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Abstract

Artificial Intelligence (AI) is considered to be the next general-purpose technology, with the potential of performing tasks commonly requiring human capabilities. While it is commonly feared that AI replaces labor and disrupts jobs, we instead investigate the potential of AI for overcoming increasingly alarming skills shortages in firms. We exploit unique German survey data from the Mannheim Innovation Panel on both the adoption of AI and the extent to which firms experience scarcity of skills. We measure skills shortage by the number of job vacancies that could not be filled as planned by firms, distinguishing among different types of skills. To account for the potential endogeneity of skills shortage, we also implement instrumental variable estimators. Overall, we find a positive and significant effect of skills shortage on AI adoption, the breadth of AI methods, and the breadth of areas of application of AI. In addition, we find evidence that scarcity of labor with academic education relates to firms exploring and adopting AI.

JEL codes: J63, M15, O14
Keywords: Artificial Intelligence, skills shortage, CIS data

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1 Introduction

In both academic research and popular media, recent advancements in Artificial Intelligence (AI) have not only generated enthusiasm about its potential benefits on economic growth, but also about its potential capability in solving alarming skills shortage in firms. “The near-term threat to developed economies isn’t a lack of jobs - it’s not enough workers”, explains Schwarz (2023) in a recent *Forbes* article, “[…] the latest AI tool is much less likely to steal someone’s job than to help fill roles that desperately need to be filled”. Similarly, in a recent report from the *Chartered Institute of Personnel and Development* (CIPD) the question of whether artificial intelligence can cover skills shortages is analyzed by examining the potential advantages of generative AI (Boys, 2023).

More generally, the diffused interest on how AI could offer solutions to increasing skills shortage is motivated by the fact that the problem of scarcity of labor has become a major concern in highly developed and innovation-oriented economies (Cedefop, 2015). Skill constraints can have a detrimental impact on labour productivity and hinder the ability to innovate and embrace technological advancements. Firms facing skill shortages experience extended periods with unfilled positions or resort to the recruitment of workers with inadequate skills. National economies with persistent skill gaps and mismatches incur remarkable economic and social costs (Brunello and Wruuck, 2021). Moreover, as documented by a 2023 Eurobarometer survey (European Commission, 2023), skills shortages are a serious problem for majority of European SMEs.

Germany, for instance, faced a significant policy challenge regarding skills shortage towards the end of the 2010s. The country's robust economic growth created a surge in labor demand, while demographic changes further exacerbated the gap between retiring workers and new entrants to the labor market. Consequently, Germany witnessed a decline in the unemployment rate to 3.4% in 2018, the second lowest value in the European Union (Eurostat, 2019). Unemployment rates for skilled labor were even lower, less than half of the overall rate (Röttger, Weber, and Weber, 2019), presenting a growing challenge for firms seeking to fill positions requiring high qualifications.

Previous studies consistently document the negative effects of skills shortage on productivity (e.g., Coad et al., 2016) and on the development of new technologies (e.g., Toivanen and Väänänen, 2016). Innovative firms are more susceptible to skills shortage, which can lead to innovation failures and the abandonment of projects (Horbach and Rammer, 2022). Based on data from the 2019 German Community Innovation Survey (Rammer, 2020), skills shortage emerges as a major obstacle to innovation in the German business sector. The survey revealed that finding qualified personnel ranked first among the hindrances to innovation, with approximately 18% of firms citing skills shortage as a barrier to further innovative activities; additionally, nearly 15% of firms reported delays in ongoing innovation projects due to a lack of qualified personnel.

In this paper, we explore whether firms experiencing a scarcity of labor explore Artificial Intelligence (AI) to mitigate this problem. The remarkable advancements in AI technologies have led scholars to regard it as the next general-purpose technology, with the potential to perform tasks that typically require human capabilities (Brynjolfsson et al., 2017). Most notably, the recent achievements made in AI, particularly in areas such as image and speech recognition, natural language processing, and predictive analytics, are mostly due to its advancements in its machine learning component (Agrawal et al., 2019a). The benefits of AI are witnessed by the extensive, rapid, and penetrating adoption of AI across various industrial sectors (Agrawal et al., 2019b; Nolan, 2020). And besides the ample literature on the link between AI or automation and its effects on productivity and innovativeness (see Czarnitzki et al., 2023; Rammer et al., 2022; Brynjolfsson et al., 2021; Acemoglu and Restrepo, 2020;

Niebel et al., 2019; Ghasemaghaei and Calic, 2019; Graetz and Michaels, 2018), significant attention in both academic research and popular media has been devoted to the potential impact of AI on employment, with a generalized notion that the introduction of AI could reduce labor demand and thus generating unemployment (Brynjolfsson & McAfee, 2014). This idea is in line with the fact that, in general, technological progress has provoked important concerns about the substitution of capital for human labor.

In our study, however, we consider a different perspective and study the adoption of AI methods in response to the difficulty of firms in finding suitable employees that meet their human capital demands (see, e.g., Acemoglu, 2010). In other words, we aim to shed light on the effect of AI technologies in aiding firms to overcome increasingly alarming skills shortages.

To the best of our knowledge, this is one of the first papers that addresses this issue in detail by studying the relationship between AI and skills shortage. We use data from a representative, large-scale survey that contains rich information on both AI usage and skills shortage. We employ cross-sectional data from the German part of the Community Innovation Survey (CIS). In particular, the German innovation survey for the reference year 2018 incorporated specific questions on AI adoption, encompassing various AI methods and business areas in which AI can be applied (see Rammer et al., 2022). Following Czarnitzki et al. (2023) we model the adoption of AI as (i) dummy variable (yes/no), (ii) AI breadth in terms of areas of application, i.e., products/services, automatization of processes, communication, data analysis, and (iii) AI breadth in terms of methods, i.e., speech recognition, image recognition, machine learning, knowledge-based systems.

In order to measure skills shortage we exploit detailed information on the extent to which firms could fill open job vacancies from the previous survey wave with the reference year 2017.

We perform multiple regressions in which we control for lagged firm size as measured by employment, lagged R&D intensity of the firm, lagged share of high-skilled employees, firm age, the acquisition of new or improved technologies, path dependence of skills shortage, and economic sectors. To account for the potential endogeneity of skills shortage, we implement instrumental variable (IV) regressions in which we utilize information on strong price competition in the focal firm's market as an instrumental variable. Overall, we find a positive and significant effect of skills shortage on all three variants of our dependent variable, i.e., AI adoption, the breadth of AI methods, and the breadth of areas of application of AI. We also find that our instrumental variable is relevant and it has the expected sign in the first stage of the IV regression.

Finally, by using detailed information on the type of unfilled skills demanded by firms, we study the role of the level of qualifications and job fields in the adoption of AI technologies. We find evidence that a shortage of labor with academic education is positively associated with AI adoption. This finding is especially interesting, as it suggests that firms do not (only) adopt AI for process automation and robotization, but also for the completion of tasks that require (highly) skilled personnel.

The rest of the paper is organized as follows. Section 2 relates this study to previous articles on skills shortage, AI technologies, and on the link between these two areas. Section 3 presents the conceptual model used to identify how AI adoption can be linked to skills shortage, the measurement of the relevant variable, and some descriptive results. Section 4 describes the estimation results and Section 5 concludes.

