same time, the adoption of new technologies stems from active external knowledge collaborations with suppliers, customers, universities, and competitors (Kobarg et al., 2019), in addition to sourcing knowledge via spillovers or buying R&D from other firms and industries. Following these arguments, reading the TOE framework through the lens of the recombinant knowledge approach seems the most appropriate in the study of AI adoption in business contexts.

2.2. AI adoption and internal knowledge contexts: Technological and Organizational

Investment in R&D and ICT is a significant source of relative competitive advantage for firms (Antonelli & Colombelli, 2017; Cohen & Levinthal, 1989; Hall et al., 2013; Hall & Mairesse, 2009; Khalil & Belitski, 2020). Firm's R&D and ICT spending on revenue is reasonably considered one of the main drivers of new technology adoption (Kinkel et al., 2022). R&D and ICT investment enrich organizational and technological contexts of a firm by creating new knowledge internally as well as significantly increasing firm's ability to effectively capture, transform, integrate external knowledge (Jantunen, 2005; Straub & Watson, 2001) within technological and organizational context and in doing so to improve firm's competitive market position.

Firms with greater intensity of R&D and ICT are more likely to adopt new technologies (Agostini & Nosella, 2019; Hall et al., 2013), such as AI, (Kinkel et al., 2022).

Both R&D and ICT investments aim to develop specific capabilities and skills to enable the adoption of AI technology. Companies with a high R&D intensity are likely to have the ability and willingness to develop a strong organizational context, act more innovatively, and adopt new technologies (Bolton, 1993), such as AI (Kinkel et al., 2022). Investment in ICT, software and hardware development tools are crucial for the adoption of AI, (Bughin et al., 2018). Johannessen (2020) found that technological context is important in the digital age and that new technologies adoption requires aligned business and digital competencies (e.g., collaboration, change, science, engineering, social, leadership, values). Our motivation is to examine investments in R&D and ICT for AI adoption. Both investments facilitate technological and organizational competences, generating new knowledge (Hall et al., 2013) and recognizing external knowledge (Cohen & Levinthal, 1989) such as new technologies. We hypothesize:

H1: Investment in internal R&D increases the propensity to adopt AI.

H2: Investment in internal ICT increases the propensity to adopt AI.

There is a lack of research on how the investment in R&D will affect AI adoption across different industries and how the knowledge embedded in the organization can be effectively aligned with the technological context. A firm which simultaneously increases investments in R&D and ICT (Cassiman & Valentini, 2016) may expect synergetic affects from both types of internal knowledge (R&D and ICT). Black and Lynch (2001) focus on the interaction between ICT, human capital, and organizational innovation, while Hall et al. (2013) focus on the interaction between investment in ICT and R&D for firm performance. These studies have two important omissions; first, they assume a direct relationship between knowledge investment and firm performance, potentially bypassing an important step in knowledge acquisition that enables to development and adopt new technologies to achieve higher performance. Second, it is the intensity of knowledge investment that matters (Kinkel et al. 2022), rather than how much you invest in R&D and ICT.

The TOE framework is relevant in addressing the RKA effects within internal and external knowledge contexts, including investment in R&D and ICT. It enables us to account for the diversity of organizational and technological contexts which may enhance firms to adopt AI. The investment in ICT, in addition to general investment in knowledge, increases digital competencies that allow to adopt AI . Technological and organizational contexts altogether support the successful realization of strategic decisions, leading to higher competencies and cognition regarding what technology to adopt and how. We hypothesize:

H3: There is a positive interaction effect between investment in internal R&D and ICT and the propensity to adopt AI.

2.3. AI adoption and external knowledge context: environmental

Buying R&D

Investing in external R&D makes easier and faster to access the resources needed to adopt new technologies and thus innovate. Being open to external knowledge allows companies to increase innovation productivity and reducing costs (Cassiman & Valentini, 2016; Chesbrough, 2003; Faems et al., 2010). The environmental context represents varies sources of external knowledge, the access to this context enable to overcome the problems related to the increasing costs of internal R&D (Chesbrough, 2003). Firms that become more permeable to the external environment and thus rely on externally developed knowledge and new technologies can generate new revenues and decrease the cost and time of internal R&D and new technology adoption. Buying external knowledge gain firms to access to valuable knowledge more quickly (Chesbrough, 2003; Laursen & Salter, 2006).

Studies Firms that are open to external knowledge can identify a large number of knowledge transfer opportunities (Cassiman & Valentini, 2016; Rothaermel & Deeds, 2006) and transform them into new ideas and products. Adoption of new technology, such as AI, requires time for learning the new technologies and also how to adapt and utilize it, while buying R&D speeds up the learning process. As a consequence, acquiring external knowledge in a form of R&D creates ready-made solutions for firms, facilitating prompt technology adoption and decreases the costs of engaging in AI technology adoption. We hypothesize:

H4: External R&D investment increases the propensity to adopt AI.

Knowledge collaboration

Active knowledge collaboration with external partners and knowledge spillovers brings new knowledge to a firm that can further contribute to existing internal knowledge and become important knowledge inputs. The probability of innovation increases with recombination of investment in internal knowledge (e.g., R&D, training, ICT) (Audretsch & Belitski, 2020; Griliches, 1979; Hall et al., 2013) as well as external knowledge such as knowledge collaboration and spillovers (Antonelli & Colombelli, 2015; Faems et al., 2010).

Knowledge collaboration provides access to inter-organisational knowledge, expertise and skills (Faems et al., 2005) which can be used to recognize the type of new technology and appreciate its usefulness and value. Collaboration reduces innovation costs among partners per unit of production (Veugelers, 1997), and mutually benefits from the technological knowledge of partners (Feldman & Audretsch, 1999). Knowledge collaboration with external partners increases each firm's and joint competitiveness in a market by integrating, modifying and creating new combinations of resources (Cohen & Levinthal, 1989; Motti & Sachwald, 2003; Mowery et al., 1998) that could create a springboard for developing technology in-house or adopting external technologies such as the most advanced digital technologies - AI. Knowledge collaboration is also a channel for the adoption of new technologies as it allows advancement of innovation and reduction of innovation costs. We hypothesize:

H5: Knowledge collaboration increases the propensity to adopt AI.

Knowledge spillovers

In addition to knowledge collaboration, where financial compensation is sought, knowledge spillovers can become useful input to understand and adopt technologies (Agarwal et al., 2010; Link & Scott, 2019).

Knowledge sourcing via knowledge spillovers (KS) (Feldman & Audretsch, 1999) may facilitate firm's competitive advantage by sharing existing knowledge and technologies as well as increasing the productivity, innovation by new product development internally or co-creation of new products (Audretsch & Belitski, 2020). KS over via different open channels such as through conference attendance, membership in technology conferences, patent filings and publications (Audretsch & Keilbach, 2008; Cassia et al., 2009). Internal knowledge generated as a result of KS further contributes to the firm's ability to recombine and create new knowledge (Weitzman, 1996).

KS (Audretsch & Feldman, 1996) can facilitate the adoption of new technologies, such as AI, as they carry tacit information on new approaches of working, that is further absorbed by a firm. KS carry information which is then used by a firm to make sense out of available sources of innovation, including new technologies such as AI. For example, high-tech companies, that were previously leaders in the adoption of digital technologies, are now leaders in the adoption and use of AI (Bughin & Hazan, 2017). We hypothesize:

H6: KS increase the propensity to adopt AI.

Recombination of new knowledge further becomes possible when spillovers are embedded in knowledge collaboration with external partners (Bogers et al., 2017). Easy access to KSs enables new knowledge generated by active collaboration between firms and external partners (Antonelli & Colombelli, 2015; Van Beers & Zand, 2014). Moreover, firms have an incentive to invest in such collaboration to facilitate the adoption of new technologies, for several reasons. First, knowledge collaboration enables recognition of tacit knowledge from different external partners and assimilating it via spillovers (Audretsch & Feldman, 1996; Cassiman & Veugelers, 2002). Second, knowledge collaboration eases learning within an organization and adapt KS to the firm's routines. Third, knowledge collaboration helps firms increase their economic value of KS by integrating and modifying external knowledge, including collaborating with external partners (Bogers et al., 2017; Kobarg et al., 2019; Motti & Sachwald, 2003).

For example, a firm can combine KS with other external knowledge sources such as purchasing external R&D or collaborating with external partners to adopt new technology. Finally, increased collaboration on knowledge with external partners when KS are high allows for greater exploitation of the outgoing firm's technology (Veugelers & Schneider, 2018), as well as unpacking a complexity of knowledge by increasing the speed of knowledge recognition, adoption and commercialization. Antonelli (1999) described innovation as a recombinant knowledge process in which existing technological knowledge is an input for the generation of new knowledge and can be further accumulated (Griliches, 1979), and exploited for the adoption of new technologies. We hypothesize:

H7a: There is a positive interaction effect between investment in external R&D and KS on a propensity to adopt AI.

