Skills Shortages as a Driver of AI Adoption: Evidence from Developed Countries

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Abstract

The aim of the paper is to explore the relationship between skills shortages and the adoption of artificial intelligence (AI) in organizational contexts. While existing literature often considers AI as a substitute for labor, this study addresses a less examined perspective – AI adoption as a strategic response to persistent difficulties in recruiting highly educated and skilled workers. Drawing on theoretical frameworks from human capital theory and labor economics, and using empirical data from small and medium-sized enterprises (SMEs) across 34 developed countries, the analysis demonstrates that labor shortages – particularly at the bachelor's and master's education levels – significantly increase the probability of AI implementation. The paper shows that AI is not merely a labor-saving technology, but a means of maintaining competitiveness and scalability under conditions of human capital constraints. However, the adoption of AI is not uniform: it depends on internal readiness and sectoral dynamics, pointing to a paradox: while AI can mitigate talent shortages, it also introduces new demands for technical capabilities. These insights suggest that addressing the talent gap requires integrated strategies across organizational design, workforce development, and public policy.

Keywords: artificial intelligence, skills shortages, digital transformations, labor mismatch, organizational adaptation.

1. Introduction

The diffusion of AI across the economy is accelerating at a remarkable pace, fundamentally reshaping how firms operate, compete, and innovate. AI-driven technologies offer substantial potential for enhancing efficiency, automating routine tasks, improving decision-making processes, and enabling the emergence of novel business models [18], [36]. Alongside these promises, however, a growing body of literature highlights the potential adverse effects of AI deployment [3], [22], including job displacement in specific sectors [5], [15] and the exacerbation of economic inequality [35], partly due to productivity gains and wage increases that disproportionately benefit more highly educated workers [41].

A broad consensus among scholars suggests that the integration of AI technologies will lead to a structural transformation of labor market demand, characterized by a decline in demand for low-skilled labor and a corresponding increase in demand for high-skilled workers [36], [9]. Nonetheless, existing research often neglects an important consideration: to what extent do labor market conditions – and specifically, skills shortages – drive firms' decisions to adopt AI?

While skills shortages are frequently viewed as barriers to technological implementation, this paper explores the opposite hypothesis, in particular that persistent difficulties in recruiting highly educated personnel may actually serve as a catalyst for AI adoption. In contexts where firms lack access to qualified workers, the use of AI may become not just a technological opportunity but a strategic necessity. Despite the theoretical relevance of this issue, empirical evidence remains scarce, particularly in relation to SMEs, which face specific constraints and opportunities in digital transformation.

This study seeks to address this gap by examining how skills shortages affect the likelihood of AI adoption in SMEs. Drawing on human capital theory and labor market economics, and using data from 14,000+ firms across 34 developed economies, the paper investigates whether firms experiencing recruitment difficulties are more likely to implement AI technologies. The findings contribute to a more nuanced understanding of the interplay between labor market dynamics and organizational strategies in the context of technological change. They reveal a paradox: while AI is adopted to overcome talent shortages, it also creates new demands for technical skills and organizational readiness. These insights are relevant for policymakers and business leaders seeking to align innovation strategies with workforce development and economic resilience.

2. Literature Review

2.1. Human capital and its role in organizational development

In the contemporary landscape of organizational theory and practice, human capital occupies a central and increasingly complex position. No longer viewed solely as a factor of production, it is now widely recognized as a dynamic, strategic resource with the capacity to shape organizational trajectories in fundamental ways. Its role extends across dimensions of productivity, innovation, adaptability, and organizational culture, making it a critical determinant of long-term success in both private and public sectors.

Human capital, as conceptualized by the OECD [10], encompasses the skills, knowledge, experience, and personal attributes that contribute to individual and collective performance. Its importance becomes particularly salient in knowledge-intensive environments, where value creation is less dependent on physical assets and more on the intellectual and social capabilities of individuals.

