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Drivers of AI adoption in SMEs: Missing skills and other firm-level factors

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Abstract

This paper empirically examines factors and firm-level determinants of artificial intelligence (AI) adoption. It is particularly focused on factors related to missing skills in European small and medium-sized enterprises (SMEs). It uses micro-level data from Flash Eurobarometer 537, which includes more than 19,000 firms from 27 EU and 9 non-EU countries. The aim was to identify the key characteristics associated with the likelihood of AI adoption and the anticipation of significant skill transformations related to AI adoption. Results of probit and bivariate probit regressions reveal that firms with younger employees, growing turnover, and membership in industry clusters are more likely to adopt AI. Moreover, firms that have problems with shortages of skills in specific areas (such as IT, R&D, marketing, and customer care) are more likely to adopt AI. These firms also expect that AI adoption will significantly change their skill demands in the future. Interestingly, community size and difficulties with recruiting are closely related to the adoption of AI but have a limited effect on firms' expectations of its impact on skills demanded in the future. Furthermore, the analysis revealed significant differences across industries. These findings contribute to the emerging literature on digital transformation and expand the knowledge on the decision-making process for AI introduction by clarifying the drivers of AI adoption and its perceived skill implications.

Keywords: artificial intelligence (AI), factors of AI adoption, determinants of AI adoption, skills needs, small and medium-sized enterprises (SMEs).

1. Introduction

Artificial intelligence (AI) is one of the few technologies that has currently gained considerable attention in public as well as in business. Despite a significantly growing body of research on this topic, certain areas remain underexplored, including the decision-making process related to AI adoption in small and medium-sized enterprises. The adoption of AI in firms could change business processes and operations while enhancing automation. It has the potential to change the structure of the workforce and alter the types of skills demanded. This paper aims to cover this research gap based on the empirical analysis of micro-level data.

Its main goal is to identify firm-level characteristics associated with AI adoption as well as factors correlated with the anticipated effect of AI on skill needs. The results may help to better understand the decision-making process for AI introduction, provide evidence on factors affecting their choices, and predict its potential consequences for skills. The following three main research questions (RQs) have been examined in the paper:

- RQ1: Which firm-level characteristics and factors are associated with the likelihood of AI adoption in SMEs?
- RQ2: Which firm-level characteristics and factors are associated with SMEs' perception of AI's impact on future skill needs?
- RQ3: To what extent are AI adoption and the expectations of significant skill shifts jointly driven by firm-level characteristics and existing skill shortages in firms?

This research paper is significantly extended and improved version of previous paper (Hunady, 2024). As far as we are aware, there is no other study focused on examining a similar set of factors for AI adoption based on such extensive micro-level data. Most of the research examining micro-levels deals with the attitudes of individuals, such as, for example, customer perceptions of digitalization (Garai-Fodor et al., 2023) or correlations with personal traits (Stein et al., 2024). On the other hand, studies investigating firms' characteristics and factors are mostly based on much smaller samples (such as Kinkel et al. 2022) or focused on more general problems such as Industry 4.0 (such as Corò and Volpe, 2020).

The following section briefly summarizes the results of previous research focused on similar research problems. However, there are currently only a limited number of studies dealing with the factors affecting AI adoption at companies. The next section describes the methodology and data used in the analysis. Key results are summarized in the fourth section. The final section contains an explanation of the main conclusions resulting from the results.

2. Literature review

Adoption of artificial intelligence (AI) in companies changes their business operations by optimizing existing processes. It enhances automation while interacting with humans (Wamba-Taguimdje et al., 2020). Successful adoption of AI can increase a company's total turnover (Czarnitzki et al., 2023), improve the efficiency and accuracy of logistics (Liu, 2024), improve the safety and security of suppliers (Pap et al., 2025) and support economic growth (Babina et al., 2024). Businesses can take advantage of AI adoption, regardless of their size. While large companies usually employ AI in robotics and resource management, SMEs mostly use it to improve knowledge management and quality control (Seifert et al., 2018).

The decision on AI adoption is affected by many factors, which we will further examine in more detail. However, the difference between the expected benefits and the costs associated with the adoption is an important criterion. The adoption of any new technology in a firm can be theoretically explained by the Innovation diffusion theory (Rogers et al., 2014). This research is also based on this theoretical approach, while the focus is on factors associated with AI adoption and the role of skills requirements.