H7b: There is a positive interaction effect between knowledge collaboration with external partners and KS on a propensity to adopt AI.

The conceptual model is illustrated in Figure 1.

FIGURE 1

3. Data and method

3.1. Sample description

To test our research hypothesis we used three datasets from the Office of national statistics in the UK as well as we did selected interviews to better understand the context of AI adoption. Three database include the Business Structure Database (BSD) (Office for National Statistics, 2021a), the UK Innovation Survey (UKIS) (Office for National Statistics, 2022), and the E-commerce micro data (Office for National Statistics, 2021b) during 2004-2020. We started by identifying the companies that adopted AI in the in a form of using AI and robotics for services and operations. First, we collected data on companies that use AI from the E-commerce survey. Second, we matched E-commerce data on AI adoption to BSD and CIS micro data by firm identifier and year.

The Given that BSD and E-commerce produce annual data and UKIS is a biannual we matched E-commerce and BSD variable for the years 2005, 2007, 2009, 2011, 2013, 2015, 2017 and 2019 to a correspondent CIS survey wave. The BSD and E-commerce data includes information on what technology is used and for what purpose, the firm legal status, ownership, export, turnover, employment, industry and postcode. Our final sample has 13516 firms with 23041 observations over 2004-2020, with 8171 firms observed only once during 2004-2020, 2855 firms observed two times, 1598 firms observed three times, 435 firms observed four times, 243 firms observed five times, 119 firms observed six times, 66 firms observed seven times and 29 firms observed eight times (all UKIS waves). Tables A.1, A.2 and A.3 show the firms distribution across UK regions, sectors and firms' size.

After cleaning data for the missing values of the variables of interest, and non-active and dormant firms, we were left with a total of 24286 observation (out of 1165584). We replaced non-missing values with zeros for knowledge collaboration partners. This extended the original samples of 24286 observations and the extended sample (non-zero) for 52920 observations, used in the robustness check (see Table A.7. in Appendix).

The geographical and industrial structures of firms do not change neither the distribution of firms across different sizes between two samples.

3.2. Methodology

The main shortcoming in the previous models that aimed to analyze the role of knowledge investment in firm performance and technology adoption (Griliches, 1979) has overlooked the role of internal and external knowledge as a boundary condition for technology adoption (Li et al., 2016). Thus, the prior approach has been limited in assigning external knowledge sources as a key conduit in technology adoption (Antonelli & Colombelli, 2017).

In this study we are interested in estimating a model for AI adoption using a multivariate logistic regression analysis (Wooldridge, 2009). Our econometric model is as follows:

$$Prob(y_{it} = 1) = \beta_0 + \beta_i x_{it-1} + \lambda_i z_{it-1} + \omega_r + \rho_j + a_t + u_{it} \qquad (1)$$

Equation (1) is the logistic cumulative distribution function. x_{it} is a vector of explanatory variables such as investment in R&D and other technology in-house, buying external R&D (Hall et al. 2013), engaging in collaboration with external knowledge partners (Audretsch et al., 2021; Audretsch & Belitski, 2020) and accessing KS (Cassiman & Veugleres, 2002) in t-1 for firm i, while z_{it} is a vector of other firm's characteristics such as age, employment, ownership and other at time t-1 for firm i, u_{it} is an error term for firm i at time t (Wooldridge, 2009: 517). Vectors ω_r, ρ_j, a_t are region, industry and time fixed effects. There has been no multicollinearity found in all variables. Table 1 illustrates the list of variables used in equation (1).

3.3. Variables

Dependent variables

For our empirical model, we used a single dependent variable, AI. It is s a binary variable equal to one when the firm adopts AI. We used three different inclusion criteria. First, the firm is known to adopt AI if it belongs to one of the industries (SIC2007) that adopt AI. The information on firm adopting AI was imported from the external source – Beauhurst data(Beauhurst, 2021) that collects information on companies of different size and stage in the United Kingdom and their five digits SIC 2007 industry location, that allowed us to identify firms located within the same five-digit sectors in UKIS. Second, it has invested in advanced equipment, and ICT, soft and hardware. Third, the proportion of employees who hold a university and higher in math, engineering or technology degree is greater than zero.

Explanatory and control variables

Our main explanatory variables are an investment in R&D and ICT (internal knowledge), KS and knowledge collaboration (external knowledge). Investment in R&D and ICT were used in prior research (Griffith et al. 2006; Hall et al. 2012, 2013) and are associated with firms' absorptive capacity (Cohen & Levinthal, 1990). We use the R&D and ICT expenditure to sales ratio known as R&D and ICT intensity. We take a natural logarithm of one plus R&D and ICT intensity to account for the non-linear effects of absorptive capacity (Denicolai et al., 2016) on innovation and productivity.

Incoming KS are calculated drawing on Audretsch and Keilbach (2008) and Cassiman and Veugelers (2006) as of the importance of innovation activities knowledge from various external sources such as conferences, trade fairs; professional and industry associations; technical, industry or service standards; scientific journals, trade/technical publication. The variables have been summed up and rescaled between zero and one.

Prior studies have used various forms of KS including patent citations that mirror (unobservable) knowledge flows (Almeida, 1996; Jaffe, et al. 1993) and, thus, are frequently used as a proxy for KS. To capture the effect of high-tech spillovers in the past authors constructed a KS that represents the count of patent citations (Belenzon & Schankerman, 2013).

Knowledge collaboration is an important channel of knowledge transfer: therefore, we included further collaboration variables across six main types of collaboration partners (Cassiman & Veugelers, 2002; Faems et al., 2005) including government, universities, consultants, customers, suppliers, and the enterprise groups.

Factors that may directly affect the adoption of AI constitute our control variables. First, we used *"employment" as* the number of employees (small, medium, and large) taken in logarithms as well as firm age (Roper et al., 2017). We control for the firm's absorptive capacity by controlling for a share of employees with a BSc degree in science, i.e., "scientists" (Cohen & Levinthal, 1989). We controlled for the appropriability of innovation (Arora et al., 2016), measured as the average of appropriability strategies used by firms (patents) and "foreign" as firm foreign ownership (Love et al., 2014). We add the firm's "*Reporting units"* (i.e. count of the number of units reported) and for "product innovation".

Finally, we include industry and region fixed effects. We refer the reader to Table A.4 for a description of the variables and Table A.5 for summary statistics, whereas Table A.6 contains the correlations between examined study variables.

4. Interview Data and methods

As a follow up of our empirical estimation we deployed additional research method to shed more light on the context and reasoning for AI adoption. Using the Beauhurst data on firms that adopt AI (as we were unable to identify a firm from using the ONS micro-data), we selected four key companies who reported AI adoption in the leading industries where AI is a common-p;lace , but also where AI is an emerging technology. We approached founders and managers directors and carried out five semi-structured interviews with firms of different sizes, industries and operating in different markets from February 2022 to June 2022 (see Table B.1). This enabled a topic-based approach to the theme and based on these topics, asked open, directed and even confrontational questions within the scope of the interview (Flick, 2019). The script contained two sections. The first presented the research project with a brief explanation of the research topic and clarification of the interview structure before requesting information from the interviewee to characterize the sample and description of the company's business and AI use. The second section raised topics referring to internal knowledge, knowledge spillovers and knowledge collaboration, and to what extent this process represented a reality inside the organization, for example how KS function within its framework, what were the main form of collaborations, how the organization defined the relevance of different knowledge and how this may affect the AI use and adoption. To undertake the interviews, the first contact invited respondents to participate while informing them of the anonymous nature of the research in terms of names and organizations. The choice of interviewees took place through means of nomination by specialists in the area who provided suggestions on whom to invite. We held the interviews by Teams, in keeping with the same position of other qualitative research studies (Sarkar, 2017; Shankar & Clausen, 2020). We recorded all of the interviews for their subsequent transcription and with the average interview time recorded as 35 minutes. With the data collected, we applied content analysis to identify what constitutes KS. This method is derived from how the phenomenon under study belongs to an organizational context, enabling the codification and categorization of behaviors, acts, activities, strategies, relationships and interactions, conditions and limitations, among other aspects. We manually completed the coding and categorization of the data obtained from the interviews. The interview transcript extracts and the major results and conclusions are reported in Appendix B.

5. Results

5.1. Hypotheses testing

We estimated equation (1) using the sample of matched BSD-UKIS with AI adoption as a binary dependent variable (Table 1).

TABLE 1

Our H1 is supported by the positive effect of internal R&D intensity on AI adoption (1.008, p<0.10). Consistent with the R&D- AI adoption results, the effect of ICT intensity on the propensity to adopt AI is positive and significant (1.055, p<0.01), supporting H2. The role of internal R&D and ICT investments in adopting AI advances what we know about absorptive capacity and a firm's competencies for firm performance (Leiponen & Helfat, 2010). Consistent with prior research on innovation, investment in internal knowledge has had an essential effect beyond firm performance on a firm's ability to recognize, adopt and implement AI. In testing the complementarities between R&D and ICT, the interaction coefficient of internal R&D and ICT is insignificant, hence not supporting H3. This finding is unexpected and intriguing, which means that investment in R&D and ICT could be used interchangeably for the adoption of AI.