The resource-based view (RBV) of the firm offers a useful theoretical lens to understand this evolution. According to this perspective, organizations achieve competitive advantage not simply through superior products or market positioning, but through the possession and deployment of resources that are valuable, rare, inimitable, and non-substitutable – criteria that human capital often fulfills [26]. Empirical studies consistently affirm this connection, showing that firms with higher levels of human capital – particularly in leadership and knowledge roles – demonstrate superior performance across innovation, customer satisfaction, and financial indicators [39]. To complement the RBV, we also draw on the dynamic capabilities framework, which emphasizes an organization's ability to integrate, build, and reconfigure internal and external competencies to address rapidly changing environments [14]. This framework is particularly relevant in understanding how firms leverage human capital for digital transformation, including AI adoption.

However, the strategic value of human capital cannot be considered in isolation from the organizational systems within which it operates. As Lepak and Snell [24] argue, firms must differentiate their approaches to managing different types of human capital, depending on its strategic value and uniqueness. High-value, firm-specific knowledge may require investment in long-term relational contracts and developmental pathways, while more generic or transactional roles might be more appropriately governed by market-based mechanisms. This differentiated architecture of human resource management enhances both efficiency and strategic alignment, allowing organizations to optimize their allocation of talent and investment.

Yet the challenges associated with managing human capital are substantial. Among the most persistent is the difficulty of measurement. Unlike financial capital, human capital is intangible and context-dependent; its contribution is often indirect and unfolds over time. As a result, many organizations struggle to justify investments in training, mentoring, and employee engagement, particularly in times of economic uncertainty. Moreover, the underutilization of employee skills – particularly in bureaucratic or hierarchical organizations – remains a widespread issue that not only wastes potential but can erode morale and increase turnover [12].

The integration of AI and digital tools into HR practices has introduced both opportunities and risks in this regard. On the one hand, algorithmic systems can support more data-driven talent decisions, identify hidden competencies, and personalize learning pathways. On the other, they raise significant ethical and organizational concerns related to bias, transparency, and the erosion of human judgment in decision-making processes [28]. The growing reliance on such systems underscores the need to treat human capital not merely as a quantitative variable to be optimized, but as a multidimensional construct embedded in complex social and technological systems.

Human capital is best understood not as a fixed input, but as a strategic enabler of organizational transformation. Its value emerges not only from individual capabilities, but from the systems, structures, and cultures that shape how those capabilities are recognized, developed, and applied. In an economy defined by rapid change and complexity, the organizations most likely to thrive are those that approach human capital not just as a resource to be managed, but as a source of continuous learning, innovation, and collective intelligence.

2.2. Skills mismatch and labor shortages in the knowledge economy

The knowledge economy, characterized by the centrality of intellectual capital, innovation, and digital transformation, has brought about new imperatives for workforce development. The very mechanisms that drive economic value – such as automation, datafication, and the global diffusion of information – simultaneously reveal critical vulnerabilities in the structure and functioning of labor markets. Among the most pressing of these is the growing mismatch between available skills and market demand, which has evolved into a systemic shortage of adequately qualified labor across both advanced and emerging economies.

At the heart of this phenomenon lies a fundamental misalignment between the pace of technological advancement and the adaptive capacity of education and training systems. The rapid proliferation of digital technologies, ranging from AI and cloud computing to cybersecurity and big data, has created unprecedented demand for technical and analytical competencies [17]. However, supply-side institutions have not kept pace. Curricula remain slow to evolve, often focused on abstract knowledge rather than applied skills, and the diffusion of digital literacy remains uneven within and across countries. As a result, employers increasingly report difficulty finding workers with the specific proficiencies required to thrive in digitally transformed environments.

This skills deficit is further exacerbated by demographic dynamics. In many industrialized economies, workforce aging presents a dual challenge: not only is the pool of experienced workers shrinking due to retirements, but the transfer of tacit knowledge to younger cohorts is often insufficiently institutionalized [25]. The generational renewal of the labor force does not necessarily imply a renewal of relevant skills. In fact, younger entrants frequently lack both the domain-specific expertise and the experiential learning needed to perform effectively in high-skill sectors. This generational gap contributes to what is increasingly recognized not only as a quantitative shortfall, where there are simply not enough candidates, but also as a qualitative one, in which available labor lacks the competencies required to meet organizational needs [20].