There are many internal and external factors that could influence the willingness and actual decision to adopt AI in the company. Organizational factors such as digital skills, company size, and R&D intensity appear to have the most significant effect on the adoption of AI (Kinkel et al., 2022). Some studies argue that larger companies are more likely to implement AI tools (Ransbotham et al., 2017; Seifert et al., 2018). On the contrary, Coró and Volpe (2020) found that firm size does not matter for Industry 4.0 and especially for the adoption of digital technologies. This paper is trying to resolve this inconsistency and carefully examine this problem with a larger sample of companies. It is likely that SMEs could struggle with AI adoption due to a lack of sufficient data as well as problems with financial and human resources (Dukino et al., 2019). The smaller size of the company can be partly eliminated by its membership in an industry cluster or any other similar business organization. Membership in the industry cluster provides a conducive environment that supports digitalization (Olsen et al., 2020) and

business transformation towards Industry 4.0 (Götz, 2021). The analysis in this paper considers the size of the company as well as its potential membership in an industry cluster or similar organization.

The financial situation of the company is also considered an important factor affecting AI adoption. Especially, the ability to generate significant turnover and profit are both positively related to the adoption of digital technologies (Corò and Volpe, 2020; Romano, 2019). Moreover, the growth in total turnover is positively associated with process and product innovation in companies (Morone and Testa, 2008).

Besides companies' internal factors, there are certain external factors that are also playing an important role. Country-specific factors such as regulations, labor market specifics, quality of institutions, and cultural differences are affecting the adoption of digital technology or innovation (Vagnani et al., 2019). The geographical location of the company in a city or rural area seems to also be important. Considerable heterogeneity among SMEs with respect to the adoption of advanced digital technologies has been found based on their location (Holl and Rama, 2024). Rural and small-town SMEs are less frequently adopting digital technology. In line with these findings, we considered the size of the community where the company is located as an independent variable in regressions.

Despite several positive effects of the adoption of AI, there are also some crucial problems resulting from this rather major change. It can mostly lead to significant shifts in the workforce composition (Babina et al., 2024) and a rising need for highly qualified workers (Xie et al., 2021). The usage of digital technologies requires trained professionals who have the competencies and skills to thrive in the new digital environment (Hernandez-de-Mendez et al., 2020). Adoption of AI in the company will likely lead to increased demand for soft skills such as critical thinking, problem-solving, communication skills, and creativity (Poláková et al., 2023) can replace some technical skills but increases the need for soft skills in firms (Grennan and Michaely, 2020).

The effect of AI on skill needs after its adoption seems to be more evident. However, the availability of certain skills is also considered a prerequisite for the adoption of digital technology. Several previous studies found that human capital and skills are essential for the adoption of digital technologies (Corò and Volpe, 2020). Adoption of new digital technologies such as AI requires employees with specific digital skills (Canhoto and Clear, 2020; Mikalef et al., 2020). Technical skills such as software development, IT design, and complex data analysis, along with the involvement of some soft skills (such as intercultural collaboration or customer handling), are essential for the ability to introduce digitally integrated solutions and technologies (Kinkel et al., 2022). Shortages of such skills in the company represent a significant challenge for the process of digital technology adoption.

A firm's absorptive capacity, which is often proxied by R&D intensity, is considered one of the key determinants for the implementation of new technology (Agostini and Nosella, 2020). This indicator shows how effectively a company can adopt and use new technology to gain certain benefits. The shortage of R&D skills can therefore represent a barrier to the adoption of AI. Firms with this problem may therefore be less likely to use AI. However, these hypotheses need to be further empirically tested.

It is evident that the relationship between skill requirements and adoption of AI is debatable and needs further empirical investigation based on larger samples of firms. This paper covers this research gap and examines how shortages of different types of skills could be associated with AI adoption. Furthermore, the paper is also focused on examining factors related to the expected effects of AI on the skills needed.

3. Methodology and data

The main aim of this paper is to identify the key factors associated with AI adoption in SMEs. In addition, the paper also examines firm-level characteristics linked to SMEs' expectations regarding the impact of AI adoption on future skill needs. By showing and comparing the factors influencing both AI adoption and the anticipated skill changes, we provide comprehensive analysis and results with managerial implications.

The analysis is based on secondary data collected by Flash Eurobarometer Survey No. 537 (European Commission, 2023). A questionnaire survey was conducted in Iceland, Norway, Switzerland, the United Kingdom,

North Macedonia, Turkey, the United States, Canada, Japan, and all 27 EU countries between September 11 and October 13, 2023. More than 19,000 respondents' companies were interviewed. The paper is focused on two main questions related to the usage of AI in the company and the expected effects of AI on future skills and needs in the company. These questions were used as dependent variables in probit and bivariate probit regressions. They are described in Table 1.