In search of sources of knowledge, firms buy external R&D, ally with external partners in R&D collaborations or access KS. Model 4 in Table 4 demonstrates that an increase in investment in external R&D intensity is positively associated with the propensity to adopt AI (1.091, p<0.01), supporting H4. Considering different forms of knowledge collaboration, Models 4-6 report that collaboration with suppliers (1.216, p<0.01), customers (1.541, p<0.01), competitors (1.381, p<0.01) and universities (1.226, p<0.01) is associated with an increased in AI adoption propensity, supporting H5. The role of KS has been discussed as the availability of "free" knowledge; however, it may still require a cost of engagement with external knowledge (Audretsch & Belitski, 2023; Saura et al., 2023). However, not all firms are ready to endure spillovers. We found that an increase in the availability of KS increases the propensity to adopt AI, however the coefficient is significant under 6 percent (H6 is supported). The interaction between KS and various forms of external knowledge sourcing via knowledge collaboration are not statistically significant. For example a simultaneous increase in KS and external R&D does not change the likelihood of AI adoption, not supporting H7a. External knowledge collaboration bears a cost and in the environment with available KS from competitors (Cappelli et al., 2014) as well as suppliers and customers (Laurtsen and Salter, 2006) firm managers may want to choose between investing in knowledge collaboration or relying on spillovers. Given that spillovers is a form of an externality availability of knowledge and its transfer via spillovers is likely to be preferred form of external knowledge nd technology sourcing. To prove the argument our interaction analysis of knowledge spillover and collaboration with suppliers are negative which demonstrates that an increase in spillovers and subsequent collaboration with suppliers reduces the propensity of AI adoption by 3.9% (0.961, p<0.01). There is a similar case with customers when an increase in spillovers and collaboration reduces the propensity of AI adoption with costumers by 4.8 % (0.952, p<0.01) not supporting H7b (Models 5 and 6, Table 4). We demonstrate that there could be a general perception that KS is an alternative pathway of knowledge transfer, and it is a substitute to collaboration with suppliers and customers. This means that the company who will wish to increase the likelihood of adoption of AI will choose between engagement with customers and suppliers versus accessing spillovers, as spillovers have a cost (Mansfield et al., 1981; Audretsch & Belitski, 2020).

5.2 Robustness check

Based on the outcomes of estimation (1) and Models 6, we plotted the moderating effects of KS on AI adoption (Figure 2), predicting also the level of the interaction between KS and external R&D (Figure 3), and collaborations with partners – supplier collaboration (Figure 4), competitors collaboration (Figure 5), customers collaboration (Figure 6), consultant collaboration (Figure 7), universities collaboration (Figure 8) and government collaboration (Figure 9). Predictive margins diagrammatically illustrate the relationship between knowledge spillovers, collaboration and the propensity to adopt AI in a company. One of the most interesting findings here is that an increase in KS (Figure 2) as well as collaboration with different external partners (Figure 4 - 9) may either complementary, no effect or a substitution effect on AI adoption. The choice depends on the type of external partner and the type of knowledge embedded in the partner.

FIGURE 2

FIGURE 3

For example, Figure 2 demonstrates that an increase in KS increases the probability of AI adoption by a firm (from 0.095 to 0.12), supporting H6. Figure 3 demonstrates that an increase in KS does not facilitate the effect of external R&D on the propensity to adopt AI. The more external R&D collaboration the better, but KS does not moderate it, not supporting H7a.

FIGURE 4

FIGURE 5

Figures 4 shows that an increase in KS (from 0 to 12) does not change the expected level of AI adoption even is KS increases not supporting H7b.

Figure 5 demonstrates that an increase in KS and collaboration with competitors increases the probability of AI adoption by firms, supporting H7b. The increase of AI adoption is higher for firms that consider collaboration with competitors relatively important or very important (from 0.11 to 0.14). This finding suggest that it is a combination of KS and high level of collaboration with competitors is mutually reinforcing and complementary for adopting AI.

FIGURE 6

FIGURE 7

Figure 6 shows that an increase in KS (from 0 to 12) increases the propensity of AI adoption, especially for firms with low or no level of collaboration and vice versa, demonstrating that collaboration with customers and spillovers are substitutes. For firms with low KS (from 0 to 6.5) collaboration with customer increase the probability to adopt AI (from 0.06 to 0.11); while for those firms with high knowledge spillover (from 7 to 12) and with high collaboration with customer reduces the AI adoption propensity, not supporting H7b.

Figure 7 demonstrates the vital role of collaboration with consultants on absence of knowledge spillover does not increase to probability of AI adoption (from 0.085 to 0.12 with H7b not supported.

FIGURE 8

FIGURE 9

Figure 8 and Figure 9 show the moderating effect of knowledge spillover and university and government collaboration, respectively, on the propensity to adopt AI. In both figures, the propensity to adopt AI increases when KS increases, while collaboration with government and university does not enhance it further, not supporting H7b.

6. Discussion and Conclusion

This study uses the recombinant knowledge approach to TOE framework where the role of organizational, technological and external contexts is used to explain firm's propensity in AI technology adoption. Our empirical evidence is based on using both industry and time perspectives in a large-unbalanced panel data sample of the UK firms.

6.1 Theoretical implications

Building on the pervasive critique of research that discusses a binary choice between investing in knowledge internally (Cohen & Levinthal, 1989, 1990; Miotti & Sachwald, 2003) or externally (i.e., open innovation) (Bogers et al., 2017, 2019), our study also demonstrates the vital role of technological context for adoption of new technology.

In this study, we argue that innovation inputs originate from firm's investment in knowledge and from sourcing knowledge via collaboration and spillovers from third parties (van Beer & Zand, 2014; Antonelli & Colombelli, 2017; Audretsch et al., 2021). To this extent we consider that internal and external knowledge sources are complementary for new technology adoption.

Our findings add to prior research on TOE and on the limits to apply external context to firm's competences and expands the recombinant knowledge approach (Antonelli, 1999) by overcoming an assumption that innovation is mainly R&D driven (Cohen & Levinthal, 1990).

Following the prior research on knowledge collaboration between sectors (Audretsch & Belitski, 2020) and between firm's own investment in ICT and R&D, we draw on earlier knowledge management studies and show that it is either investment in technological (ICT) or organizational context (R&D) that increases the likelihood of AI adoption. Knowledge collaboration with external partners, in particular suppliers and customers also increase the likelihood of AI adoption, unlike accessing KS or buying external R&D. In our opinion, these are important and unexpected findings as prior research has focused substantially on knowledge recombination between internal sources – R&D - and external sources – open innovation and knowledge collaboration (Bogers et al., 2017; Roper et al., 2017; Kobarg et al., 2019).

This study also expands prior research of Kinkel et al. (2022) who used the TOE framework to explain the AI adoption in manufacturing. Unlike their argument, our research using the UK data has demonstrated that both technological and organizational context matter and both could become a conduits of AI adoption. While prior research has paid an overwhelming attention to the role of investment in digital tools and learning e-skills to use the most advanced technologies (Li et al., 2016), our study has demonstrated investment in human capital (R&D) and digital technology investment remain important conduit of AI adoption (Ferraris et al., 2019; Kinkel et al., 2022).Technological and organizational context were proved as key pillars of AI adoption in contrast to prior research on TOE framework (Duan et al., 2019) putting various TOE elements into a competitive test.

The findings of this study have demonstrated that a firm manager when deciding to adopt new external technology should decide between what internal source of knowledge – R&D or ICT and what external source of knowledge – spillover or collaboration, which can be use both together and one at a time. Using various knowledge sources within external and internal context is not recommended as it increases the costs of knowledge sources e.g., transaction, coordination and management costs (Audretsch & Belitski, 2023; Bustinza, Gomes, et al., 2019; Demircioglu et al., 2019) and reduces resources available within organizational context for innovation and new technology adoption.

The limits to open innovation originate from the fact that a firm needs to be selective in choosing which external partner to collaborate with and weather access knowledge spillovers if it has already built collaborative relationships with external partners. We also find that knowledge spillovers do not complement to buying R&D in increasing the likelihood of AI adoption. It appears that more in depth collaboration with external knowledge sources is needed (Kobarg et al., 2019) beyond spillovers in order to utilise outside technology through buying R&D.

Expanding upon the benefits and costs of external context for technology adoption (Alaassar et al., 2021; Enkel et al., 2009), firms may be most affected by selective strategies of external context and the type of collaborator (Audretsch et al., 2021). As long as the knowledge collaboration with suppliers, customers and consultants increases (van Beer & Zand, 2014; Kobarg et al. 2019), accessing knowledge spillovers may no longer be critical for innovation and hence does not add to the propensity of AI adoption.