2 Skills shortage and Artificial Intelligence

2.1 Skills shortage

Skills shortage refers to a situation in which the demand for workers in a specific occupation surpasses the supply of suitable and available workers willing to work under existing market conditions (Shah and Burke, 2005). From a neoclassical perspective, it represents a temporary imbalance in the labor market due to the slow adjustment of wages caused by high adjustment costs. Firms encounter difficulties in increasing wages for new employees without affecting the compensation of existing staff (Arrow and Capron, 1959).

Addressing skills shortage goes beyond wage adjustments and requires a focus on aligning innovation with workforce skills, since multiple factors contribute to temporary imbalances between the supply and the demand of skills. Technological advancements and demographic changes in aging societies lead to a decline in the number of young workers entering the labor market, which creates a gap in meeting the increasing demand for skills in knowledge-intensive economies. Education systems often struggle to keep up with the rapid pace and direction of technological changes, exacerbating the phenomenon of skills shortage (Toner, 2011).

Furthermore, the cyclical variations in the demand for emerging technologies and new products can result in a temporary surge in the demand for specific qualifications, exceeding the available supply of skilled workers (Berman, Bound, and Machin, 1998).

Existing research on skills shortage has mainly focused on its detrimental effects on both firm productivity and the advancement of new technologies. High-productivity firms are particularly hindered by skills shortages, as they represent barriers to innovation (Coad et al., 2016). Additionally, skills shortages lead to innovation failures, i.e., abandonment of projects (Horbach and Rammer, 2022). Similarly, proximity to technical universities, which helps to mitigate skills shortages, is associated with a greater number of patents filed by inventors (Toivanen and Väänänen, 2016). In a complementary way, other studies emphasize the crucial role played by skills and training activities in driving innovation performance (Freel, 2005), and the importance of both technical-academic skills and relational-social skills in the innovation process (Sousa and Rocha, 2019).

2.2. AI and skills shortage

Firms may opt for certain compensating mechanisms to mitigate the harms of scarcity of labor. Artificial Intelligence (AI) technologies could offer a solution to firms that encounter difficulties in finding human capital in line with their skill demand. AI technologies are considered to have the potential to perform tasks that have commonly relied on human capabilities (Brynjolfsson et al., 2017), since they enable machines or algorithms to mimic human cognitive functions, including understanding, learning, reasoning, and interacting (Baruffaldi et al., 2020).

An ample body of literature investigates the potential impact of AI-related technologies on the labor market and productivity outcomes. Frey and Osborne (2017) examine the extent to which tasks currently performed by humans could be automated by AI, estimating that around 47% of U.S. jobs are at high risk of automation. Felten et al. (2021) explore the exposure of industries to AI, finding that occupations in financial services, legal, accounting and consulting services, and IT services have higher AI occupational exposure scores. Manufacturing industries, except electronics, generally have lower AI occupational exposure scores.

The impact of AI on employment is a subject of ambiguity in theoretical economic models. Based on the notion of substitution of capital for human labor due to technological progress, the focus of scholars has been on the potential replacement effects of humans by AI-based machines (Brynjolfsson & McAfee, 2014). Viewing AI as an automation technology that reduces the share of tasks performed by labor, its short-term effect may be a decrease in labor demand, but in the long run, some authors argue that it could lead to an increase given its potential to complement and augment human capabilities (Lane and Saint-Martin, 2021).

Acemoglu and Restrepo (2018) present a task-based framework that explains the reduction in labor demand as a displacement effect, where capital takes over tasks previously performed by labor. However, there are several counteracting forces to consider. First, the productivity effect arises from cost savings through automation, which can increase consumer demand and, consequently, the demand for labor in non-automated tasks. Second, the capital accumulation effect raises the demand for labor in tasks where automation complements human labor. Third, the deepening of automation, driven by technological advancements, enhances the productivity effect. Last, the creation of new labor-intensive, high-productivity tasks further contributes to increased labor demand (Acemoglu and Restrepo, 2019).

Agrawal et al. (2019a) refined this theoretical task-based framework to specifically examine the impact of machine learning, an advanced method in the realm of human prediction tasks that has been instrumental in recent AI advancements and has the potential to significantly influence firm decision-making.

Existing empirical studies do not provide conclusive evidence on the labor implications of AI adoption. This is due to the limited availability of comprehensive datasets and suitable measurement tools for assessing firms' usage of AI (Mondolo, 2022). Raj and Seamans (2018) and McElheran (2018) emphasize the challenges involved in accurately measuring AI usage and highlight the limitations of available data for empirically studying the impact of AI on employment. No systematic and substantial evidence exists to support that AI has led to a reduction in employment during the past decade. For instance, Felten et al. (2019) investigate the relationship between employment and an AI occupational impact measure, which serves as a proxy for AI advancements in US occupations, such as image recognition.

Their findings indicate that occupational exposure to AI does not exhibit a significant association with changes in employment.

By employing a similar AI indicator as Felten et al. (2019) and using US individual-level panel data, Fossen and Sorgner (2019) show that advancements in AI are more likely to enhance job stability for individuals, as indicated by a lower likelihood of becoming non-employed or switching occupations. The positive impact of AI is particularly pronounced among highly educated and experienced employees. Georgieff and Hyee (2022) examine 23 OECD countries and employ the AI measure developed by Felten et al. (2019) but fail to identify a clear relationship between AI occupational exposure and employment growth. Acemoglu et al. (2022) study changes in US job postings over time for firms and occupations based on their exposure to AI. Overall, their results indicate no significant effect of AI exposure on job quantity or the required sets of new skills in these occupations.

Some articles have also examined the types of jobs that require AI skills as a way to measure firm investment in AI. Acemoglu et al. (2022) utilized job posting data to determine the level of exposure to AI within firms based on their occupational structure, subsequently analyzing the firms' labor demand. Building upon this approach, Babina et al. (2022) investigated the influence of AI technologies on growth and product innovation. They used worker resume data and job posting data related to AI skills as a proxy for firms' AI investment. The findings reveal that firms investing in AI experience greater growth in sales, employment, and market valuations, primarily driven by increased product innovation.

Bäck et al. (2022), focusing on a sample of Finnish firms, employed data on job advertisements about AI skills. They discovered that the adoption of AI enhances productivity, but primarily for larger firms. Early adopters do not observe productivity gains, and there is evidence of a delay of at least three years between AI adoption and its impact on productivity.

In this study, we adopt a different angle to address the complex nature of the association between AI and labor market dynamics. Instead of focusing on the heterogeneous effects on labor markets and firms' behavior caused by AI adoption, we consider labor scarcity as an antecedent of firms' decision to integrate AI into their business processes (see Acemoglu, 2010 for a seminal contribution). In general, labor scarcity should encourage AI adoption if technology is strongly labor-saving but should discourage it if digital advances are labor-complementary. For instance, AI can automate routine tasks, allowing employees to focus on more complex and strategic activities, thus alleviating the burden of labor shortages and boosting productivity. Additionally, AI's data analysis capabilities enable organizations to extract valuable insights from large volumes of data at a high speed and large scale, allowing data-driven decision-making even in the absence of specialized expertise.