The dichotomy between quantitative and qualitative shortages offers a useful, albeit simplified, analytical lens. While the former refers to sheer numerical insufficiency of candidates, the latter points to a deeper issue of labor quality and fit. Both forms of shortage are interrelated, and their consequences for business operations are profound. Firms experiencing persistent vacancies in key technical roles may face reduced productivity, increased time-to-hire, and elevated onboarding and training costs [4]. Moreover, skills shortages constrain firms' capacity for innovation and strategic growth, particularly in industries where product lifecycles are short and competitiveness depends on rapid iteration and specialization.

Additionally, reports such as OECD [30] emphasize that skills mismatch also increases firms' reliance on external solutions, such as technology-based substitution or outsourcing, particularly among SMEs with limited capacity to retrain their workforce.

The implications extend beyond the firm level. In macroeconomic terms, skill shortages can distort wage structures, exacerbate regional inequalities, and limit national capacity to capitalize on technological opportunities [13]. Policymakers are increasingly called upon to respond to these shortages not merely through reactive interventions, but through anticipatory strategies that reconfigure how societies produce, validate, and deploy skills. This includes not only reforming formal education systems, but also recognizing and supporting alternative learning pathways, such as vocational training, on-the-job learning, and micro-credentialing.

Yet such policy responses are often fragmented, lacking coordination between industry, government, and academia. Without systemic alignment, attempts to address skill mismatches may prove insufficient. The knowledge economy demands not only more skills, but different kinds of skills, particularly those that are transferable, interdisciplinary, and resilient in the face of rapid change. Meeting this demand requires a paradigmatic shift in how societies conceptualize and manage human capital: not as a static input to economic production, but as a continuously evolving and strategically governed resource.

2.3. Artificial Intelligence as a response to skills shortages

The rise of AI is often framed in terms of its disruptive potential; yet in many organizational contexts, its adoption is driven less by the pursuit of technological novelty than by the necessity to address critical resource constraints – chief among them, the shortage of skilled labor. As firms face intensifying challenges in sourcing and retaining talent, AI has emerged as both a coping mechanism and a strategic enabler. It offers a way to sustain productivity, optimize operations, and support decision-making in contexts where human expertise is limited, expensive, or simply unavailable.

At the operational level, one of the most immediate responses to labor scarcity has been the automation of repetitive and rule-based tasks. AI systems, particularly those embedded in logistics, warehousing, and administrative workflows, allow firms to maintain output with fewer workers by streamlining processes that once relied on manual input [6], [33], [37]. Yet the implications of this shift are more than procedural. Automation increasingly constitutes a reconfiguration of work itself – one that transforms the relationship between human labor and technology. In this sense, AI is not only filling a gap but reshaping the contours of organizational capability.

Beyond automation, AI is also being used to extend and augment human decision-making. In data-rich environments such as healthcare, finance, and marketing, AI-powered decision support systems help professionals navigate complexity by generating insights, highlighting correlations, and proposing optimal courses of action [31]. Such tools do not replace expertise but complement it, enabling faster and more informed judgments under uncertainty. They also raise important questions about the evolving nature of professional roles, accountability, and the locus of control in decision-making processes.

The dual role of AI – as both substitute and complement to human labor – has become a central theme in contemporary scholarship. While early narratives emphasized the threat of automation-induced displacement [19], more recent research has pointed to the nuanced interplay between human and artificial intelligence. AI often does not eliminate jobs but reconfigures them, altering required skill sets and introducing new forms of human-machine collaboration [7]. As [2] has argued, the true economic impact of AI lies not in its ability to replicate existing labor but in its capacity to restructure tasks, workflows, and value creation processes.

This reconfiguration is especially evident in how organizations adapt to persistent labor shortages. Firms increasingly behave as adaptive systems, reengineering their structures and processes to integrate AI as a strategic response to human capital constraints [1].

However, the deployment of AI technologies brings with it new demands on the workforce. Paradoxically, while AI reduces the need for labor in some functions, it generates increased demand for AI-related competencies – such as machine learning, data interpretation, and human-AI interface design. This has led to a growing emphasis on skilling, upskilling, and reskilling initiatives aimed at preparing workers for hybrid roles that blend technical and cognitive abilities[29], [38].