6.2 Implications for managers

Innovation literature has demonstrated that firms are insufficiently engaged with the organizational and technological context in the process of AI adoption (Link et al., 2020). The major issue remains investment in-house, in external collaboration and via buying external R&D. Limited resources could be invested inefficiently, and t relying on spillovers may still work as external knowledge sourcing strategy as collaboration with suppliers. Managers need to examine what sources of knowledge and within what context could be applied to get a greater innovation outcome, and the selectivity of knowledge investment is a key. That said, investment in technical skills and tools for technology adoption via ICT and software investment is required for digital transformation in organization and is part of the e-leadership strategy of many small and mediums firms (Li et al., 2016). In addition, managers need to invest in technical understanding of IT processes and software before moving to new technologies adoption. For managers willing to reduce cost of external collaboration access to knowledge spillovers is an efficient strategy to increase technological readiness, however this is unlikely to facilitate AI adoption if R&D are acquired rather than created in-house. This finding contributes to what know from Zahra and George (2002) and Roper et al. (2017) on the role of absorptive capacity for understanding knowledge spillovers. Creating internal context by investment in absorptive capacity is an efficient strategy to recognise and use knowledge spillovers and knowledge collaboration.

This study unlocks the complex relationship within internal and external context enabling managers to decide on the source of innovation inputs. Since the acquisition of technological context may take some time, it may seem advisable to develop external context, and in doing so the selectiveness of knowledge partnership types, forms of knowledge spillovers and the sources of buying R&D is important. Our study guides proactive managers looking for technology adoptions and adaptations instead to consider make – buy – ally strategies altogether rather than focusing on investing in R&D and ICT as a starting point.

6.3 Limitations and future research

The first limitation is data related. It was collected using a survey with substantial missing values for various types of external context of knowledge spillovers and collaboration. A more balanced long-term longitudinal study with firm representation across industries, type of innovation, regions, firm size, and age could improve the precise estimation. Future research will focus on understanding the different combinations of knowledge and using the industry or regional perspective of TOE framework.

Another limitation is the period of the innovation survey. The global financial crises likely impacted the availability and efficiency of internal and external resources and in particular, the willingness to collaborate and the availability for knowledge spillovers. We call for future research to examine simultaneous estimation where several dependent parameters that can characterize the adoption of AI could be used (Crupi et al., 2021).

Our empirical test has demonstrated that the use of the recombinant knowledge approach may provide further insights into unpacking firm innovation strategy for “make”, “buy” or “ally” on innovation (Bustinza, Lafuente, et al., 2019; Mudambi & Tallman, 2010).

References

Aboelmaged, M. G. (2014). Predicting e-readiness at firm-level: An analysis of technological, organizational and environmental (TOE) effects on e-maintenance readiness in manufacturing firms. *International Journal of Information Management*, *34*(5), 639–651.

Agostini, L., & Nosella, A. (2019). The adoption of Industry 4.0 technologies in SMEs: results of an international study. *Management Decision*, *58*(4), 625–643.

Alaassar, A., Mention, A. L., & Aas, T. H. (2021). Ecosystem dynamics: exploring the interplay within fintech entrepreneurial ecosystems. *Small Business Economics, 1-26.*

Antonelli, C. (1999). The evolution of the industrial organisation of the production of knowledge. *Cambridge Journal of Economics*, *23*(2), 243–260.

Antonelli, C., & Colombelli, A. (2015). The knowledge cost function. *International Journal of Production Economics*, *168*, 290–302.

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

Arora, A., Athreye, S., & Huang, C. (2016). The paradox of openness revisited: Collaborative innovation and patenting by UK innovators. *Research Policy*, *45*(7), 1352–1361.

Audretsch, D. B., & Belitski, M. (2020). The role of R&D and knowledge spillovers in innovation and productivity. *European Economic Review*, *123*, 103391.

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

Audretsch, D. B., & Feldman, M. P. (1996). R&D spillovers and the geography of innovation and production. *The American Economic Review*, *86*(3), 630–640.

Audretsch, D. B., & Keilbach, M. (2008). Resolving the knowledge paradox: knowledge-spillover entrepreneurship and economic growth. *Research Policy*, *37*(10), 1697–1705.

Babina, T., Fedyk, A., He, A. X., & Hodson, J. (2020). Artificial intelligence, firm growth, and industry concentration. *Firm Growth, and Industry Concentration (November*, *22*, 2020.

Beauhurst. (2021). *Beauhurst data collection*.

Berchicci, L. (2013). Towards an open R&D system: Internal R&D investment, external knowledge acquisition and innovative performance. *Research Policy*, *42*(1), 117–127. https://doi.org/https://doi.org/10.1016/j.respol.2012.04.017

Bhattacharya, M., & Wamba, S. F. (2018). A conceptual framework of RFID adoption in retail using TOE framework. In *Technology adoption and social issues: Concepts, methodologies, tools, and applications* (pp. 69–102). IGI global.

Black, S. E., & Lynch, L. M. (2001). How to compete: the impact of workplace practices and information technology on productivity. *Review of Economics and Statistics*, *83*(3), 434–445.

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., Hagedoorn, J., Hilgers, D., Laursen, K., Magnusson, M. G., Majchrzak, A., McCarthy, I. P., Moeslein, K. M., Nambisan, S., Piller, F. T., … Ter Wal, A. L. J. (2017). The open innovation research landscape: established perspectives and emerging themes across different levels of analysis. *Industry and Innovation*, *24*(1), 8–40. https://doi.org/10.1080/13662716.2016.1240068

Bolton, M. K. (1993). Organizational innovation and substandard performance: when is necessity the mother of innovation? *Organization Science*, *4*(1), 57–75.

Bresnahan, T. F., Brynjolfsson, E., & Hitt, L. M. (2002). Information technology, workplace organization, and the demand for skilled labor: Firm-level evidence. *The Quarterly Journal of Economics*, *117*(1), 339–376.

Bughin, J., & Hazan, E. (2017). The new spring of artificial intelligence: A few early economies. *VoxEU. Org*.

Bughin, J., Hazan, E., Lund, S., Dahlström, P., Wiesinger, A., & Subramaniam, A. (2018). Skill shift: Automation and the future of the workforce. *McKinsey Global Institute*, *1*, 3–84.

Bustinza, O. F., Gomes, E., Vendrell-Herrero, F., & Baines, T. (2019). Product–service innovation and performance: the role of collaborative partnerships and R&D intensity. *R&d Management*, *49*(1), 33–45.

Bustinza, O. F., Lafuente, E., Rabetino, R., Vaillant, Y., & Vendrell-Herrero, F. (2019). Make-or-buy configurational approaches in product-service ecosystems and performance. *Journal of Business Research*, *104*, 393–401.

Cappelli, R., Czarnitzki, D., & Kraft, K. (2014). Sources of spillovers for imitation and innovation. *Research Policy*, *43*(1), 115–120.

Cassia, L., Colombelli, A., & Paleari, S. (2009). Firms' growth: Does the innovation system matter? *Structural Change and Economic Dynamics*, *20*(3), 211–220.

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). *Complementarity in the innovation strategy: internal R&D, external technology acquisition and cooperation*.

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

Chesbrough, H. W. (2006). Open innovation: a new paradigm for understanding industrial innovation. *Open Innovation: Researching a New Paradigm*, *400*, 0–19.

Chesbrough, H. W., & Brunswicker, S. (2013). Managing open innovation in large firms. *Garwood Center for Corporate Innovation at California University, Berkeley in US & Fraunhofer Society in Germany*.

Chui, M., & Malhotra, S. (2018). AI adoption advances, but foundational barriers remain. *Mckinsey and Company*.

Ciarli, T., Kenney, M., Massini, S., & Piscitello, L. (2021). Digital technologies, innovation, and skills: Emerging trajectories and challenges. *Research Policy*, *50*(7), 104289.

Cohen, W. M., & Levinthal, D. A. (1989). Innovation and learning: the two faces of R & D. *The Economic Journal*, *99*(397), 569–596.

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

Crupi, A., Del Sarto, N., Di Minin, A., Phaal, R., & Piccaluga, A. (2021). Open innovation environments as knowledge sharing enablers: the case of strategic technology and innovative management consortium. *Journal of Knowledge Management*, *25*(5), 1263–1286.

Dachs, B., Kinkel, S., & Jäger, A. (2019). Bringing it all back home? Backshoring of manufacturing activities and the adoption of Industry 4.0 technologies. *Journal of World Business*, *54*(6), 101017.

Daugherty, P. R., & Wilson, H. J. (2018). *Human+ machine: Reimagining work in the age of AI*. Harvard Business Press.

Demircioglu, M. A., Audretsch, D. B., & Slaper, T. F. (2019). Sources of innovation and innovation type: firm-level evidence from the United States. *Industrial and Corporate Change*, *28*(6), 1365–1379.