Moreover, AI technologies can enhance efficiency by streamlining workflows, optimizing processes, and improving operational efficiency, compensating for the shortage of skilled workers. Acemoglu and Restrepo (2017) argue that in situations where capital is abundant, scarcity in younger and middle-aged workers can prompt a significant increase in the adoption of new automation technologies and robots. This heightened adoption has the potential to completely offset or even reverse the adverse impacts of labor scarcity.

To the best of our knowledge, no existing studies have examined the role of skills shortage in the adoption of AI technologies by firms. This paper fills this gap by providing robust empirical evidence on how unfilled open job vacancies affect the implementation of AI technologies, methods, and applications. Our paper also offers novel information on the type of skills (or lack thereof) that influence the decision to adopt AI, using detailed data on both the level of qualifications (i.e., academic, vocational, and semiskilled/unskilled) and job fields or sectors (e.g., STEM, manufacturing professions or production processes) that are in demand.

3 Estimating the relationship between skills shortage and AI

3.1 Conceptual model

The primary goal of this paper is to examine how firms' skills shortage impacts firms' adoption of AI. A firm's decision on whether and how to implement AI methods is closely tied to its internal resources, human capital, and demand for labor. AI is a technology that enables the realization of specific tasks that commonly require human capabilities, but the integration of AI methods into the firm's products and business operations also requires certain skills within the workforce. A firm's demand for skills and the decision to invest in a specific technology, such as AI, are two intertwined aspects of a strategic decision-making process. Therefore, we will conduct a regression analysis, considering various factors related to firms' AI usage, while also controlling for other variables that may influence AI (see Rammer et al., 2022).

When establishing the association between skills shortage and AI, a potential endogeneity issue may arise due to the non-random nature of the decision to demand labor which influences the likelihood to experience shortage of skills and its severity. To account for the potential endogeneity of skills shortage, we thus implement instrumental variable regressions.

Our empirical study is guided by a conceptual model which is based on three main groups of variables. AI is measured by a set of variables that denote the adoption of this technology and the breadth of its usage across different methods and areas of application. These AI-related variables are linked to skills shortage and other determinants including innovation input measures, general firm capabilities, and market characteristics (refer to Figure 1). The details are described in the following subsections.

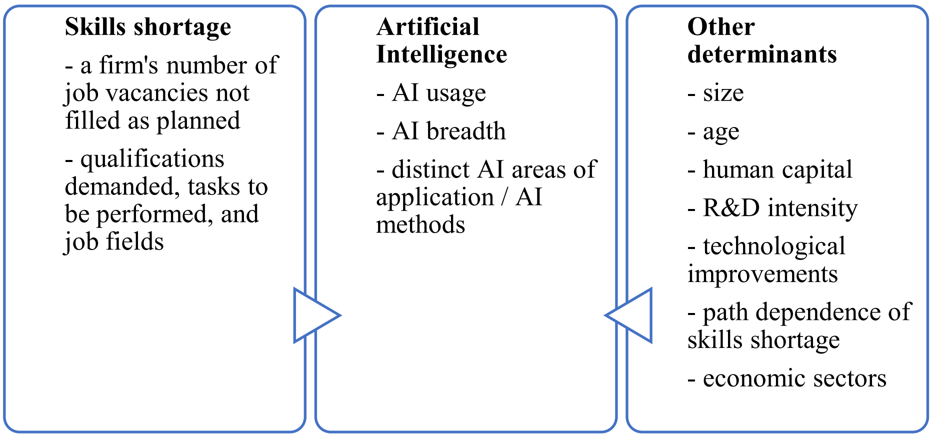


Figure 1. Variables considered to identify the role of skills shortage for AI usage in firms.

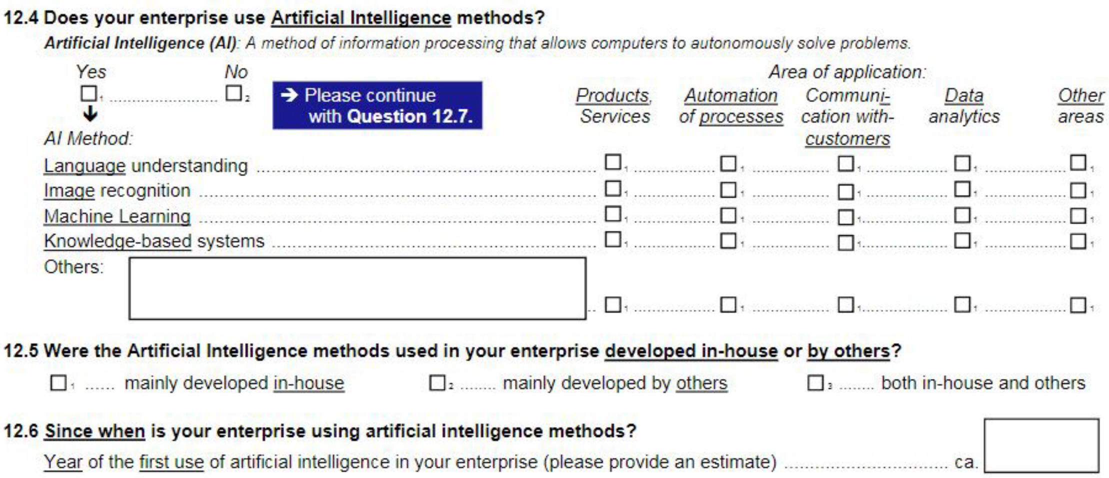
3.2 Data source

We use cross-sectional data of firms from the German part of the European-wide Community Innovation Survey (CIS), which is implemented by the Leibniz Centre for European Economic Research (ZEW) in Mannheim, Germany. Differently from other CIS national innovation surveys, the German survey, known as the Mannheim Innovation Panel (MIP), is structured as an annual panel survey (Peters and Rammer, 2013). The MIP gathers information from firms in Germany that operate in sectors such as manufacturing, mining, utilities, and business-oriented services, including wholesale trade, transportation, financing and insurance, information and communication, as well as professional, scientific, technical, administrative, and support services. To ensure the data's representativeness, the MIP adheres to the methodological guidelines specified by the Statistical Office of the European Commission (Eurostat) for the CIS, encompassing sampling procedures, data processing, and quality control. The survey employs a stratified random sampling approach and employs a standardized questionnaire that can be completed through paper or online formats. The MIP achieves a response rate ranging between 25% and 35%. To assess potential bias among participating firms, an extensive non-response survey is conducted (Peters and Rammer, 2013).

After combining consecutive survey waves, we consider only firms with full information on all model variables, thus reducing the final sample size to 2961 firms (we exclude missing values, erroneous responses, and outliers).[1]

3.3 AI variables

In this study, we make use of different waves of the German Innovation Survey. In particular, the survey conducted in 2019, with the reference year 2018, included specific questions aimed at capturing the adoption and usage of artificial intelligence (AI) within firms. These questions allowed for the classification of firms as either AI-using or non-AI-using (refer to Figure 2).


12.4 Does your enterprise use Artificial Intelligence methods?

Artificial Intelligence (AI): A method of information processing that allows computers to autonomously solve problems.