Table 1. Description of Dependent variables included in the regressions

Name	Question	Coding
Use/Plan to use AI (Using AI or have concrete plans to do so)	Which of the following statements best describes the deployment of Artificial Intelligence Technologies (AI) in your company over the next 5 years? 1. You use AI, or you have concrete plans to do so, and you expect a significant impact on your company's skill needs 2. You use AI, or you have concrete plans to do so, but you do not expect a significant impact on your company's skill needs 3.You have no concrete plans to use AI, but in case you would use it, you expect a significant impact on your company's skill needs 4. You have no concrete plans to use AI and you expect no significant impact of AI on your company's skill needs	Use AI, or have concrete plans to do so (answers 1 and 2) coded as 1; Otherwise = 0
AI impacts skills (Expect impact of AI on skills)		Expect a significant impact of AI on your company's skill needs (answers 1 and 3) coded as 1; Otherwise = 0

Source: Authors based on the data from European Commission (2023).

Both dependent variables are binary variables created based on the answers of respondent companies. Descriptive statistics of the variables capturing the answers to the main question are shown in Table 2.

Table 2. Description of Independent variables included in the regressions

Variables/Answers	Proportion/Std. Error	95% Conf. Interval
Use AI, or have concrete plans to do so, and expect a significant impact on company's skill needs	0.1121/ 0.0023	0.108-0.117
Use AI, or have concrete plans to do so, and do not expect a significant impact on company's skill needs	0.0935/ 0.0022	0.089-0.098
You have no concrete plans to use AI, but in case you would use it, you expect a significant impact on your company's skill needs	0.1681/ 0.0028	0.163-0.174
You have no concrete plans to use AI and you expect no significant impact of AI on your company's skill needs	0.5648/ 0.0037	0.558-0.572
Dont know/No answer (excluded in regressions)	0.0615/ 0.0018	0.058-0.065

Source: Authors based on the data from European Commission (2023).

More than 56% of companies in the sample reported that they have no concrete plans to use AI, and they also do not expect a significant impact of AI on a company's skill needs. More than 11% are either already using AI or at least have concrete plans to do so soon and expect a significant impact on a company's skill needs. On the other hand, approximately 9.4% of the firms use AI or plan to use it and do not expect an effect on skill needs. Hence, the subsample of those firms using AI or planning to use AI is divided into two almost equally represented groups concerning their expectations towards the effect of AI on skills needed. We will further examine factors associated with their attitudes, represented by independent variables shown in Tab. 3. They have been chosen based on the theoretical background and expected potential effects. The choice was also limited by data availability. Hence, only the variables capturing the questions in the questionnaire can be used in the regression. The company's size was represented by the number of employees in intervals, coded from 1 to 6. Variables such as employees'

average age, recent changes in turnover, type of industry, community size, and membership in the industry cluster have also been used. Moreover, we introduced independent variables capturing the skills shortage for a specific type of job (IT, administrative jobs, HR, technician, customer care, R&D, and marketing).

Table 3. Description of Independent variables included in the regressions

Name	Question	Coding
Employees	What is the size of your company in terms of number of employees?	1 to 4 employees = 1; 5 to 9= 2; 10 to 49= 3; 50 to 249 = 4; 250 to 499 = 5; 500 or more = 6
Employees' age	What is the average age of your employees?	Under 20 years = 1; 20-29 = 2; 30-39 = 3; 40-49 = 4; 50 or above = 5
Age of the company	Year when the company was estabilshed – year 2023	Years
Increased annual turnover	Over the past 2years, has your company's annual turnover increased/decreased/remained unchanged?	Increased = 1; Decreased/remain unchanged = 0
Community size	Which of the following best describes the area where your company is located	A rural area = 1; less than 20,000 inhabitants = 2; 20,000-100,000 inhabitants = 3; 100,000-500,000 inhabitants = 4; Over 500,000 = 5
Industry cluster	Are you a member of an industry cluster or another SME business support organisation?	Yes = 1; No = 0
Difficult to hire skills	Over the past 24 months, how difficult was it for your company to find and hire staff with the right skills?	Very difficult = 4; Slightly difficult = 3 Not difficult at all = 2; Not relevant. We did not need to hire anyone in the past 24 months = 1
IT shortage	Does your company face skill shortage for any of these job roles?	Yes = 1 (IT experts skills); No = 0
Administrative shortage		Yes = 1; No = 0
HR shortage		Yes = 1; No = 0
Technician shortage		Yes = 1; No = 0
Customer care shortage		Yes = 1; No = 0
R&D shortage		Yes = 1; No = 0
Marketing shortage		Yes = 1; No = 0
Other shortage		Yes = 1;No = 0
Industry (dummy)	What is the main activity of your company?	11 dummy variables created based on NACE categories.