Denicolai, S., Ramirez, M., & Tidd, J. (2016). Overcoming the false dichotomy between internal R&D and external knowledge acquisition: Absorptive capacity dynamics over time. *Technological Forecasting and Social Change*, *104*, 57–65.

Duan, Y., Edwards, J. S., & Dwivedi, Y. K. (2019). Artificial intelligence for decision making in the era of Big Data–evolution, challenges and research agenda. *International Journal of Information Management*, *48*, 63–71.

Ebersberger, B., Galia, F., Laursen, K., & Salter, A. (2021). Inbound open innovation and innovation performance: A robustness study. *Research Policy*, *50*(7), 104271.

Enkel, E., Gassmann, O., & Chesbrough, H. (2009). Open R&D and open innovation: exploring the phenomenon. *R&d Management*, *39*(4), 311–316.

Faems, D., De Visser, M., Andries, P., & Van Looy, B. (2010). Technology alliance portfolios and financial performance: value-enhancing and cost-increasing effects of open innovation. *Journal of Product Innovation Management*, *27*(6), 785–796.

Faems, D., Van Looy, B., & Debackere, K. (2005). Interorganizational collaboration and innovation: Toward a portfolio approach. *Journal of Product Innovation Management*, *22*(3), 238–250.

Feldman, M. P., & Audretsch, D. B. (1999). Innovation in cities:: Science-based diversity, specialization and localized competition. *European Economic Review*, *43*(2), 409–429.

Ferraris, A., Mazzoleni, A., Devalle, A., & Couturier, J. (2019). Big data analytics capabilities and knowledge management: impact on firm performance. *Management Decision*, *57*(8), 1923–1936.

Flick, U. (2019). The concepts of qualitative data: Challenges in neoliberal times for qualitative inquiry. *Qualitative Inquiry*, *25*(8), 713–720.

Griffith, R., Huergo, E., Mairesse, J., & Peters, B. (2006). Innovation and productivity across four European countries. *Oxford Review of Economic Policy*, *22*(4), 483–498.

Griliches, Z. (1979). Issues in assessing the contribution of research and development to productivity growth. *The Bell Journal of Economics*, 92–116.

Grover, P., Kar, A. K., & Dwivedi, Y. K. (2022). Understanding artificial intelligence adoption in operations management: insights from the review of academic literature and social media discussions. *Annals of Operations Research*, *308*(1), 177–213. https://doi.org/10.1007/s10479-020-03683-9

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*, 120392.

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.

Hall, B. H., & Mairesse, J. (2009). Measuring corporate R&D returns. *Presentation to the Knowledge for Growth Expert Group, Directorate General for Research, European Commission, Brussels, January*.

Iammarino, S., & McCann, P. (2006). The structure and evolution of industrial clusters: Transactions, technology and knowledge spillovers. *Research Policy*, *35*(7), 1018–1036.

Jaffe, A. B., & Lerner, J. (2001). Reinventing public R&D: Patent policy and the commercialization of national laboratory technologies. *RAND Journal of Economics*, 167–198.

Jantunen, A. (2005). Knowledge-processing capabilities and innovative performance: an empirical study. *European Journal of Innovation Management*.

Johannessen, J.-A. (2020). *Artificial intelligence, automation and the future of competence at work*. Routledge.

Khalil, S., & Belitski, M. (2020). Dynamic capabilities for firm performance under the information technology governance framework. *European Business Review*.

Kinkel, S., Baumgartner, M., & Cherubini, E. (2022). Prerequisites for the adoption of AI technologies in manufacturing – Evidence from a worldwide sample of manufacturing companies. *Technovation*, *110*, 102375. https://doi.org/https://doi.org/10.1016/j.technovation.2021.102375

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.

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.
Leiponen, A., & Helfat, C. E. (2010). Innovation objectives, knowledge sources, and the benefits of breadth. *Strategic Management Journal*, *31*(2), 224–236.
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*(2), 185–206.
Lippert, S. K., & Govindarajulu, C. (2006). Technological, organizational, and environmental antecedents to web services adoption. *Communications of the IIMA*, *6*(1), 14.
Love, J. H., Roper, S., & Vahter, P. (2014). Learning from openness: The dynamics of breadth in external innovation linkages. *Strategic Management Journal*, *35*(11), 1703–1716.
Miotti, L., & Sachwald, F. (2003). Co-operative R&D: why and with whom?: An integrated framework of analysis. *Research Policy*, *32*(8), 1481–1499.
Motti, L., & Sachwald, F. (2003). Co-operative R&D: why and with whom. *Research Policy*, *32*(8), 1481–1499.
Mowery, D. C., Oxley, J. E., & Silverman, B. S. (1998). Technological overlap and interfirm cooperation: implications for the resource-based view of the firm. *Research Policy*, *27*(5), 507–523.
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.
Oliveira, T., Thomas, M., & Espadanal, M. (2014). Assessing the determinants of cloud computing adoption: An analysis of the manufacturing and services sectors. *Information & Management*, *51*(5), 497–510.
Office for National Statistics. (2021a). *Business Structure Database, 1997-2021: Secure Access*. [data collection]. *14th Edition.* UK Data Service. SN: 6697, DOI: http://doi.org/10.5255/UKDA-SN-6697-14
Office for National Statistics. (2021b). *E-commerce Survey, 2001-2019: Secure Access*. [data collection]. *11th Edition.* UK Data Service. SN: 6700, DOI: http://doi.org/10.5255/UKDA-SN-6700-11
Office for National Statistics. (2022). *UK Innovation Survey, 1994-2020: Secure Access*. [data collection]. *8th Edition.* UK Data Service. SN: 6699, DOI: http://doi.org/10.5255/UKDA-SN-6699-8
Rammer, C., Fernández, G. P., & Czarnitzki, D. (2022). Artificial intelligence and industrial innovation: Evidence from German firm-level data. *Research Policy*, *51*(7). https://doi.org/10.1016/j.respol.2022.104555
Razzaque, A. (2021). Artificial Intelligence and IT Governance: A Literature Review. *Studies in Computational Intelligence*, *974*(August), 85–97. https://doi.org/10.1007/978-3-030-73057-4_7
Roper, S., Love, J. H., & Bonner, K. (2017). Firms' knowledge search and local knowledge externalities in innovation performance. *Research Policy*, *46*(1), 43–56.
Rothaermel, F. T., & Deeds, D. L. (2006). Alliance type, alliance experience and alliance management capability in high-technology ventures. *Journal of Business Venturing*, *21*(4), 429–460.
Samoili, S., López Cobo, M., Gómez, E., De Prato, G., Martínez-Plumed, F., & Delipetrev, B. (2020). AI Watch - Defining Artificial Intelligence. Towards an operational definition and taxonomy of artificial intelligence. In *Joint Research Centre (European Commission)*. https://doi.org/10.2760/382730
Sarkar, S. (2017). Uncorking knowledge- purposeful spillovers as a strategic tool for capability enhancement in the cork industry. *International Entrepreneurship and Management Journal*, *13*(1), 251–275. https://doi.org/10.1007/s11365-016-0395-6
Saura, J. R., Palacios-Marqués, D., & Ribeiro-Soriano, D. (2023). Exploring the boundaries of open innovation: Evidence from social media mining. *Technovation*, *119*, 102447.

https://doi.org/https://doi.org/10.1016/j.technovation.2021.102447
Schroll, A., & Mild, A. (2011). Open innovation modes and the role of internal R&D: An empirical study on open innovation adoption in Europe. *European Journal of Innovation Management*, *14*(4), 475–495.
Shankar, R. K., & Clausen, T. H. (2020). Scale quickly or fail fast: An inductive study of acceleration. *Technovation*, *98*, 102174.
Straub, D. W., & Watson, R. T. (2001). Research commentary: Transformational issues in researching IS and net-enabled organizations. *Information Systems Research*, *12*(4), 337–345.
Tornatzky, L. G., Fleischer, M., & Chakrabarti, A. K. (1990). *Processes of technological innovation*. Lexington books.
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.
Van Roy, V. (2020). *AI Watch-National strategies on Artificial Intelligence: A European perspective in 2019*. Joint Research Centre (Seville site).
Veugelers, R. (1997). Internal R & D expenditures and external technology sourcing. *Research Policy*, *26*(3), 303–315.
Veugelers, R., & Schneider, C. (2018). Which IP strategies do young highly innovative firms choose? *Small Business Economics*, *50*(1), 113–129.
Weitzman, M. L. (1996). Hybridizing growth theory. *The American Economic Review*, *86*(2), 207–212.
West, J., & Bogers, M. (2017). Open innovation: current status and research opportunities. *Innovation*, *19*(1), 43–50.
Wooldridge, J. M. (2009). On estimating firm-level production functions using proxy variables to control for unobservables. *Economics Letters*, *104*(3), 112–114.
World Economic Forum Boston Consulting Group. (2018). Towards a reskilling revolution: A future of jobs for all. *World Economic Forum*.
Xiao, J., & Boschma, R. (2022). The emergence of Artificial Intelligence in European regions: the role of a local ICT base. *The Annals of Regional Science*, 1–27.
Zahra, S. A., & George, G. (2002). Absorptive capacity: A review, reconceptualization, and extension. *Academy of Management Review*, *27*(2), 185–203.