Yes ☐1 .... *No* ☐2 → Please continue with **Question 12.7.**

Area of application:

AI Method:	*Products, Services*	*Automation of processes*	*Communi-cation with customers*	*Data analytics*	*Other areas*
Language understanding	☐1	☐1	☐1	☐1	☐1
Image recognition	☐1	☐1	☐1	☐1	☐1
Machine Learning	☐1	☐1	☐1	☐1	☐1
Knowledge-based systems	☐1	☐1	☐1	☐1	☐1
Others:	☐1	☐1	☐1	☐1	☐1

12.5 Were the Artificial Intelligence methods used in your enterprise developed in-house or by others?

☐1 ...... mainly developed in-house ☐2 .... mainly developed by others ☐3 .... both in-house and others

12.6 Since when is your enterprise using artificial intelligence methods?

Year of the first use of artificial intelligence in your enterprise (please provide an estimate) .... ca.

Figure 2. Question on AI use in the German Innovation Survey 2019.

To measure the extent of AI implementation, a matrix-style question asked whether the firm uses AI methods at the time of the survey and the application areas in which these methods are employed. The question differentiated between five broad AI methods: language understanding, image recognition, machine learning, knowledge-based systems, and other unspecified methods. The application areas encompassed five categories: products/services,

[1] When compared to the original sample, the reduced sample shows a similar distribution in terms of economic sectors (see Table 8 in the Appendix) as in the raw data.

process automation, customer interaction, data analytics, and other unspecified areas. Additional questions regarded the origin of the AI technology utilized by the firms, specifically whether it was developed in-house or sourced from external entities. Furthermore, the survey sought to determine the initial year of AI adoption by each firm.

For this study, the adoption of AI is first modeled as a dummy variable (*AI*), regardless of whether the firms developed the AI applications in-house or utilized AI methods developed by external sources, and encompassing firms that adopted AI by 2017 or at any point after 2017.[2] In addition, to capture the breadth of usage of AI methods and areas of applications, we construct a measure of the breadth of AI usage (*AIbreadth*), which counts the distinct combinations of methods and areas of application of AI within a firm (this variable potentially ranges from 0 to 25). Furthermore, we distinguish between the breadth in terms of areas of application of AI (*AIbreadth_area*) and the breadth in terms of AI methods (*AIbreadth_method*). Last, we also consider the distinct methods and areas of applications (see Czarnitzki et al., 2023 and Rammer et al., 2022 for similar variables).

[2] The choice of this timeframe reflects the objective of our analysis, i.e., investigating the impact of skills shortage (measured in 2017) on AI usage. Results using different timeframes remain robust and are available upon request.

Table 1: AI methods and areas of application in AI-using firms.

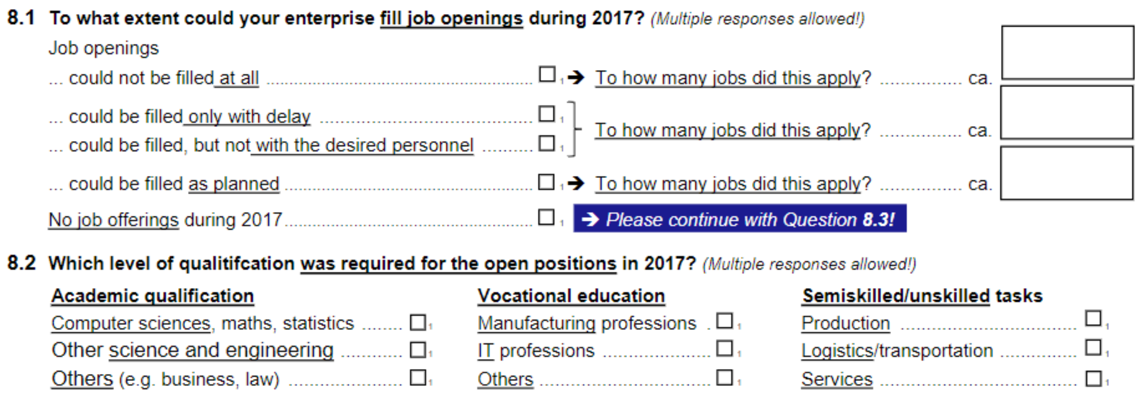
	AI-using firms (89 obs.)			
	Mean	St. Dev.	Min	Max
Breadth variables				
AIbreadth	2.719	1.784	0	8
AIbreadth_area	1.798	0.979	1	4
AIbreadth_method	1.764	0.879	1	5
Areas of application				
Products, services	0.517	0.503	0	1
Automation of processes	0.517	0.503	0	1
Interaction with clients	0.180	0.386	0	1
Data analysis	0.427	0.497	0	1
Other areas	0.112	0.316	0	1
AI methods				
Language understanding	0.303	0.462	0	1
Image recognition	0.506	0.503	0	1
Machine learning	0.494	0.503	0	1
Knowledge-based system	0.382	0.489	0	1
Other methods	0.079	0.271	0	1

Sources: German CIS, 2019 survey wave.

As shown in Table 1, our cross-sectional sample contains 2961 firms out of which 89 can be classified as AI users (around 3%), by considering only firms that introduced AI after 2017. Among the AI-using firms, on average, firms used 2.7 out of the 25 possible combinations of AI methods and areas of application (*AIbreadth*). In terms of breadth of AI methods (*AIbreadth_method*), AI-using firms employed on average around 1.8; similarly, around 1.8 areas of applications of AI characterized AI-using firms (*AIbreadth_area*). About 52% of AI-using firms used AI in products or services or for the automation of processes, 43% for data analysis, and 18% for interaction with clients. In terms of methods, about 51% of AI-using firms employ image recognition, followed by machine learning (about 49%), knowledge-based systems (38%), and language understanding (30%).

3.4 Skills shortage and other independent variables

To measure skills shortage, we exploit detailed information from the 2018 wave of the MIP, with the reference year 2017, on the extent to which firms could fill job openings and on the different levels of qualifications required for the vacancies (refer to Figure 3). Following Horbach and Rammer (2022), skills shortage (*lnSkillsShort*) is operationalized as the number of vacancies that could not be filled at all, that could be filled only with delay, or that could not be filled with the required personnel in 2017 (logged).[3] This variable encompasses the scarcity of skills experienced at the firm level, which may arise from the inability to fill a job vacancy, delays in the hiring process for required employees, or a mismatch between the skills required for the vacancy and the skills possessed by the newly hired individual(s). In our sample, about 37% of firms reported that they could not fill (some of) their job openings as planned.



8.1 To what extent could your enterprise fill job openings during 2017? *(Multiple responses allowed!)*

Job openings

... could not be filled at all ☐ → To how many jobs did this apply? ca.

... could be filled only with delay ☐

... could be filled, but not with the desired personnel ☐ → To how many jobs did this apply? ca.

... could be filled as planned ☐ → To how many jobs did this apply? ca.

No job offerings during 2017 ☐ → *Please continue with Question 8.3!*

8.2 Which level of qualitifcation was required for the open positions in 2017? *(Multiple responses allowed!)*

Academic qualification	**Vocational education**	**Semiskilled/unskilled tasks**
Computer sciences, maths, statistics ☐	Manufacturing professions ☐	Production ☐
Other science and engineering ☐	IT professions ☐	Logistics/transportation ☐
Others (e.g. business, law) ☐	Others ☐	Services ☐

Figure 3. Question on skill demand in the German Innovation Survey 2018.