Source: Authors based on the data from European Commission (2023).

Specific types of skills that are missing in the company can potentially affect the decision on AI adoption. Some skills are more likely to be substituted by AI, while others are less replaceable. The overall difficulty of hiring adequate skills can also affect AI adoption. On one hand, companies with lower skill availability in the labor market

could consider introducing AI more often. On the other hand, the adoption of AI itself also requires highly skilled employees.

The effects of factors represented by independent variables on both binary dependent variables have been identified by probit regression and bivariate probit regression. While the first set of regressions has been estimated with individual probit regressions, the second set is using bivariate probit regression. In the case of bivariate probit, both dependent variables (AI adoption and perceived effect of AI adoption on skills) have been used simultaneously in a model, and the set of independent variables has been identical. Bivariate probit is considering the correlation between both dependent variables. Each individual single probit regression is examining the first two research questions. The bivariate probit allows us to further examine the third research question. The robust standard errors have been used in all models to avoid problems with heteroscedasticity. Standard errors are also clustered by countries to reduce potential problems with sampling design while interpreting the results. This method is widely used in economic and social research.

4. Results and disscusion

Considering the size of the firm, there are rather significant differences among companies in the perceived impacts of AI on a company's skill needs. It can be assumed that bigger companies with more employees will likely experience less impact on skill needs than smaller ones. Surprisingly, the results show us the opposite (Figure 1). Companies with fewer employees are usually reported to perceive the effect of AI adoption on skills as irrelevant. Smaller businesses are often not considering using AI, and even if they did, the extent of its application in day-to-day business would be smaller. However, these interesting findings need to be investigated in future research.

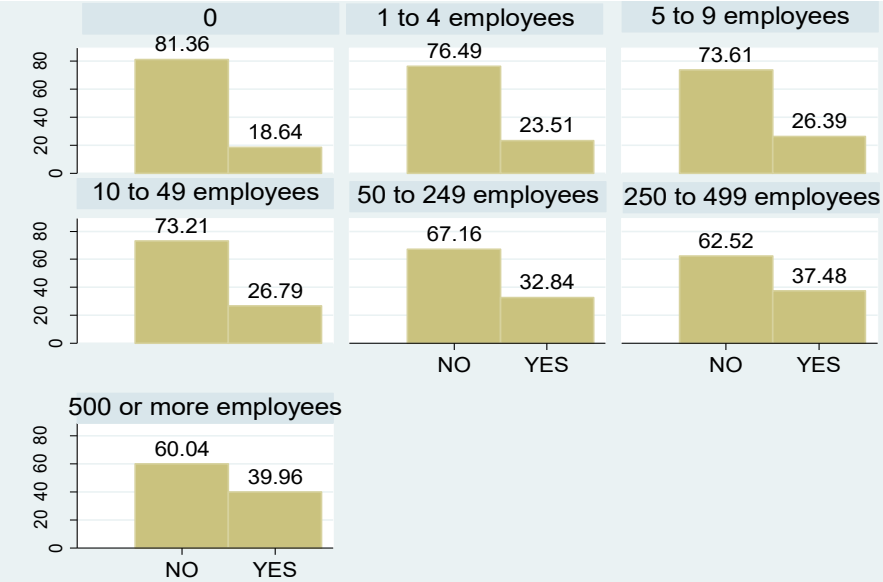

Figure 1. Impact of AI adoption on skill needs in companies – size differences
Source: Authors based on the data from European Commission (2023).

The next two figures illustrate the geographical differences among EU countries. The share of companies that are using or planning to use AI soon is shown in Figure 2. It explores differences among the countries where the respondent firms are located. The differences among countries are notable, and the proportion of firms that do not even plan to introduce AI appears to be highest in Japan, followed by France and Poland. On the other hand, companies from Canada, Denmark, and Malta are the leaders in AI adoption. Comparing the situation in EU countries, the differences between the top and bottom countries are more than 20 percentage points.

