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THE COMPLEMENTARITY TRAP: AI ADOPTION AND VALUE CAPTURE

Zamka komplementarnosti: usvajanje veštačke inteligencije i ostvarivanje vrednosti

Abstract

Despite rapid advances and diffusion of artificial intelligence (AI), productivity growth has remained weak across many economies. This apparent disconnect has revived the long-standing productivity paradox, now in a new form shaped by digitalization and generative AI. This paper examines why widespread AI adoption has not translated into commensurate productivity gains, with a particular focus on Central and Eastern European economies. We develop a theoretical framework – the productivity funnel – that traces how technological potential narrows through successive stages, from access and digital infrastructure, through organizational absorption and human capital adaptation, to ultimate value capture. Within this framework, we identify a complementarity trap: firms lacking organizational readiness become stuck in the funnel, unable to convert AI diffusion into productivity gains. Drawing on firm-level data covering a subset of Central and Eastern European economies (Serbia, Croatia, Czechia, and Romania), combined with AI diffusion indicators, we show that AI productivity effects are not direct but conditional on organizational readiness. While AI adoption rates differ across countries and firm sizes, measurable productivity gains remain modest for firms lacking standardized processes and management systems. The findings suggest that the AI productivity paradox reflects organizational constraints rather than technological failure, with important implications for enterprise strategy and economic policy in early-stage AI adoption environments.

Keywords: *productivity paradox, artificial intelligence, productivity funnel, complementarity trap, organizational readiness, digital economy*

Sažetak

Uprkos ubrzanom napretku i difuziji veštačke inteligencije (VI), rast produktivnosti ostao je slab u mnogim ekonomijama. Ovaj očigledan raskorak oživeo je dugogodišnji paradoks produktivnosti, sada u novom obliku oblikovanom digitalizacijom i generativnom veštačkom inteligencijom. Ovaj rad istražuje zašto široka primena VI nije rezultirala odgovarajućim rastom produktivnosti, sa posebnim fokusom na ekonomije Centralne i Istočne Evrope. Razvijamo teorijski okvir – levak produktivnosti – koji prati kako se tehnološki potencijal sužava kroz uzastopne faze, od pristupa i digitalne infrastrukture, preko organizacione apsorpcije i prilagođavanja ljudskog kapitala, do krajnje vrednosti. U okviru ovog modela identifikujemo zamku komplementarnosti: firme kojima nedostaje organizaciona spremnost ostaju zaglavljene u levku, ne uspevajući da difuziju VI pretvore u produktivnost. Na osnovu podataka na nivou firmi koji obuhvataju podskup ekonomija Centralne i Istočne Evrope (Srbija, Hrvatska, Češka i Rumunija), u kombinaciji sa indikatorima difuzije VI, pokazaćemo da efekti VI na produktivnost nisu direktni, već uslovljeni organizacionom spremnošću. Iako se stope usvajanja VI razlikuju među zemljama i veličinama firmi, merljivi porast produktivnosti ostaje skroman za firme kojima nedostaju standardizovani procesi i sistemi upravljanja. Nalazi ukazuju da paradoks produktivnosti VI odražava organizaciona ograničenja pre nego tehnološki neuspeh, sa značajnim implikacijama za strategiju preduzeća i ekonomsku politiku u okruženjima rane faze usvajanja VI.

Ključne reči: *paradoks produktivnosti, veštačka inteligencija, levak produktivnosti, zamka komplementarnosti, organizaciona spremnost, digitalna ekonomija*

Introduction

"You can see the computer age everywhere but in the productivity statistics" [24, p. 36]. Robert Solow's famous observation has found renewed relevance in the age of generative AI. Despite unprecedented advances in artificial intelligence – and rapid enterprise adoption – aggregate productivity growth has remained stubbornly weak across both advanced and emerging economies. While AI adoption among European enterprises doubled from 8% to 20% between 2023 and 2025, annual TFP growth remained below 1% [14]. This newly identified divergence between technological progress and measured productivity outcomes defines the new productivity paradox.

The emergence of generative AI has intensified these concerns. Unlike earlier waves of digitalization, AI promises broad applicability across sectors, tasks, and organizational functions. It is widely regarded as a general-purpose technology capable of reshaping production, decision-making, and innovation. Yet macroeconomic productivity indicators show little immediate response to rapid AI diffusion, particularly outside a narrow set of frontier firms and economies. At a firm level, a growing body of evidence suggests that the binding constraint lies not in technology access, but in the organizational capacity to absorb and leverage AI effectively. While prior research has examined AI adoption barriers and aggregate productivity trends, less attention has been paid to the firm-level organizational conditions under which AI diffusion translates into productivity gains.

This paper addresses the following research question: Under what conditions does AI diffusion translate into firm-level productivity gains, and what role does organizational readiness play in enabling value capture from AI adoption?

A sample of four Central and Eastern European economies (Serbia, Croatia, Czechia, and Romania) provides a particularly revealing context for this question. These economies are often early technology adopters – Serbia, for instance, adopted a national AI strategy in 2019, ahead of many larger EU members – yet they frequently lack the complementary assets needed to convert adoption into productivity gains: standardized processes, management systems, and organizational maturity – what we term organizational readiness. Understanding this disconnect is crucial for both enterprise strategy and economic policy.