We use 2017 data on the type of qualifications that firms demanded and the job subfields or subsectors that required these skills to create a set of independent dummy variables. The dummy variables *Academic_qual, Vocational_qual*, and *Unskilled_tasks* represent the aggregate levels of qualifications that the firm needed for the open job position. They are equal to 1 if the firm marked at least one corresponding subfield and 0 otherwise (see question 8.2 in Figure 3). We also create seven additional dummy covariates based on the subfields for each qualification category: *STEM* (computer sciences, maths, statistics, other science and engineering), *Other_academic* (e.g., business, law), *Vocational_IT* (IT

[3] Since the variable is skewed, we use a logarithmic transformation of it. To account for firms reporting zero vacancies not filled as planned, we add 0.5 to the variable before log-transforming it, and we then deduct log (0.5) from the generated variable.

professions requiring vocational education), *Vocational_manuf* (manufacturing professions requiring vocational education), *Unskilled_production* (unskilled/semiskilled tasks in the production area), *Unskilled_services* (unskilled/semiskilled tasks in the services area), and *Unskilled_logistics* (unskilled/semiskilled tasks in the logistics/transportation area). We use the data on the type of qualifications and job subfields to analyze the heterogeneous effects of skills shortage on AI adoption, as explained below.

In our analysis of the impact of skills shortage on AI adoption, we include a set of control variables to account for various factors. We control for lagged firm size (*lnEmpl*),[4] measured by the number of employees (logged), as well as the number of years since the firm started the business (logged) (*lnAge*). Firms that perform R&D may possess a larger stock of technological knowledge both from their own R&D activities and from absorbing relevant external knowledge (Cohen and Levinthal, 1990), which may lead to the decision to implement AI technologies or broaden their usage if compared to non-R&D-performers, or firms that conduct R&D only to a lower extent. We thus control for firms' absorptive capacity by including the firm-level, lagged R&D intensity (*RDint*) in our empirical model. We define lagged R&D intensity as the ratio of R&D expenditures to total sales in 2017. Additionally, we control for the lagged share of employees with a university degree (*ShareGrad*), which reflects the significance of academic knowledge embedded in the firm's human capital (Lewandowska, 2015).

Furthermore, we include the variable *Techpath* which equals to 1 if the firm has adopted, from 2016 to 2018, new or improved production technology relative to the machinery and equipment that has been used prior to the survey period (i.e., before 2016) (Czarnitzki et al., 2023). With this variable we aim to control for supplier-induced innovation

[4] To avoid double counting, we subtract the number of vacancies that were filled as planned from the total number of employees in 2017.

and technical progress embedded in acquired machinery or equipment, which may indicate that the firm is following a technological improvement path and hence may be more likely to explore AI. We also control for path dependence of skills shortage (*Pathdep*), which is constructed as the average by sector and size class of an indicator denoting the lack of suitably qualified staff in the previous period 2014–2016. Last, we include industry dummies (16 in total) to account for different propensities for AI adoption across industries.

3.5 Methods and endogeneity of skills shortage

We run OLS and Probit regressions with the dependent variable *AI* (binary indicator) and OLS regressions with the breadth variables *AIbreadth, AIbreadth_area,* and *AIbreadth_method*.

We expand the abovementioned methods to instrumental variable (IV) regressions to address the potential endogeneity of skills shortage. Various factors can introduce bias in the assessment of the impact of skills shortage on AI due to the endogenous nature of firms' decision to demand skills. First, firms may experience a scarcity of labor as a result of AI adoption, since AI technologies require new skills for their implementation and integration in the business and innovation processes. In such cases, a firm's decision to invest in AI could be a driving factor behind skills shortage. Second, the decision to adopt AI technologies due to a shortage of skills may also alleviate the lack of skilled labor. Third, it is crucial to consider the potential presence of omitted covariates that are not accounted for in the estimated specifications, since they might be correlated with skills shortage and lead to biased estimates. For example, since more innovative firms are more likely to experience skills shortage (Horbach and Rammer, 2022), the difficulty in filling job openings could be associated with an increase in the firm's demand for labor, which originates from a firm's broader digitalization efforts or expansion of the technological infrastructure. To mitigate these concerns and obtain more reliable estimates, we perform IV regressions and compare the results obtained with OLS and Probit to the estimates obtained with IV 2SLS and IV Probit regressions.

As an instrument for skills shortage, we use a binary indicator denoting whether firms reported that price competition in their main product market induced a loss of customers. We construct this instrument based on data from the survey waves from 2015, 2017, and 2019, and closely follow the estimation strategy adopted by Horbach and Rammer (2022) in their analysis of the endogeneity of skills shortage.[5] Due to intense price competition and the resulting cost pressure, firms are less able to offer higher wages to attract potential applicants. In other words, higher labor costs cannot be directly transferred to higher prices. Consequently, these firms generally face a higher risk of experiencing a shortage of labor. It is important to note that there is no obvious and direct connection between strong price competition and the decision to use AI.

3.6 Descriptive statistics

On average, we observe that firms experiencing skills shortage are more prone to adopt AI (refer to Table 2). Around 4.4% of firms reporting not being able to fill their vacancies as planned used AI technologies, while the proportion of AI users among firms without skills shortage amounts to only 2.2%. In addition, their usage of AI is broader, both in terms of methods and areas of application, than firms not experiencing skills shortage. The score for *AIbreadth* amounts to 0.127 and 0.055 for firms with skills shortage and without it, respectively. A similar pattern is observed when we consider the breadth of areas of application or the breadth of methods, separately.

On average, around 5 job vacancies could not be filled as planned among firms with skills shortage. In terms of demand for qualifications and skills, among firms reporting skills

[5] Our instrument is a binary variable that is equal to one if firms reported, in at least one of the 2015, 2017 or 2019 survey waves, that price competition induced a loss of customers.

shortage most open job vacancies pertained to tasks that did not require an academic qualification (*Vocational_qual* and *Unskilled_tasks*); more specifically, these vacancies were mostly related to skills for manufacturing professions and production tasks.

Furthermore, firms experiencing skills shortage have, on average, a lower share of graduates than firms that could fill all their job vacancies. The variable indicating the adoption of new or improved technologies in the period 2016-2018 exhibits a higher average value for firms experiencing scarcity of labor. As expected, the indicator for past skills shortage has a higher average value among firms that could not fill some of their job vacancies as planned, in line with the path dependency of the phenomenon. Finally, around 93.7% (89.4) of firms (not) experiencing skills shortage reported that price competition induced a loss of customers.

Table 2: Descriptive statistics.