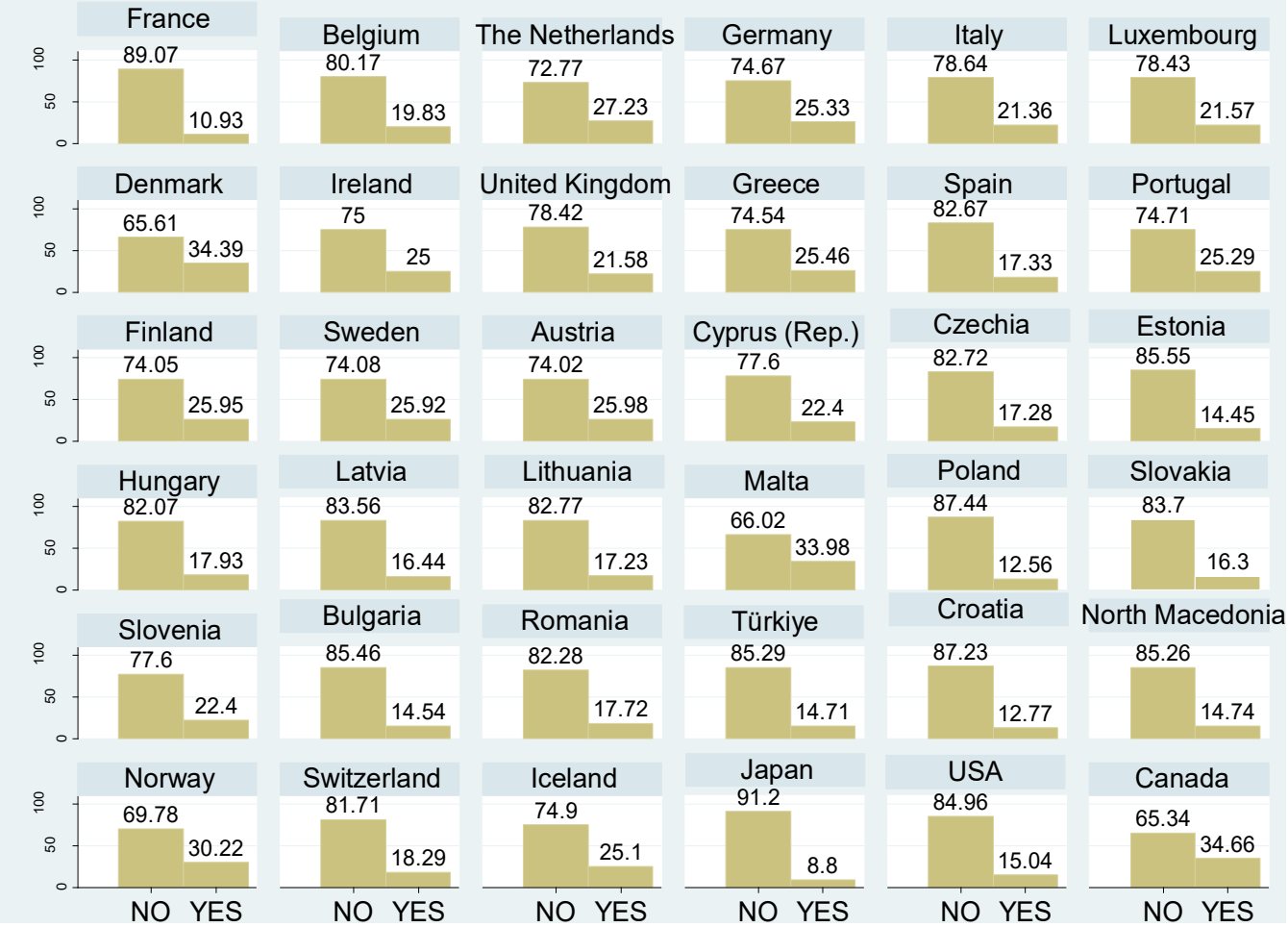

Figure 2. Share of firms using AI or have concrete plan to do so
Source: Authors based on the data from European Commission (2023)

Figure 3 shows the differences in perceived effects of AI adoption on skills among European countries. The results are to some extent similar to previous ones. However, compared to the adoption of AI, firms are more frequently expecting a major shift in skill needs due to the AI adoption. The highest share of these firms was found in Portugal, followed by Malta and Romania. On the contrary, more than 80% of firms from the USA, Hungary, and Estonia are not expecting such dramatic changes in skills demand due to AI.