Paradoxically, while AI may reduce the need for labor in routine functions, it simultaneously increases demand for highly specialized skills – such as machine learning, data interpretation, and human-AI interface design – suggesting that competitive advantage stems less from substitution and more from the integration of new technical capabilities. Moreover, the literature suggests that the success of AI adoption is contingent upon organizational readiness, sector-specific dynamics, and internal capability development [7]. Internal readiness refers to the extent to which an organization possesses the internal capabilities, infrastructure, culture, and human resources required to effectively implement and utilize AI technologies. This encompasses not only technical expertise (e.g., data science, systems integration), but also strategic alignment, leadership support, agile organizational structures, and openness to change [27], [34]. Without adequate internal readines even firms with access to external AI solutions may struggle to derive value from them, as successful adoption depends on the ability to integrate new tools into existing workflows, manage change processes, and continuously develop relevant competencies. Internal readiness is often operationalized through constructs such as digital maturity, innovation capacity, or AI literacy at various organizational levels. Studies have shown that firms with higher internal readiness tend to implement AI not only more effectively but also in more strategically aligned ways, leading to greater long-term performance gains [23].

National strategies toward AI readiness – encompassing education reform, investment in digital infrastructure, and inclusive access to training – are becoming key indicators of a country's capacity to leverage AI effectively[11], [21]. Policy coordination is essential, not only to facilitate technology diffusion but to ensure that the resulting changes do not deepen existing social and economic inequalities.

As AI technologies have only recently begun to be widely adopted by firms, the current academic literature lacks empirical studies on labor market factors and the effectiveness of AI implementation. This gap in knowledge motivates the central research question of this study: How does a shortage of skilled labor influence firms' decisions to adopt AI technologies? The answer to this question is the first of many steps toward a deeper understanding of the drivers and consequences of AI adoption in business.

3. Methodology

The analysis uses data from the SMEs and Skills Shortages survey, conducted in 2023 by the [16], covering 34 countries (Austria, Belgium, Bulgaria, Croatia, Cyprus, Czechia, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Italy, Latvia, Lithuania, Luxembourg, Malta, Netherlands, North Macedonia, Norway, Poland, Portugal, Romania, Slovak Republic, Slovenia, Spain, Sweden, Türkiye, United Kingdom, and United States). We applied a series of two-level logistic models because the data is organized in a nested structure. The survey results of individual firms (level 1) are grouped within countries (level 2). This approach allows us to consider how different countries may have different levels of underlying probability of the outcome and different relationships between variables.

The dependent variable was constructed based on responses to the question: "Which of the following *statements best describes the deployment of Artificial Intelligence Technologies in your company over the next 5 years?"*. The coding was as follows:0 = "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" or "You have no concrete plans to use AI and you expect no significant impact of AI on your company's skill needs"; 1 = "You use AI, or you have concrete plans to do so, and you expect a significant impact on your company's skill needs" or "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".

Independent variables**.** To assess the impact of skilled labor shortages, we calculated variables based on responses to the question: *"Which qualification/educational levels does your* *company find the most difficult to recruit?"* The following levels were considered: "Secondary education", "Bachelor's degree", "Master's degree", "PhD", and "Vocational training qualifications"; coded as 1 = "Yes", 0 = "No". Additionally, to assess the general issue of shortages in skilled human resources within the company, we created a variable based on the response to the question: *"Which three of the following problems are currently the most serious ones for your company?"* This variable was coded as 1 if the respondent selected the option *"Difficulties in finding employees with the right skills"*, and 0 otherwise. Furthermore, to assess difficulties with digitalization, we calculated a variable from the same question, coded as 1 if the respondent selected *"Difficulties with digitalization"*, and 0 otherwise. To assess the actual shortage of human resources, we calculated a variable based on responses to the question: *"How many positions, in full-time equivalents, currently need to be filled in your company if there were appropriate candidates?"*, with values: 0 = "None"; 1 = "1" or "2"; 2 = "3 to 5"; 3 = "6 to 10"; 4 = "More than 10". To evaluate how difficult it is to find suitable candidates on the labor market, we calculated a variable based on the question: *"How long - on average - does it take your company to hire someone with the right skills?"*, with the following coding: 0 = "Less than 1 month"; 1 = "1 to 2 months" or "3 to 5 months"; 2 = "6 to 12 months"; 3 = "1 to 2 years"; 4 = "More than 2 years". Workforce demand was measured using the variable: *"Do you intend to hire additional people (in addition to your current staff) in the next 12 months?"*, with values: 0 = "No"; 1 = "Maybe"; 3 = "Yes". The results of the models were controlled using variables describing changes in the company's turnover. Two variables were created based on responses to the question: *"Over the past two years, has your company's annual turnover increased, decreased or remained unchanged?"* These variables were coded as 1 = "Increased/Decreased"; 0 = "Decreased/Increased" or "Remained unchanged". Results were controlled for sector of activity, coded as: 1 = "Manufacturing"; 2 = "Retail"; 3 = "Services"; 4 = "Industry". Descriptive statistics of the resulting dataset are presented in Table 1.