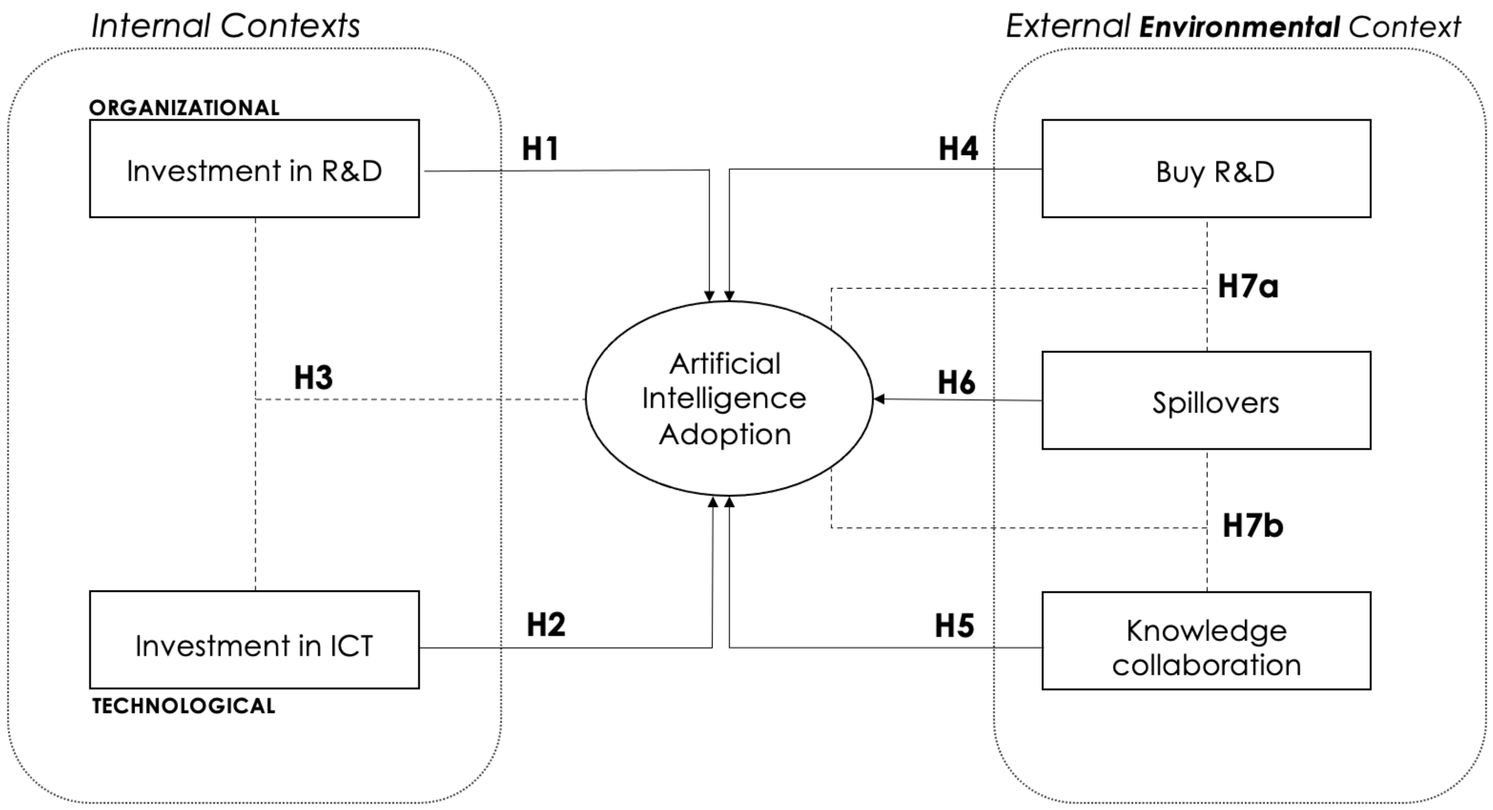
Table 1: Logistic estimation of propensity to adopt AI - original sample.

Specification	(1)	(2)	(3)	(4)	(5)	(6)
Age	1.048	1.080	1.080	1.059	1.058	1.081
	(.046)	(.048)	(.048)	(.048)	(.048)	(.049)
Employment	1.026	1.040	1.040	0.996	0.995	1.006
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.021)
Scientists	1.039***	1.038***	1.038***	1.038***	1.038***	1.038***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Appropriability	2.466***	2.345***	2.345***	1.520***	1.543***	1.539***
	(.24)	(.23)	(.23)	(.16)	(.16)	(.16)
Foreign	0.981	0.992	0.992	1.077	1.070	1.069
	(.063)	(.064)	(.064)	(.07)	(.07)	(.071)
Reporting units	0.966*	0.963**	0.963**	0.961**	0.961**	0.959**
	(.014)	(.014)	(.014)	(.014)	(.014)	(.014)
Product innovation	2.437***	2.305***	2.305***	1.879***	1.890***	1.852***
	(.15)	(.14)	(.14)	(.12)	(.12)	(.12)
Internal R&D intensity (H1)		1.008***	1.008***			1.045***
		(.003)	(.004)			(.005)
ICT intensity (H2)		1.055***	1.055***			1.045***
		(.005)	(.005)			(.005)

Internal R&D intensity x ICT intensity (H3)			1.000 (.000)			1.000 (.000)
External R&D intensity (H4)				1.091*** (.024)	1.054 (.053)	1.016 (.053)
Suppliers (H5)				1.314*** (.045)	1.541*** (.096)	1.483*** (.093)
Customers (H5)				1.314*** (.045)	1.541*** (.096)	1.483*** (.093)
Competitors (H5)				1.185*** (.045)	1.381*** (.093)	1.389*** (.094)
Consultants (H5)				1.028 (.04)	0.933 (.068)	0.939 (.69)
Universities (H5)				1.110*** (0.41)	1.226*** (0.097)	1.223* (0.097)
Government (H5)				1.069 (.049)	1.092 (.12)	1.083 (.12)
Spillover (H6)				0.992 (.045)	1.010 (.11)	1.022 (.12)
Spillover x External R&D intensity (H7a)					1.006 (.007)	1.005 (.008)
Spillover x Suppliers (H4b)					0.960*** (.011)	0.961*** (.011)
Spillover x Customers (H4b)					0.952 (.012)	0.952 (.012)
Spillover x Competitors (H4b)					1.020 (.013)	1.020 (.013)
Spillover x Consultants (H4b)					0.983 (.012)	0.983 (.012)
Spillover x Universities (H4b)					0.999 (.016)	0.999 (.016)
Spillover x Government (H4b)					1.000 (.016)	0.999 (.016)
Sample weighting	No	No	No	No	No	No
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Region fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
N	24286	24286	24286	24286	24286	24286
Chi2	5934.595	6086.35	6086.35	6245.09	6305.692	6401.105

Note: reference category for legal status is Company (limited liability company), industry (mining), city-region (Newcastle). Industry, year and city region controls are suppressed to save space. Robust standard errors are in parenthesis. Robustness check for standard errors included their clustering by 2-digit SIC.
Significance level: * p<0.10; ** p<0.05, *** p<0.01.
Source : Office of National Statistics (2021a, 2021b, 2022)

Figure 1: Conceptual model



Source : Authors

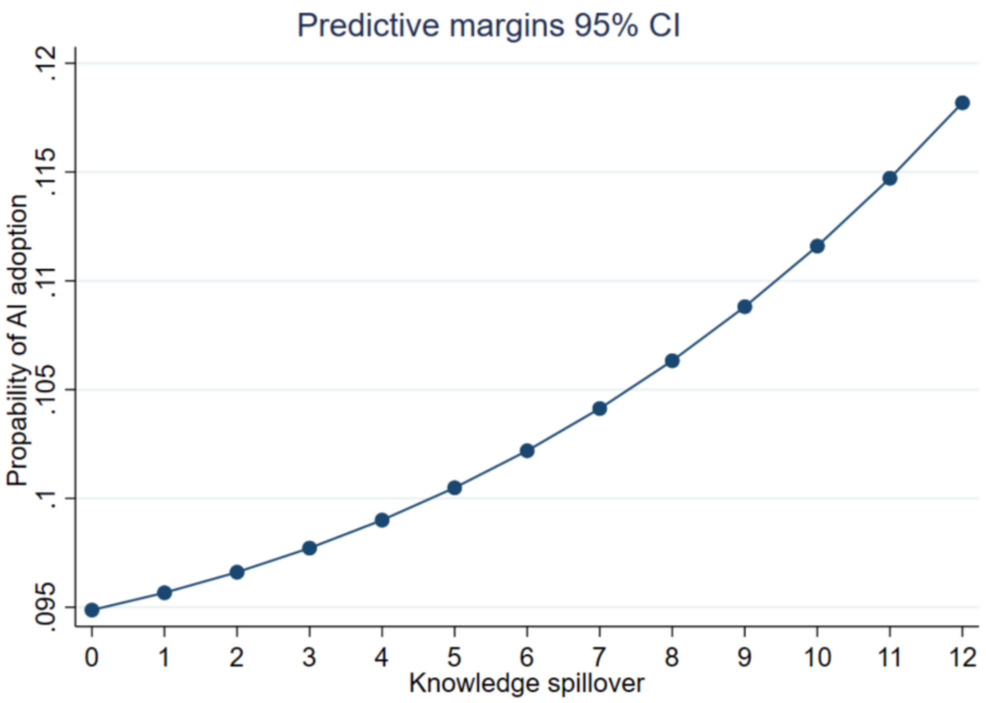


Figure 2: Predictive margins for the effect of ***KS on a propensity to adopt AI***
Source : Office of National Statistics (2021a, 2021b, 2022)