The following part of the research is focused on more detailed examination of the potential effect of individual factors on the adoption of AI and its expected effects on skills needed in the company. The results of probit regression and bivariate probit are shown in Table 4. Bivariate probit regression was used to simultaneously analyse the factors influencing both AI adoption and its perceived effect on skill needs within SMEs. The Wald test for the bivariate probit model (shown under Table 4) gives a highly significant result, indicating a strong correlation between the adoption of AI and the expectation that AI will impact skill needs. This further justifies the use of the bivariate probit in this case.

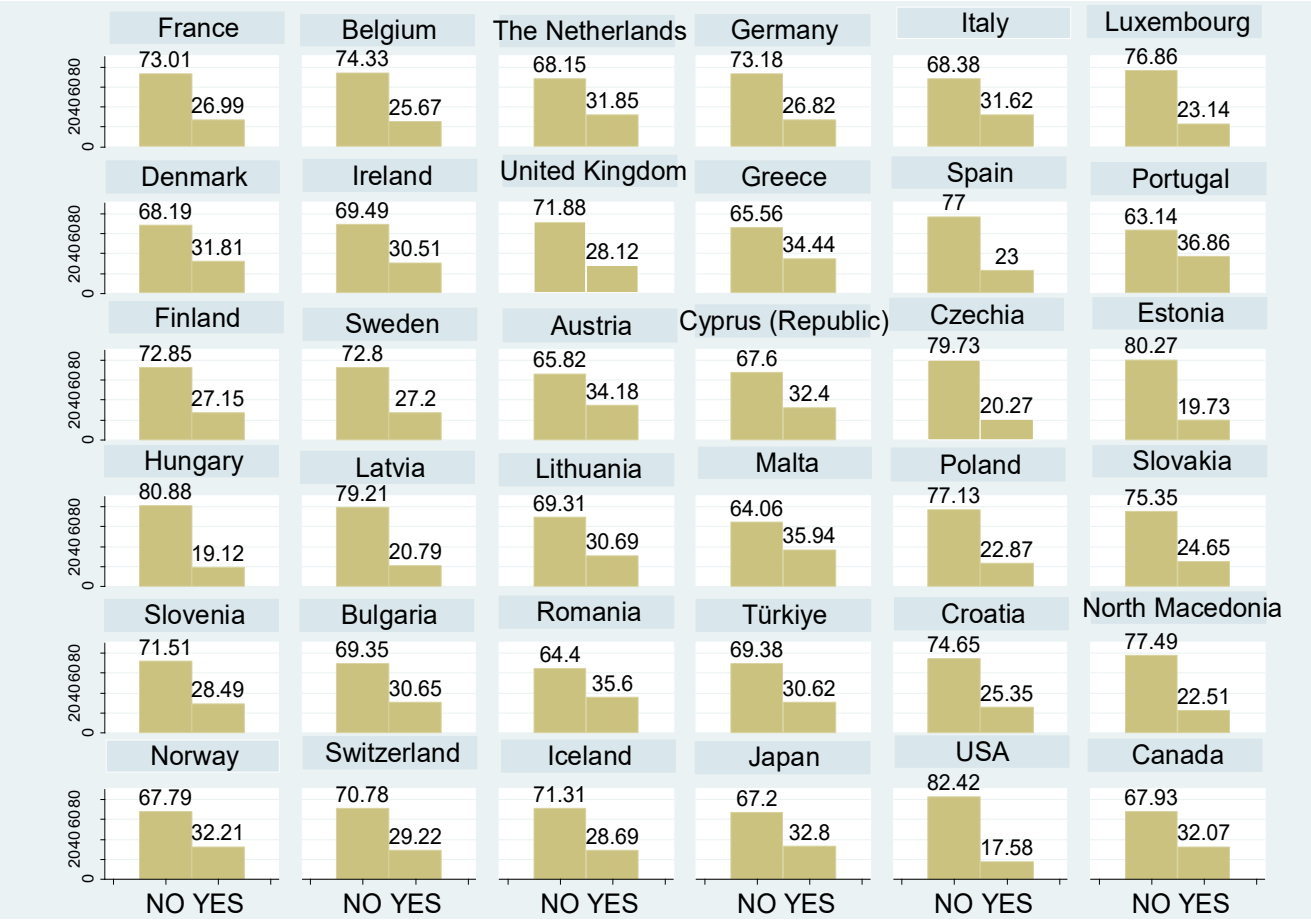

Figure 3. Share of firms that expect a significant impact of AI on your company's skill needs
Source: Authors based on the data from European Commission (2023).