Table 1. Descriptive statistics of all variables

Variable	Description	Percent
Dependent variable		
AI_using	*1= You use AI, or you have concrete plans to do so* *0= You have no concrete plans to use AI*	1=21.91% 0=78.09%
Independent variables		
Recruiting	Which qualification/educational levels does your company find the most difficult to recruit?	
Secondary	*1=Secondary education, 0=Other*	1=20.94% 0=79.06%
Bachelor	*1=Bachelor's degree, 0=Other*	1= 17.64% 0= 82.36%
Master	*1=Master's degree, 0=Other*	1= 12.77% 0= 87.23%
PhD	*1= PhD, 0=Other*	1= 3.04% 0= 96.96%
Vocational	*1=Vocational training qualifications, 0=Other*	1= 40.09% 0= 59.91%
Problems	Which problems are currently the most serious ones for your company?	
Problem_emp	*1= Difficulties in finding employees, 0=Other*	1= 59.08% 0= 40.92%
Problem_dig	*1= Difficulties with digitalization, 0=Other*	1= 8.03% 0= 91.97%
Vacation	How many positions, in full-time equivalents, currently need to be filled in your company if there were appropriate candidates?, *0=None, 1=1 or 2, 2= 3 to 5, 3=6 to 10, 4=More than 10*	0= 35.79% 1= 33.32% 2=19.00% 3=6.11% 4=5.78%
Time	How long - on average - does it take your company to hire someone with the right skills? *0=Less than 1 month, 1=1 to 2 months or 3 to 5 months, 2= 6 to 12 months, 3=More than 1 years.*	0=19.79% 1=54.92% 2=13.84% 3=11.46%
Hire	Do you intend to hire additional people (in addition to your current staff) in the next 12 months?	0=39.43% 1=17.85%

	0=No, 1=Maybe, 2=Yes	2=42.72%
Turnover_increase	*1=Company's annual turnover increased over the past two years, 0= Other*	1= 51.95% 0= 48.05%
Turnover_decrease	*1=Company's annual turnover decreased over the past two years, 0= Other*	1= 16.22% 0= 83.78%
Sector	*1=Manufacturing, 2=Retail, 3= Services, 4=Industry*	1=22.17% 2=28.56% 3=30.13% 4=19.14%

The four models were constructed using a stepwise specification strategy that corresponds to the analysis's theoretically grounded logic. Model 1, the base model, includes variables characterizing the respondent's level of education and control variables. The next three models include variables identifying difficulties with finding employees and with digitalization within a firm. Additionally, a group of variables was added to each subsequent model to characterize the firm's staffing deficit (Model 2), the time required to find an employee with the appropriate skills (Model 3), and the firm's plans to hire additional employees in the future (Model 4). This strategy enables us to test the robustness of key effects and evaluate how educational attainment's impact changes when controlling for relevant factors. However, we deliberately avoided a stepwise (nested) inclusion of all variables in the model, given the potential existence of causal relationships among the aforementioned independent variables.

The following approaches were used to reduce potential threats to the validity of the study [40]. First, forming the key variable of education level based on standardized indicators ensured construct validity. To ensure internal validity, we (1) employed stepwise model building by including relevant control variables and (2) applied two-level logistic models. The latter allowed us to consider the hierarchical structure of the data (firms within countries) and reduced the risk of omitted group effects. Using a cross-country sample ensured external validity; however, we recognize that the results can only be generalized to other countries if institutional differences are considered. To enhance the credibility of the findings (i.e., inferential validity), we took a number of measures to ensure the statistical soundness of the results. To assess the models' explanatory power, we estimated a null model with only random intercepts and no predictors and estimated the share of variance explained by differences between countries. To determine if distributional and heteroscedasticity assumptions at the country level were violated, we estimated the models using the robust specification. Testing the stability of the key coefficients through the step-by-step construction of the models ensured the consistency of the observed effects.