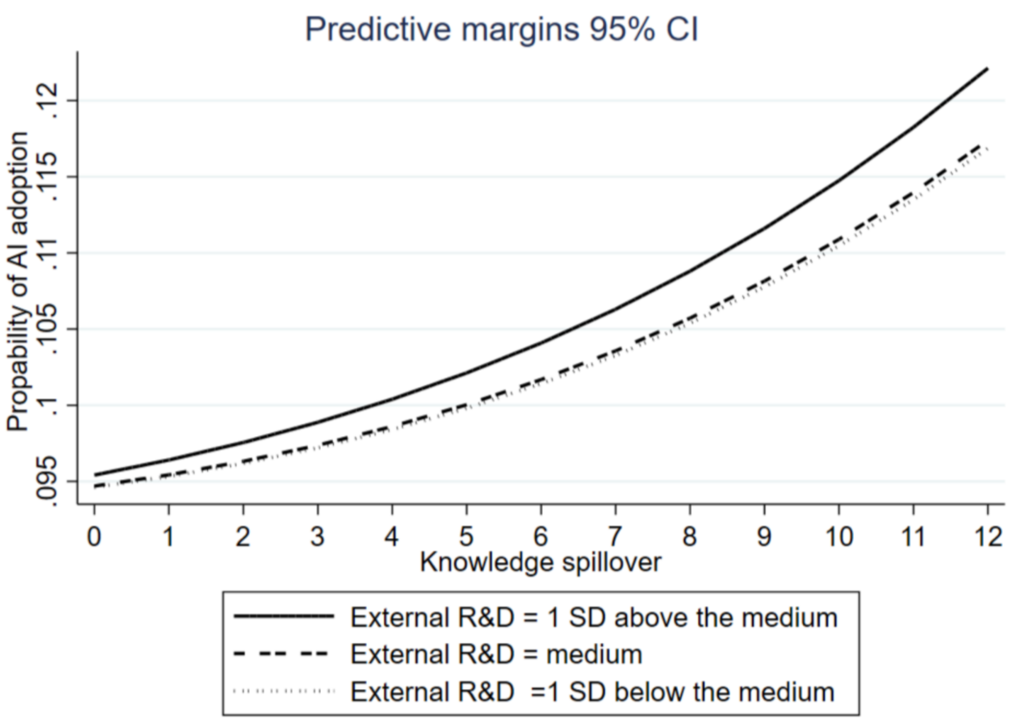


Figure 3: Predictive margins for the moderating effect ***between investment in external R&D and KS on a propensity to adopt AI***
Source : Office of National Statistics (2021a, 2021b, 2022)

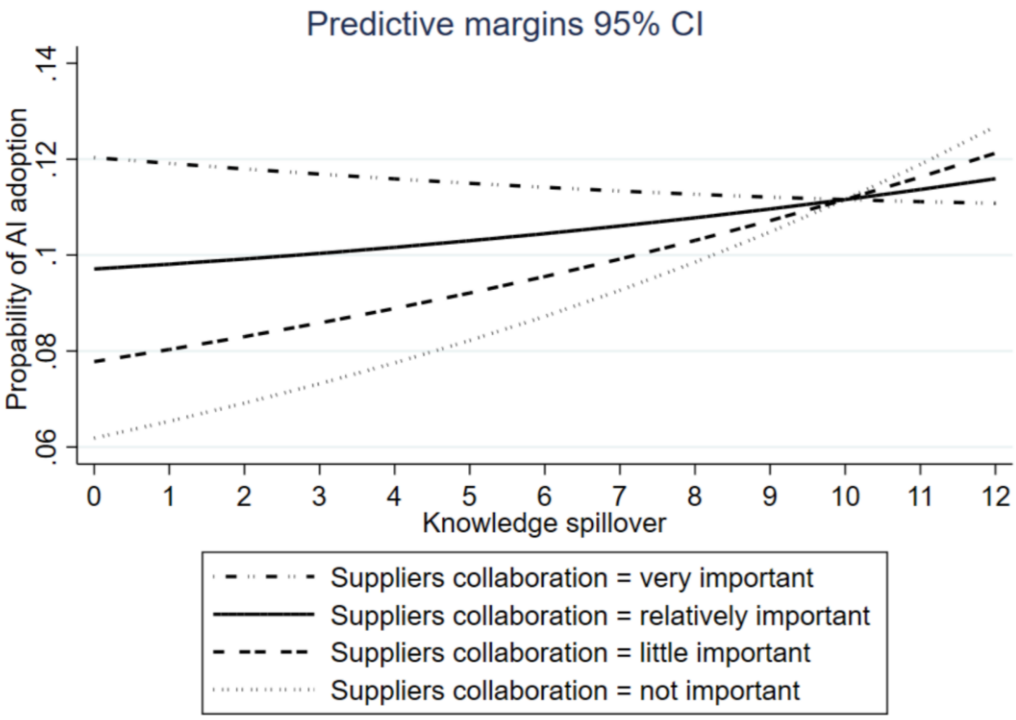


Figure 4: Predictive margins for the moderating effect ***between collaboration with suppliers and KS on a propensity to adopt AI***
Source : Office of National Statistics (2021a, 2021b, 2022)

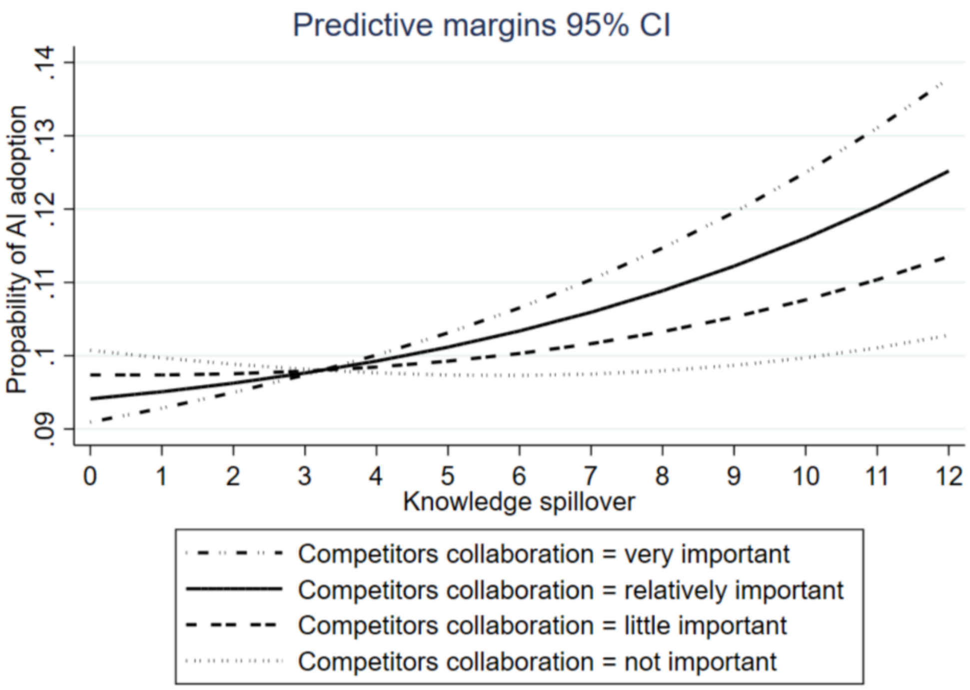


Figure 5: Predictive margins for the moderating effect ***between collaboration with competitors and KS on a propensity to adopt AI***
Source : Office of National Statistics (2021a, 2021b, 2022)