		Firms with skills shortage (1097 obs.)				Firms without skills shortage (1864 obs.)			
Variable	Source	Mean	St. Dev.	Min	Max	Mean	St. Dev.	Min	Max
AI variables									
AI	MIP19	0.044	0.205	0	1	0.022	0.147	0	1
AIbreadth	MIP19	0.127	0.705	0	8	0.055	0.445	0	7
AIbreadth_area	MIP19	0.083	0.447	0	4	0.035	0.273	0	4
AIbreadth_method	MIP19	0.078	0.407	0	5	0.038	0.288	0	4
Skills variables									
SkillsShort	MIP18	4.996	10.851	1	150	0	0	0	0
Academic_qual[a]	MIP18	0.450	0.498	0	1	0.187	0.390	0	1
Vocational_qual[a]	MIP18	0.717	0.450	0	1	0.301	0.459	0	1
Unskilled_tasks[a]	MIP18	0.519	0.500	0	1	0.209	0.407	0	1
STEM[a]	MIP18	0.364	0.481	0	1	0.139	0.346	0	1
Other_academic[a]	MIP18	0.151	0.358	0	1	0.068	0.252	0	1
Vocational_IT[a]	MIP18	0.130	0.336	0	1	0.046	0.208	0	1
Vocational_manuf[a]	MIP18	0.368	0.482	0	1	0.145	0.352	0	1
Unskilled_production[a]	MIP18	0.250	0.433	0	1	0.108	0.311	0	1
Unskilled_services[a]	MIP18	0.209	0.407	0	1	0.076	0.266	0	1
Unskilled_logistics[a]	MIP18	0.190	0.393	0	1	0.068	0.252	0	1
Control variables									
lnEmpl	MIP18	3.630	1.473	-0.693	10.270	2.887	1.465	-0.693	10.987
lnAge	MIP18	3.066	0.801	0	6.809	3.117	0.785	0	5.268
RDint	MIP18	0.016	0.063	0	0.78	0.022	0.086	0	0.997
ShareGrad	MIP18	0.210	0.256	0	1	0.251	0.292	0	1
Techpath	MIP19	0.624	0.484	0	1	0.518	0.500	0	1
Pathdep	MIP18	0.681	0.102	0	1	0.663	0.091	0	1
Instrumental variable									
Pricecomp	MIP15-MIP19	0.937	0.243	0	1	0.894	0.308	0	1

Sources: German CIS. (a) The variables denoting the type of qualification demanded are available for 2918 observations (1072 firms with skills shortage and 1846 firms without skills shortage).

4 Estimation results

Table 3 shows the estimates obtained in the baseline model in which the outcome variable is the binary indicator for AI usage. For the variable *lnSkillsShort* in the OLS model, we observe a positive coefficient of 0.010 indicating that if the number of vacancies that are not filled as planned increases by 10%, the probability of adopting AI is estimated to increase by 0.1 percentage points. The coefficient is statistically significant at the 1% significance level. In the IV 2SLS model, the coefficient is 0.084 with a similar interpretation, and it is statistically significant at the 5% level. A similar result is obtained with the Probit and IV Probit models: an increase in skills shortage is associated with a higher probability of using AI technologies. The coefficient in both models is statistically significant at the 1% level.

Table 9 in the Appendix shows the first-stage regression of the IV 2SLS estimation. The instrumental variable, namely the indicator for price competition faced by firms, exhibits statistical significance at the 1% level, with a first-stage F-statistic above the conventional levels (11.84). Furthermore, the positive sign of the instrument aligns with our expectations. Due to the intense price competition and the subsequent financial constraints, firms might find their ability to offer competitive salaries limited. This makes them less enticing to job seekers, leaving them more vulnerable to a general lack of workforce.

We find that the expected probability to adopt AI for a firm with average employment and no unfilled positions is about 2.4%. The average marginal effect of hiring five new employees only amounts to 0.2%. Instead, the average marginal effect of having five positions that could not be filled is about ten times larger, namely 2.2%. We therefore conclude that skill shortage is an economically significant reason for firms exploring AI technology.

In Table 4 we look at the impact of skills shortage on the breadth of AI methods/areas of application. We observe a positive and significant effect of skills shortage on *AIbreadth,*

AIbreadth_area, and *AIbreadth_method*, which is robust to different specifications (OLS and IV 2SLS). For instance, if we consider the 2SLS estimated coefficient in column (4), we find that a 10% increase in skills shortage is associated with an average increase in the breadth of AI methods of 0.016.

Table 3: Regression coefficients table: the impact of skills shortage on AI use.

	(1) OLS *AI (0/1)*	(2) IV 2SLS *AI (0/1)*	(3) Probit *AI (0/1)*	(4) IV Probit *AI (0/1)*
lnSkillsShort	0.0108***	0.0842**	0.1287***	1.0415***
	(0.0042)	(0.0404)	(0.0440)	(0.0454)
lnEmpl	0.0137***	-0.0052	0.1780***	-0.1999***
	(0.0033)	(0.0116)	(0.0341)	(0.0531)
RDint	0.2083***	0.2369***	1.6597***	0.9205**
	(0.0775)	(0.0791)	(0.4075)	(0.3950)
ShareGrad	-0.0042	0.0014	-0.0827	0.0496
	(0.0154)	(0.0162)	(0.2252)	(0.1103)
lnAge	-0.0008	0.0079	-0.0293	0.1088***
	(0.0044)	(0.0066)	(0.0643)	(0.0343)
Techpath	0.0156***	0.0124*	0.3626***	0.0731
	(0.0058)	(0.0067)	(0.1235)	(0.0880)
Pathdep	0.0088	-0.0176	0.1496	-0.3251
	(0.0709)	(0.0752)	(0.5807)	(0.3797)
Constant	-0.0555	-0.0550	-3.4207***	-1.0650
	(0.0496)	(0.0524)	(0.5320)	(0.6997)
16 sector dummies	Yes	Yes	Yes	Yes
N	2961	2961	2961	2961
R-squared	0.05			
Pseudo R-squared			0.18	
First-stage robust F stat.		11.84		

Robust standard errors in parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01

Table 4: Regression coefficients table: the impact of skills shortage on the breadth of AI methods/areas of application.

	(1) OLS	(2) IV 2SLS	(3) OLS	(4) IV 2SLS	(5) OLS	(6) IV 2SLS
	AIbreadth	*AIbreadth*	*AIbreadth_method*	*AIbreadth_method*	*AIbreadth_area*	*AIbreadth_area*
lnSkillsShort	0.0324**	0.2574**	0.0213**	0.1634**	0.0231**	0.1517**
	(0.0143)	(0.1048)	(0.0086)	(0.0688)	(0.0094)	(0.0660)
lnEmpl	0.0445***	-0.0133	0.0241***	-0.0125	0.0303***	-0.0027
	(0.0125)	(0.0301)	(0.0070)	(0.0199)	(0.0078)	(0.0190)
RDint	0.6738**	0.7613***	0.4312**	0.4865***	0.4109**	0.4609***
	(0.2854)	(0.2899)	(0.1794)	(0.1826)	(0.1685)	(0.1704)
ShareGrad	-0.0327	-0.0157	-0.0266	-0.0158	0.0054	0.0152
	(0.0466)	(0.0488)	(0.0317)	(0.0329)	(0.0289)	(0.0304)
lnAge	-0.0194	0.0073	-0.0105	0.0064	-0.0049	0.0104
	(0.0138)	(0.0188)	(0.0093)	(0.0125)	(0.0089)	(0.0124)
Techpath	0.0334*	0.0236	0.0220*	0.0158	0.0202*	0.0146
	(0.0184)	(0.0207)	(0.0116)	(0.0131)	(0.0118)	(0.0130)
Pathdep	0.0692	-0.0118	0.0593	0.0081	0.0864	0.0401
	(0.2524)	(0.2634)	(0.1339)	(0.1435)	(0.1613)	(0.1664)
Constant	-0.1468	-0.1454	-0.0905	-0.0896	-0.1541	-0.1532
	(0.1662)	(0.1725)	(0.0948)	(0.0994)	(0.1097)	(0.1123)
16 sector dummies	Yes	Yes	Yes	Yes	Yes	Yes
N	2961	2961	2961	2961	2961	2961
R-squared	0.05		0.05		0.06	
First-stage robust F stat.		11.84		11.84		11.84

Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

In Table 5, we examine the effects of skill shortages on AI adoption by differentiating between academic, vocational, and unskilled or semiskilled tasks. We thus add an interaction term between the variable *lnSkillsShort* and the three dummy variables of aggregated qualifications. This analysis aims to investigate how the lack of specific skills influences a firm's decision to invest in AI technologies or expand their use of AI methods and areas of application. First, we find that the interaction coefficient between skill shortage and academic qualification *(Academic_qual # lnSkillsShort*) is highly significant in all models. On the other hand, the coefficient of unskilled labor is only (weakly) significant in three out of four models. Second, academic qualification has a larger coefficient than vocational qualification and unskilled or semiskilled tasks in all models. This implies that unfilled positions that require a university degree have a stronger positive impact on AI usage and the measures of AI breadth (areas of application and methods) than positions related to non-academic jobs.