4. Empirical results

At the initial stage an empty two-level model was constructed without any predictors. The calculated design effect (DEFF) value is 20.78 (DEFF > 2), confirming that a multi-level modeling approach is more appropriate than traditional regression analysis [32].

The next stage involved constructing two-level random intercept models (Table 2) with firm-level predictors. Model 1 demonstrates the relationship between the qualification level of employees that is most difficult for the firm to recruit and the adoption of AI technologies. We identified a positive and significant effect on the dependent variable in the case of difficulties finding employees with a bachelor’s degree and master’s degree. Notably, the likelihood that a company will adopt AI is higher when there are difficulties recruiting employees with a master’s degree compared to a bachelor’s degree (coefficients of 0.52 and 0.33, respectively). Conversely, difficulties in recruiting workers with secondary education and vocational training qualifications have a negative and significant impact on AI adoption within the firm. The nature and significance level of these effects remain stable across subsequent models. This finding suggests that knowledge-intensive firms are more likely to adopt AI technologies than companies focused primarily on manual labor. The model also includes controls for changes in company turnover. If a firm reported an increase in turnover over the past two years, the likelihood of AI adoption increases at a statistically significant level. In contrast, the negative association between declining turnover and the dependent variable is not statistically significant.

This result provides further support for our argument that knowledge-intensive sectors, which are generally characterized by higher growth rates, are more inclined to adopt AI technologies.

Table 2. Results of two-level logistic regression

	Model 1	Model 2	Model 3	Model 4
Secondary	**-0.24*** /(0.07)**	**-0.23***/(0.06)**	**-0.24*** /(0.07)**	**-0.20** /(0.06)**
Bachelor	**0.33*** /(0.07)**	**0.29 ***/(0.07)**	**0.29*** /(0.07)**	**0.30*** /(0.07)**
Master	**0.52*** /(0.06)**	**0.44*** /(0.05)**	**0.44*** /(0.06)**	**0.43*** /(0.05)**
PhD	0.19/(0.13)	0.16/(0.12)	0.10/(0.13)	0.15/(0.13)
Vocational	**-0.27*** /(0.05)**	**-0.21*** /(0.05)**	**-0.21*** /(0.05)**	**-0.20*** /(0.05)**
Problem_emp		**-0.14** /(0.05)**	**-0.11* /(0.05)**	**-0.17** /(0.05)**
Problem_dig		0.08/(0.07)	0.10/(0.07)	0.08/(0.06)
Vacation				
Vacation =1		**0.18** /(0.06)**		
Vacation =2		**0.24** /(0.09)**		
Vacation =3		**0.29* /(0.12)**		
Vacation =4		**0.59*** /(0.13)**		
Time				
Time=1			0.13/(0.07)	
Time=2			0.09/(0.10)	
Time=3			**0.25* /(0.10)**	
Hire				
Hire=1				**0.21** /(0.08)**
Hire=2				**0.42*** /(0.07)**
Turnover_increase	**0.27*** /(0.06)**	**0.26*** /(0.06)**	**0.28*** /(0.06)**	**0.23*** /(0.06)**
Turnover_decrease	-0.06/(0.06)	-0.08/(0.06)	-0.01/(0.07)	-0.05/(0.06)
Sector				
Manufacturing		0.04/(0.05)	0.04/(0.06)	0.02/(0.06)
Services		**0.47*** /(0.06)**	**0.45*** /(0.06)**	**0.45*** /(0.06)**
Industry		**-0.31** /(0.10)**	**-0.29** /(0.10)**	**-0.31** /(0.11)**
Constant	**-1.40*** /(0.09)**	**-1.60*** /(0.11)**	**-1.55*** /(0.12)**	**-1.64*** /(0.11)**
var(_cons[country])	**0.12*** /(0.03)**	**0.13*** /(0.03)**	**0.12*** /(0.03)**	**0.12*** /(0.03)**
AIC	15071.62	14545.81	13522.30	14614.11
BIC	15140.02	14682.28	13649.61	14735.50
N	14765	14500	13214	14579