There are several companies' characteristics that appear to play a significant role in all regressions. The probability that the company will introduce AI as well as this adoption leading to changes in skills needed increases with the number of employees and decreases with the average age of the employees. Hence, the results suggest that the size of the company is positively linked with the probability of AI adoption. Although this finding is contrary to the findings provided by Corò and Volpe (2020). Driving, similar results were achieved by Ransbotham et al. (2017) and Seifer et al. (2018). On one hand, a higher average age of employees is negatively correlated with both AI adoption and its perceived impact on skills. On the other hand, the age of the company itself is not playing a significant role. Companies experiencing recent increases in annual turnover are more likely to adopt AI, and they also tend to report that AI will affect their needs for skills. This is in line with the results of previous studies such as Corò and Volpe (2020) and Morone and Testa (2008), which found a similar positive correlation between turnover and innovation. However, the exact direction of this should be further examined. Difficulties with hiring staff are negatively correlated with AI usage, which can also be the cause as well as the result of AI adoption. Hence, companies with more problems acquiring adequate skills tend to use AI less. Interestingly, this variable has no significant effect on the expected effect of AI on skill needs.

Table 4. Results of probit and bivariate probit regressions

	Probit	Bivariate probit	Probit	Bivariate probit
VARIABLES	Use/Plan to use AI Coef (Robust Std. Errors)		AI IMPACTS SKILLS Coef.(Robust Std. Errors)	
Employees (size)	0.0464***	0.0485***	0.081***	0.0823***
	(0.0158)	(0.0161)	(0.012)	(0.0119)
Employees' age	-0.0782***	-0.0793***	-0.067***	-0.068***
	(0.0230)	(0.0232)	(0.017)	(0.0165)
Age of the company	0.0005	0.0005	-0.0005	-0.0005
	(0.0007)	(0.0007)	(0.0006)	(0.0006)
Increased annual turnover	0.1625***	0.1629***	0.105***	0.105***
	(0.0324)	(0.0328)	(0.0227)	(0.0228)
Difficult to hire skills	-0.0304**	-0.00317**	-0.0014	-0.002
	(0.0136)	(0.0139)	(0.001)	(0.01)
Community size	0.0267*	0.0261*	0.008	0.008
	(0.0136)	(0.0137)	(0.010)	(0.01)
Industry cluster	0.184***	0.185***	0.135***	0.135***
	(0.0374)	(0.0379)	(0.029)	(0.029)
IT shortage	0.253***	0.248***	0.332***	0.329***
	(0.0526)	(0.0524)	(0.051)	(0.051)
Administrative shortage	0.0325	0.0372	0.056	0.059
	(0.0481)	(0.0474)	(0.041)	(0.041)
HR shortage	-0.115*	-0.109*	0.062	0.0621
	(0.063)	(0.061)	(0.095)	(0.095)
Technician shortage	0.0192	0.0217	0.053*	0.053*
	(0.0376)	(0.038)	(0.029)	(0.029)
Customer care shortage	0.0989**	0.105**	0.134***	0.136***
	(0.0431)	(0.0428)	(0.042)	(0.042)
R&D shortage	0.260***	0.265***	0.017	0.0205
	(0.0781)	(0.0763)	(0.079)	(0.0778)
Marketing shortage	0.297***	0.292***	0.262***	0.260***
	(0.0815)	(0.0811)	(0.052)	(0.524)
Other shortage	-0.0478	-0.0450	-0.053	-0.053
	(0.033)	(0.0333)	(0.033)	(0.033)
Industry variables (reference category: professional, scientific and technical activities) - selected variables:				
Manufacturing	-0.466***	-0.466***	-0.235***	-0.236***
	(0.054)	(0.054)	(0.048)	(0.048)
ICT	0.228***	0.229***	0.119***	0.119***
	(0.0589)	(0.0762)	(0.058)	(0.058)
Construction	-0.640***	-0.639***	-0.383***	0.383**
	(0.0717)	(0.071)	(0.060)	(0.060)
Sales	-0.484***	-0.484***	-0.270***	-0.272***
	(0.0496)	(0.050)	(0.047)	(0.047)
Constant	-0.449***	-0.449***	-0.471***	-0.470***
	(0.105)	(0.107)	(0.091)	(0.090)
Observations	14,780	14,780	14,780	14,780

Notes: Robust standard errors clustered on countries. *** p<0.01, ** p<0.05, * p<0.1. Bivariate probit Wald test: $\rho=0$: $\chi2(1) = 384.612$***. Source: Authors based on the data from European Commission (2023).