In Table 6, we use the information about subfields of jobs and types of tasks required in the job openings. Among skills that require academic qualifications, skills related to computer science, math, engineering, and statistics (under the label *STEM*) have a larger positive impact on the decision of firms to use AI technologies and on AI methods/areas of application than other types of academic qualifications that are related to, for example, business and law. Interestingly, vocational IT and manufacturing skills are associated with a negative effect, which could be because these skills are often more specialized and less transferable than general skills (Shiohira, 2021). Finally, the positive impact of skills shortage for semi-skilled and unskilled tasks that was observed in Table 5 is mostly driven by a scarcity of labor dedicated to production tasks. Shortage of skills for unskilled production tasks may also create higher incentives for firms to use AI technologies to automate or optimize routine and repetitive processes.

Table 5: Regression coefficients table: the impact of skills shortage on AI use and the breadth of AI use based on the type of qualification demanded or the type of tasks to be performed.

	(1) Probit *AI (0/1)*	(2) OLS *AIbreadth*	(3) OLS *AIbreadth_area*	(4) OLS *AIbreadth_method*
lnSkillsShort	-0.0632	-0.0408	-0.0346*	-0.0236
	(0.1017)	(0.0290)	(0.0196)	(0.0201)
Academic_qual	-0.0295	-0.0491	-0.0345	-0.0286
	(0.1622)	(0.0374)	(0.0241)	(0.0262)
Academic_qual # lnSkillsShort	0.3253***	0.1170***	0.0835***	0.0736***
	(0.0964)	(0.0338)	(0.0226)	(0.0215)
Vocational_qual	0.2886*	0.0271	0.0303	0.0086
	(0.1604)	(0.0288)	(0.0189)	(0.0166)
Vocational_qual # lnSkillsShort	-0.1894*	-0.0157	-0.0099	-0.0061
	(0.1021)	(0.0293)	(0.0171)	(0.0170)
Unskilled_tasks	-0.2423	-0.0449	-0.0428**	-0.0150
	(0.1750)	(0.0281)	(0.0198)	(0.0185)
Unskilled_tasks # lnSkillsShort	0.1689*	0.0563*	0.0468**	0.0286
	(0.0992)	(0.0323)	(0.0221)	(0.0205)
lnEmpl	0.1500***	0.0401***	0.0276***	0.0209***
	(0.0388)	(0.0138)	(0.0082)	(0.0077)
RDint	1.6687***	0.6471**	0.3754**	0.4226**
	(0.4093)	(0.2855)	(0.1674)	(0.1797)
ShareGrad	-0.2176	-0.0565	-0.0060	-0.0445
	(0.2504)	(0.0482)	(0.0288)	(0.0346)
lnAge	-0.0243	-0.0207	-0.0051	-0.0105
	(0.0688)	(0.0146)	(0.0094)	(0.0096)
Techpath	0.3681***	0.0363*	0.0237**	0.0242**
	(0.1252)	(0.0186)	(0.0117)	(0.0116)
Pathdep	0.1174	0.0303	0.0252	0.0320
	(0.5996)	(0.2447)	(0.1580)	(0.1301)
Constant	-3.2982***	-0.0769	-0.0875	-0.0470
	(0.5654)	(0.1589)	(0.1061)	(0.0920)
16 sector dummies	Yes	Yes	Yes	Yes
N	2918	2918	2918	2918
R-squared		0.06	0.07	0.06
Pseudo R-squared	0.19			

Robust standard errors in parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01

Table 6: Regression coefficients table: the impact of skills shortage on AI use and the breadth of AI use based on the type of qualification demanded or the type of tasks to be performed.

	(1) Probit *AI (0/1)*	(2) OLS *AIbreadth*	(3) OLS *AIbreadth_area*	(4) OLS *AIbreadth_method*
lnSkillsShort	-0.0909	-0.0431**	-0.0385**	-0.0309**
	(0.0773)	(0.0217)	(0.0166)	(0.0154)
STEM	-0.0968	-0.0548	-0.0411	-0.0321
	(0.1842)	(0.0451)	(0.0289)	(0.0302)
STEM # lnSkillsShort	0.2777***	0.1182***	0.0880***	0.0673***
	(0.1003)	(0.0383)	(0.0258)	(0.0248)
Other_academic	-0.1393	-0.0728	-0.0335	-0.0443
	(0.2331)	(0.0474)	(0.0326)	(0.0331)
Other_academic # lnSkillsShort	0.2343**	0.0839*	0.0447	0.0578**
	(0.1052)	(0.0441)	(0.0306)	(0.0287)
Vocational_IT	0.8084***	0.2237**	0.1783**	0.1042
	(0.2262)	(0.1094)	(0.0818)	(0.0644)
Vocational_IT # lnSkillsShort	-0.1993*	-0.0277	-0.0196	0.0032
	(0.1070)	(0.0637)	(0.0455)	(0.0398)
Vocational_manuf	0.1635	0.0421	0.0262	0.0281
	(0.1959)	(0.0355)	(0.0226)	(0.0223)
Vocational_manuf # lnSkillsShort	-0.2411**	-0.0592*	-0.0361*	-0.0258
	(0.1061)	(0.0323)	(0.0194)	(0.0172)
Unskilled_production	-0.2092	-0.0758**	-0.0627***	-0.0304
	(0.2348)	(0.0336)	(0.0220)	(0.0251)
Unskilled_production # lnSkillsShort	0.2321**	0.0788**	0.0607***	0.0372*
	(0.1170)	(0.0375)	(0.0230)	(0.0205)
Unskilled_services	-0.0693	0.0089	-0.0152	0.0200
	(0.2247)	(0.0468)	(0.0303)	(0.0370)
Unskilled_services # lnSkillsShort	0.0615	0.0387	0.0433	0.0199
	(0.1040)	(0.0353)	(0.0286)	(0.0278)
Unskilled_logistics	-0.1822	-0.0496	-0.0394*	-0.0326
	(0.2839)	(0.0312)	(0.0223)	(0.0251)
Unskilled_logistics # lnSkillsShort	0.1293	0.0357	0.0347	0.0315
	(0.1136)	(0.0308)	(0.0230)	(0.0229)
lnEmpl	0.1170***	0.0337**	0.0228***	0.0168**
	(0.0419)	(0.0145)	(0.0082)	(0.0080)
RDint	1.6602***	0.6387**	0.3703**	0.4134**
	(0.4054)	(0.2850)	(0.1663)	(0.1802)
ShareGrad	-0.2431	-0.0631	-0.0141	-0.0452
	(0.2436)	(0.0473)	(0.0273)	(0.0344)
lnAge	-0.0112	-0.0176	-0.0025	-0.0087
	(0.0722)	(0.0145)	(0.0091)	(0.0093)
Techpath	0.3695***	0.0370*	0.0252**	0.0238**
	(0.1257)	(0.0190)	(0.0118)	(0.0116)
Pathdep	-0.2602	-0.0464	-0.0309	-0.0233
	(0.6329)	(0.2260)	(0.1462)	(0.1192)
Constant	-2.9495***	-0.0089	-0.0348	-0.0024
	(0.6058)	(0.1424)	(0.0969)	(0.0852)
16 sector dummies	Yes	Yes	Yes	Yes
N	2918	2918	2918	2918
R-squared		0.08	0.10	0.08
Pseudo R-squared	0.22			

Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

These results provide some evidence of the fact that firms also adopt AI when they cannot find suitable employees for the completion of tasks for which they rely on highly skilled personnel. We consider this finding of particular interest since it provides support to a more nuanced view of the determinants of the diffusion of AI. While a generally accepted view in the economic literature is that AI technologies are implemented to automate routinized tasks through machines, we find some evidence that the potential of AI is broader and also enables firms to mitigate the harms of scarcity of highly qualified labor.

We further explore if skills shortage is specifically associated with one or more areas of application of AI and one or more AI methodologies. Based on the categorization of AI areas and AI methodologies in the survey question, we group areas of applications in two categories, i.e., (1) products/services and automation of processes, on the one hand, and (2) interaction with clients, data analytics, or other areas, on the other hand. Similarly, we distinguish between two classes of AI methods: (1) language understanding, image recognition, machine learning, and, on the other hand, (2) knowledge-based systems and other methods. Since we suppose that the decision to introduce AI in each category of application areas/methodologies is not independently determined, we estimate a bivariate probit regression for areas of application and methodologies of AI. The bivariate probit is a natural extension of the probit model which, similar to seemingly unrelated regression models, allows for two equations with correlated disturbances (Greene, 2003). As shown in Table 7, skills shortage seems to be positively associated with both categories of areas of application, namely automation of processes, products/processes, and interaction with clients/data analytics. Conversely, when it comes to methodologies, our results suggest that the positive association between skills shortage and AI does not entail knowledge-based systems methodologies, but involves machine learning, image recognition, and language understanding.[6]

Table 7: Regression coefficients table: the impact of skills shortage on areas of applications of AI and methodologies of AI.

	(1) Bivariate Probit		(2) Bivariate Probit	
	Products, services, automation of processes (0/1)	*Interaction with clients, data analytics, others (0/1)*	*Language understanding, image recognition, machine learning (0/1)*	*Knowledge-based system, others (0/1)*
lnSkillsShort	0.1565***	0.1132**	0.1563***	0.0454
	(0.0455)	(0.0547)	(0.0467)	(0.0546)
lnEmpl	0.1979***	0.1684***	0.1625***	0.1766***
	(0.0376)	(0.0378)	(0.0370)	(0.0449)
RDint	1.8688***	1.6661***	1.6075***	1.6786***
	(0.4124)	(0.4622)	(0.4179)	(0.4839)
ShareGrad	0.0121	-0.1807	-0.1107	-0.1825
	(0.2421)	(0.2532)	(0.2331)	(0.2953)
lnAge	-0.0281	-0.0363	-0.0550	0.0006
	(0.0694)	(0.0725)	(0.0706)	(0.0787)
Techpath	0.4744***	0.0799	0.3527***	0.3318**
	(0.1376)	(0.1332)	(0.1255)	(0.1638)
Pathdep	0.4416	0.7963	0.5610	-0.6065
	(0.6029)	(0.7335)	(0.6341)	(0.6937)
Constant	-3.9702***	-3.7810***	-3.6191***	-3.2372***
	(0.5564)	(0.6447)	(0.5718)	(0.6328)
16 sector dummies	Yes		Yes	
N	2961		2961	
Rho	0.9481***		0.8581***	
	(0.0181)		(0.0407)	
Log Pseudolikelihood	-380.53		-404.27	
Wald Chi	5039.66		9491.78	

Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

5 Conclusions

This study seeks to better understand the relationship between labor scarcity and the adoption of Artificial Intelligence (AI) as a potential solution for firms with unfilled job vacancies. Contrary to the prevailing concern that AI may lead to unemployment, our study takes a different perspective by examining the adoption of AI methods as a response to the difficulty

[6] Based on the Wald test of rho equal to 0 in Table 7, we can reject the null hypothesis of independent equations for both specifications.

of finding suitable employees who meet firms' human capital demands. Our study sheds light on the potential effects of AI technologies in helping firms overcome skills shortages.

Through the analysis of data from a representative and large-scale survey, we explore the implications of skills shortages on AI adoption. Our findings indicate a positive and significant relationship between skills shortage and AI adoption, encompassing both the breadth of AI methods and the areas of application.

Furthermore, our study distinguishes between shortages of skills of different type of qualifications (academic, vocational, and unskilled) to discern their respective influences on AI adoption. We find indications that the scarcity of labor with academic education, and in particular of skills associated with STEM fields, positively influence the adoption of AI technologies, methods, and applications. This finding emphasizes that firms adopt AI not only for process automation and robotization but also to accomplish tasks traditionally requiring highly skilled personnel.

Moreover, our analysis shows that the positive association between skills shortage and AI adoption entails various areas of application of AI, including automation of processes, products/processes, interaction with clients, and data analytics. Conversely, in terms of AI methodologies, our results suggest that the positive association between skills shortage and AI involves machine learning, image recognition, and language understanding, but not the usage of knowledge-based systems methods.

It is worth noting that our study has certain limitations. The analysis is based on cross-sectional data from the German part of the Community Innovation Survey, and hence caution should be exercised when generalizing the findings to other contexts. Future research could employ longitudinal data and expand the analysis to encompass a broader range of countries and industries.

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Appendix

Table 8: Economic sectors (N=2961).

Economic sectors	%
Consumer goods	9.46
Other materials	10.40
Chemicals and pharmaceuticals	2.94
Metals and metal products	7.40
Electronics and electrical equipment	6.32
Machinery and equipment	7.19
Vehicles	1.62
Utilities, waste management, mining	9.46
Wholesale trade	4.09
Transport and logistics services	7.36
Media services	2.23
Software, IT services	4.80
Financial services	2.63
Legal, accounting, consulting, advertising serv.	8.75
Engineering and R&D services	9.42
Other producer services	5.94
	100

Sources: German CIS reference year 2018.

Table 9: First-stage IV 2SLS regression.

	First-Stage IV 2SLS *lnSkillsShort*
Pricecomp	0.186^{***}
	(0.054)
lnEmpl	0.256^{***}
	(0.020)
RDint	-0.400^{**}
	(0.185)
ShareGrad	-0.069
	(0.072)
lnAge	-0.118^{***}
	(0.024)
Techpath	0.036
	(0.036)
Pathdep	0.382
	(0.475)
Constant	-0.196
	(0.327)
16 industry dummies	Yes
R-squared	0.17
Robust F-statistic	11.84
N	2961

Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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