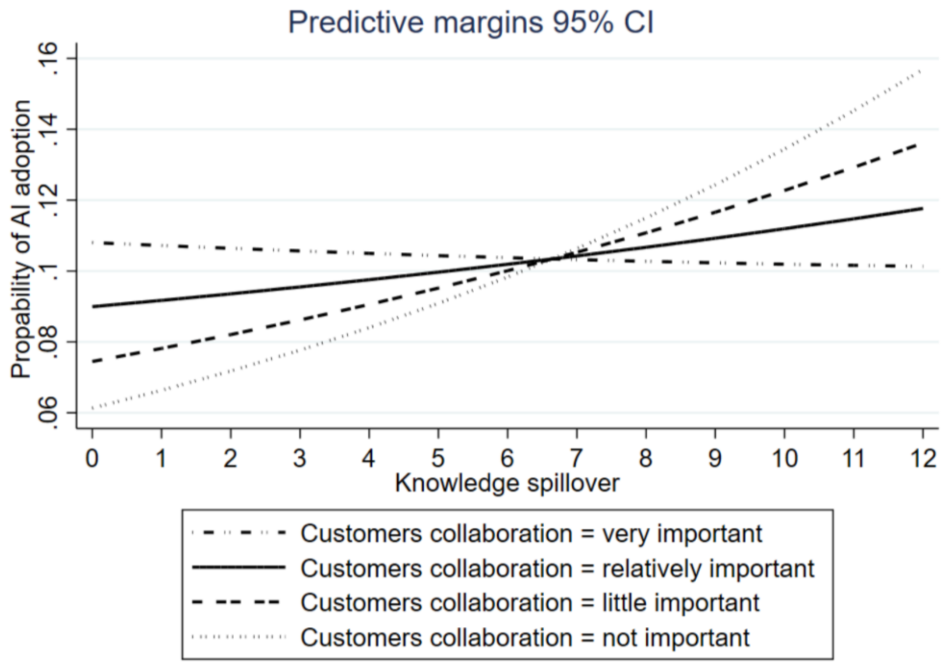


Figure 6: Predictive margins for the moderating effect ***between collaboration with customers and KS on a propensity to adopt AI***
Source : Office of National Statistics (2021a, 2021b, 2022)

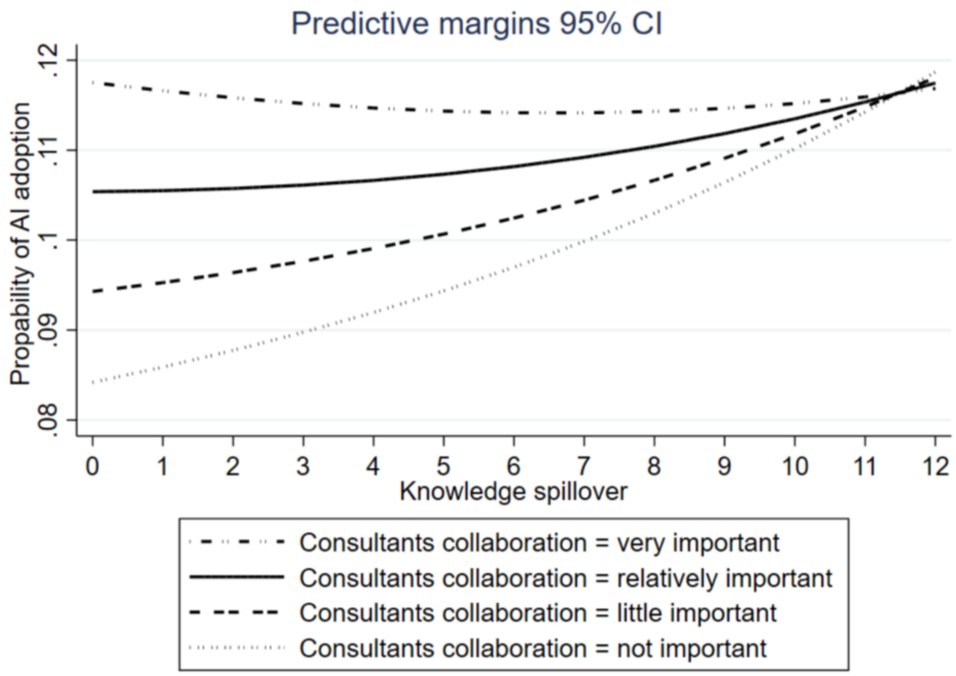


Figure 7: Predictive margins for the moderating effect ***between collaboration with consultants and KS on a propensity to adopt AI***
Source : Office of National Statistics (2021a, 2021b, 2022)

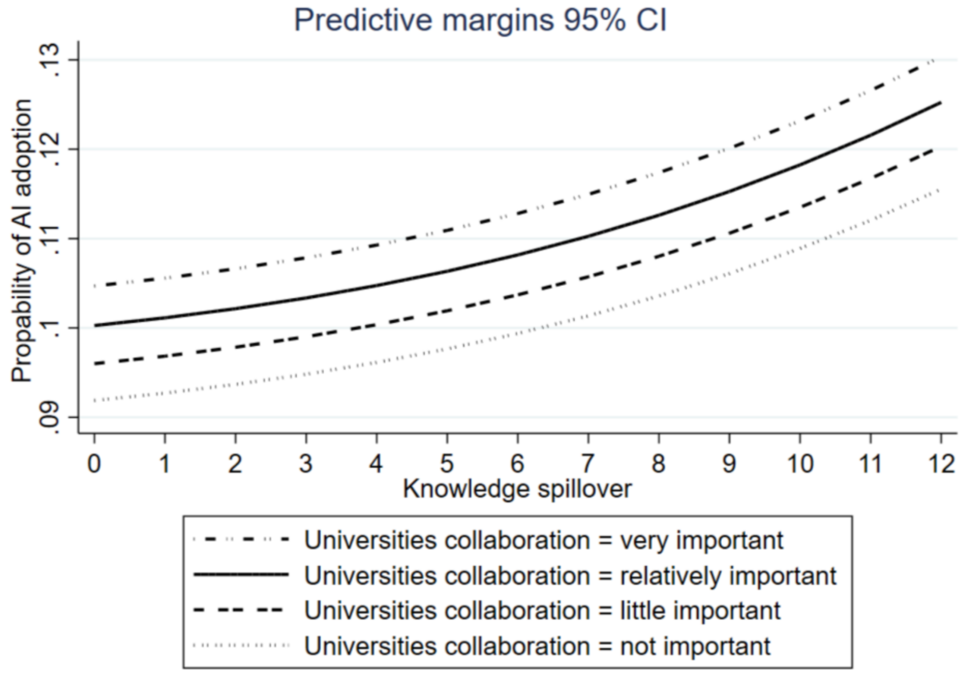


Figure 8: Predictive margins for the moderating effect ***between collaboration with universities and KS on a propensity to adopt AI***
Source : Office of National Statistics (2021a, 2021b, 2022)

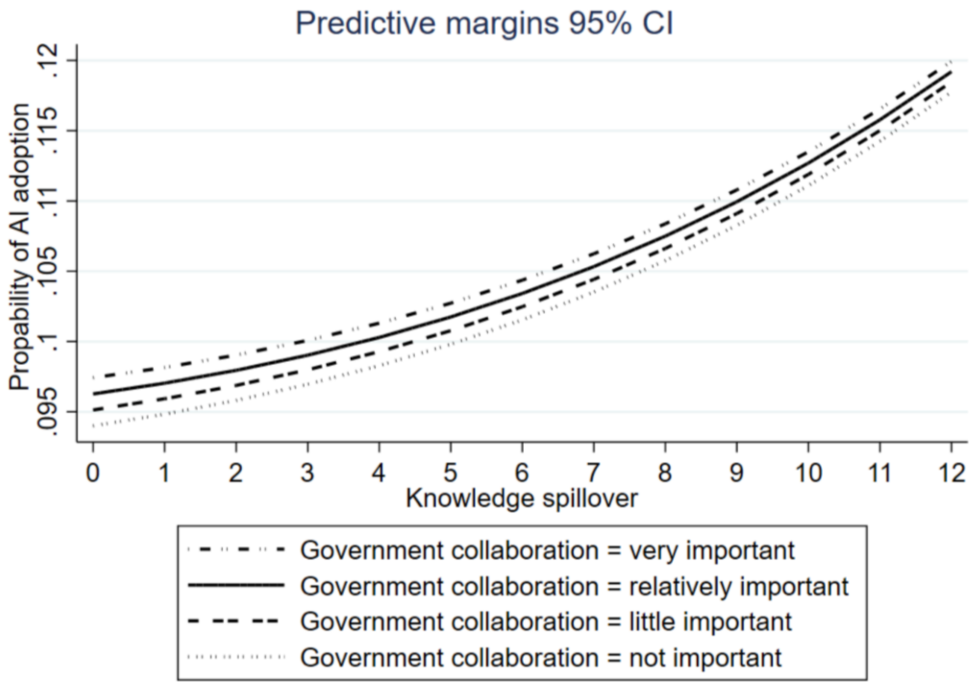


Figure 9: Predictive margins for the moderating effect ***between collaboration with government and KS on a propensity to adopt AI***
Source : Office of National Statistics (2021a, 2021b, 2022)