There is some limited evidence that the community size where the company is located could be related to the usage of AI. However, this relationship is statistically significant only at the 10% level of significance. This is partly in line with the expectations as well as the results of previous studies (Holl and Rama, 2024). The agglomeration forces should play a role in the adoption of new digital technology and innovation in general. Nevertheless, the effect of AI on skills should not directly depend on the geographic location of the company.

On the other hand, being part of an industry cluster appears to be significantly positively correlated with both dependent variables. This could be due to better access to knowledge and a more supportive environment, as previously reported by Olsen et al. (2020) and Götz (2021).

Missing skills in the company and their exact type also appear to be linked with AI usage and its effects on skills. Shortages in IT, customer care, R&D, and marketing-related skills are positively associated with a higher likelihood of AI adoption. Companies that have a problem with the availability of mentioned skills are opting for AI. On the other hand, shortages in administrative and technician job-related skills do not appear to have any evident connection to the adoption of AI in SMEs.

There are also some significant differences among industries. Compared to the professional, scientific, and technical activities (used as a reference category), most of the other industries, such as manufacturing, construction, and sales, show a lower likelihood of AI adoption. On the contrary, firms in the ICT sector are more likely to adopt AI. This result is not surprising because the ICT sector is the one that is very closely linked with AI.

Despite the best effort to provide robust and relevant results, there are still certain limitations to approach used in this paper. Firstly, it is not able to rule out potential endogeneity problems in regression models. Hence, some of the relationships found in the regression can be interpreted more as correlations than causation. Secondly, the second set of regressions is examining the potential effects of AI on skill shortages based on rather subjective measures, which might vary based on the respondent's perception. Moreover, due to the data limitation, the variable focused on AI adoption actually combines firms that are currently using AI with those having concrete plans to adopt AI in the future. These two different stages may have some distinct drivers and implications. Future research could benefit from disaggregating these categories to provide more specific results. There are also several external factors that could potentially influence the probability of AI adoption in companies. This includes financial and non-financial external support from the government or other institutions. Here we also see another potential path for future research. Achieved findings shed light on factors associated with AI adoption as well as those correlated with potential effects on skill needs in companies. The results achieved helped us answer the three research hypotheses stated in the introduction. Several significant factors related to AI adoption have been found. These factors include the size of the company, employees' ages, turnover growth, and the community size. Moreover, problems with hiring skills and shortages of certain skills, such as IT skills and customer care skills, also play a crucial role in the adoption of AI.

To some extent, similar factors were found to be associated with the expected effect of AI on skill needs. However, there are also some crucial differences. The size of the community and difficulties with hiring skills are not considered significant factors affecting the expected consequences of AI adoption on skills needed in companies.

5. Conclusion and Managerial Implications

This research empirically investigated the firm-level determinants of artificial intelligence (AI) adoption and its anticipated effects on skill needs within small and medium-sized enterprises (SMEs). Hence, the findings shed light on factors associated with AI adoption as well as those related to the perceived effect of AI on skill needs in companies. The results achieved helped us answer the three research hypotheses stated in the introduction. Several significant factors related to AI adoption have been found. These factors include the size of the company, employees' ages, turnover growth, and community size. Moreover, problems with hiring skills and shortages of

certain skills, such as IT skills and customer care skills, also play a crucial role in the adoption of AI. Achieved findings that firms with younger employees are more likely to adopt AI suggest that hiring, training, and upskilling younger employees could be beneficial for SMEs that are considering AI.

To some extent, similar factors were found to be associated with the expected effect of AI on skill needs in firms. However, there are also some differences. Community size and difficulties with hiring skills are not considered significant factors related to expected consequences of AI adoption on skills needed in companies.

Managers of SMEs facing shortages in specific skill areas such as IT, R&D, marketing, and customer care should consider the adoption of AI. This technological upgrade can also be seen as a strategic tool to improve operational efficiency. However, they should also expect certain evolution in skill demand due to the adoption of AI. It is crucial to understand that the adoption of new technology, such as AI, is not a one-time event but a transformative process that will likely alter skill demand. Hence, proactive planning of reskilling and upskilling the workforce is essential to avoid future skill mismatches, which could have a negative effect on the operation of SMEs. In order to bridge the gap in skills, SMEs should consider active participation in industry clusters or similar business support organizations. Membership can provide access to knowledge, resources, and a conducive environment that further supports digitalization and AI adoption.

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