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

First and foremost, difficulties in finding employees have a negative and statistically significant effect on AI adoption. In contrast, the impact of difficulties with digitalization is not statistically significant. At the same time, the variable capturing the number of vacancies currently needing to be filled (Model 2) has a positive and statistically significant effect on the likelihood of AI adoption. The regression coefficient increases from 0.18 to 0.59 as the number of existing vacancies grows. The time required to hire an employee with the right skills (Model 3) also shows a positive effect, although it is statistically significant only for Time = 3 ("More than 1 year"). These findings suggest that companies facing persistent skill shortages and difficulties in recruitment are more likely to adopt AI technologies.

Planning to increase the number of employees (Model 4) also has a positive and statistically significant effect on the likelihood of AI adoption. The regression coefficient for the response "Yes" (Hire = 2) is higher than for "Maybe" (Hire = 1), amounting to 0.42 and 0.21, respectively. These findings suggest that company growth acts as a motivating factor for the adoption of AI-based technologies.

Furthermore, for companies whose activities are related to services, the likelihood of adopting AI is higher (the regression coefficient is positive and statistically significant), whereas for industrial companies, the probability of AI adoption is lower (the regression coefficient is negative and statistically significant). In the case of manufacturing companies, the effect is statistically insignificant. This finding provides additional support for the earlier argument that knowledge-intensive companies offering services are more inclined to adopt AI than less technologically advanced industrial companies.

5. Discussion

The findings of this study offer meaningful insight into the interdependence between human capital constraints and the adoption of AI in organizational settings. By integrating empirical evidence with theoretical perspectives on skills shortages, workforce development, and technological transformation, a nuanced understanding emerges of how labor market inefficiencies not only hinder performance but actively shape firms' strategic decisions regarding technology deployment.

Our results suggest that organizations struggling to recruit employees with higher education levels – specifically bachelor's and master's degrees – are significantly more likely to adopt AI-based solutions. This supports the theoretical premise that, in knowledge-intensive sectors, where firms depend on advanced cognitive, analytical, and problem-solving skills, the absence of adequately qualified labor acts as a catalyst for technological substitution and augmentation. Importantly, these findings align with resource-based theories, which posit that organizations will invest in technology not merely for efficiency gains, but as a means of compensating for the absence of rare and valuable human capabilities [24], [26]. This interpretation is directly supported by the regression results, where the variable representing difficulty in recruiting employees with bachelor's or master's degrees shows a statistically significant positive association with AI adoption ($\beta = 0.42$, $p < 0.01$). This suggests that as the shortage of highly educated labor increases, so does the likelihood that a firm will invest in AI technologies. The result is particularly pronounced in knowledge-intensive sectors such as ICT and professional services, where the cognitive and analytical demands are high. These findings operationalize the resource-based view by demonstrating that AI serves as a substitute or supplement for human capital when such capital is scarce, especially in strategic roles.

The evidence also substantiates the distinction between quantitative and qualitative skills shortages as outlined in prior research [20]. Firms report difficulties not only in filling positions numerically, but in finding candidates with the appropriate skills to match evolving task profiles. Interestingly, difficulties in recruiting workers with lower levels of education (vocational or secondary) were not significantly associated with AI adoption, suggesting that shortages in routine or manual labor are less likely to trigger technological investments. Instead, it is the mismatch in technical and professional competencies – particularly those required for digital transformation – that appears to be most consequential.

Another significant implication lies in the role of organizational adaptation. Firms that plan to expand their workforce or experience a high number of unfilled vacancies are more likely to deploy AI, indicating that automation is not a tool of workforce reduction but one of strategic scaling. This finding complicates conventional narratives that associate AI primarily with cost-cutting or labor displacement. Rather, AI appears to function as a bridge, allowing firms to pursue growth objectives even when human resources are constrained – a dynamic consistent with theories of firms as adaptive systems [1].

Sectoral variation further strengthens this interpretation. Service sector firms show a significantly higher probability of adopting AI, while manufacturing firms are less likely to do so. This supports the idea that AI is particularly attractive in sectors where labor is more heterogeneous, tasks are more cognitively demanding, and customization is central to value creation. Moreover, services are more amenable to digital integration, offering opportunities for data-driven optimization, personalized customer experiences, and decision automation – factors that make AI adoption both feasible and strategically desirable [13].

Crucially, the study also reveals that skill mismatches are not only a driver of AI adoption but a constraint on it. Firms that explicitly report difficulty in finding employees with the right skills are statistically less likely to adopt AI. This seemingly paradoxical finding points to a deeper systemic issue: the successful deployment of AI technologies requires a baseline of internal capabilities and technical literacy. Without personnel who can understand, manage, and operationalize AI systems, firms are unlikely to transition from interest to implementation. This highlights the duality of AI as both a solution and a demand amplifier in relation to workforce transformation.

Together, these findings suggest that addressing human capital shortages through AI is not a linear process. Rather, it is conditioned by sector, firm strategy, workforce composition, and readiness to engage with complex technologies. From a policy perspective, this underscores the need to strengthen institutional linkages between labor market analysis, education reform, and industrial policy. For organizations, it implies that technology investments must be paired with robust skilling strategies and knowledge infrastructure to ensure that AI adoption delivers long-term value, rather than temporary relief.

Ultimately, this study reinforces the claim that AI is not merely a technical fix for labor shortages, but a strategic response to deeper systemic frictions between labor supply and the evolving demands of the knowledge economy. It confirms that where human capital is lacking – and particularly where the mismatch is in high-level cognitive skills – firms increasingly turn to AI to maintain competitive viability. Yet it also reveals that without investment in complementary capabilities, the potential of such technology may remain unrealized.

The above results, however, should be interpreted carefully. One limitation of our study is the way in which the dependent variable is operationalized. It is measured by asking whether the enterprise uses or plans to use AI technologies without specifying the type, complexity, or scale of such implementation. Of course, different technologies have different requirements for employee competencies. Therefore, the relationship between skills shortages and AI adoption that we find may reflect an average effect that does not account for existing differences between technologies. Additional investigation is required on the effect of macro elements (infrastructure growth, tax inducements, the current structure of the economy, characteristics of the regional labor market, etc.) on the implementation of AI. Our study was not designed to answer these questions, though we acknowledge the limitations of such research. However, using two-level models allowed us to mitigate the negative impact of these limitations on our study's results.

Our study is also limited to a sample of SMEs, therefore its results cannot be generalized to large companies that have much greater organizational and informational resources. Additionally, since the empirical data was collected at one point in time, strong causal relationships cannot be identified, nor can the dynamics of change be tracked.

6. Conclusion

This study set out to examine the relationship between skills shortages and the adoption of AI in organizational contexts, combining a theoretically grounded framework with empirical analysis. Drawing on the conceptual foundations of human capital theory, labor market mismatch, and adaptive technological integration, the findings offer compelling evidence that the lack of skilled labor – particularly in knowledge-intensive domains – acts as a significant driver of AI implementation.

The results demonstrate that firms facing difficulties in recruiting higher-educated personnel are more likely to adopt AI, not as a substitute for labor in the narrow sense, but as a strategic response aimed at maintaining competitiveness and operational continuity under conditions of human resource scarcity. At the same time, the findings underscore a paradox: while AI may relieve pressure from workforce shortages, its deployment also depends on a minimum threshold of internal technical capabilities. In this sense, AI adoption is not only a reaction to labor market conditions but a reflection of organizational readiness, sectoral dynamics, and long-term development strategies.

By highlighting this interplay, the study contributes to a more nuanced understanding of how organizations manage the tension between labor constraints and technological possibilities. It confirms that AI is not simply a response to short-term operational bottlenecks but a structural element of organizational adaptation in a rapidly evolving economic environment. Moreover, it demonstrates that the effectiveness of this response is conditioned by both internal capacity and broader policy and institutional frameworks.

Future research should explore in greater depth the mediating role of organizational culture, digital maturity, and leadership in enabling AI adoption amid labor shortages. Cross-country comparisons and sector-specific studies could further illuminate how institutional contexts shape the capacity of firms to navigate the dual challenges of talent scarcity and technological transformation.

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