The contribution of this paper is threefold. First, we use the productivity funnel as a theoretical framework for our empirical analysis. Within this framework, we identify a complementarity trap: a situation where firms adopt AI but fail to capture productivity gains due to insufficient organizational readiness. Second, we synthesize recent academic and policy literature to identify key mechanisms underlying the AI productivity paradox, with particular emphasis on the role of organizational complements. Third, we provide empirical evidence drawing on firm-level data from World Bank Enterprise Surveys covering four European economies, combined with Eurostat AI diffusion indicators.

The remainder of the paper is organized as follows. Section 2 reviews the relevant literature, Section 3 presents the theoretical framework, Section 4 describes data and methodology, Section 5 presents the main findings, Section 6 provides the discussion, Section 7 lists the limitations, and Section 8 closes the paper with concluding remarks.

Literature Review: Artificial Intelligence and the New Productivity Paradox

The productivity paradox has been widely documented in the literature as a recurring phenomenon accompanying major technological transitions, especially during periods of digital transformation. David [12, pp. 1-5] highlights that, despite rapid technological progress, aggregate productivity growth has remained persistently weak, arguing that the observed disconnect between visible technological advances and limited productivity performance reflects adjustment dynamics rather than technological failure. David [12, pp. 5-7] further shows that major technological breakthroughs have historically been accompanied by prolonged periods of weak productivity performance, as firms and economies divert resources toward experimentation, reorganization, and the development of complementary organizational capabilities rather than immediate efficiency gains. This transitional perspective has since been formalized in conceptual frameworks that emphasize delayed productivity effects during early phases of technology diffusion, especially in the context of artificial intelligence.

On the macroeconomic level, the literature consistently finds weak aggregate productivity responses to AI diffusion. Despite rising investment and adoption, labor productivity and total factor productivity growth remain below historical trends in most advanced economies [18, pp. 5-8], [22, pp. 22-24]. Importantly, Ajuzieogu [2, pp. 13-17] highlights that a substantial share of AI-driven value may take intangible forms, such as quality improvements, faster decision-making, and enhanced risk management, which are insufficiently captured by conventional productivity statistics.

Brynjolfsson, Rock, and Syverson [10, pp. 11-15] argue that, in the case of AI, productivity gains depend on sustained investments in skills, organizational capital, data infrastructure, and governance structures, without which adoption is unlikely to translate into durable efficiency improvements. At the same time, Ajuzieogu [2, pp. 13-17] highlights that measurement challenges complicate the assessment of AI-driven productivity gains, as standard indicators often fail to capture improvements in decision quality, speed, and risk reduction that do not translate into higher measured productivity.

A closely related body of work highlights the organizational conditions under which AI generates economic value. McKinsey & Company [19, pp. 5-6] argue that assessments of AI's economic potential often emphasize prospective value while underestimating the organizational and institutional conditions required for effective deployment. Hamm & Klesel [16, pp. 8-9] identify data readiness, managerial capabilities, governance structures, and workforce skills as critical determinants of successful deployment, suggesting that technology alone is insufficient to generate productivity gains. Complementing this view, cross-country policy analyses by World Bank emphasize the importance of foundational digital capacities and institutional readiness in enabling firms to move from experimentation to scaled deployment [27, pp. 40-43]. Together, these findings suggest that limitations in organizational and institutional foundations contribute to uneven AI adoption and delayed productivity effects.

Another stream of the literature focuses on firm-level heterogeneity in AI-driven productivity effects. Task-level evidence indicates that AI raises productivity only within specific capability ranges and often increases the need for validation and oversight [13, pp. 6-9]. Necula, Fotache, and Rieder [21, pp. 11-14] show that productivity effects depend on how AI tools are embedded into daily work practices, with substantial heterogeneity across employees and functions. These findings are consistent with analyses by Włodarczyk & Wisła [26] which emphasize that advanced technologies tend to amplify existing organizational capabilities rather than equalize performance across firms, reinforcing uneven productivity outcomes [26, pp. 18-21].

Finally, a growing body of literature highlights psychological and behavioral mechanisms that complicate the translation of AI adoption into sustained productivity gains, including job insecurity and perceived replacement risk [17, pp. 4-7], cognitive offloading and erosion of critical thinking [15, pp. 15-16], and identity threats related to professional status and autonomy [20, pp. 80-81]. On the other hand, psychological resources – particularly emotional intelligence, resilience, learning self-efficacy, and task confidence – appear to act as protective mechanisms that buffer AI-induced stress and support productivity during periods of technological change. While these micro-level factors fall outside the scope of our empirical analysis, they represent important avenues for future research on the behavioral foundations of the productivity paradox.

Theoretical Framework

Artificial intelligence is increasingly characterized as a general-purpose technology (GPT) – a transformative innovation with broad applicability across sectors, tasks, and organizational functions [8]. Like earlier GPTs such as electricity and information technology, AI is expected to generate substantial productivity gains over time. However, historical experience suggests that such gains materialize slowly and unevenly, often following a J-curve pattern in which initial adoption is accompanied by productivity stagnation or decline before eventual gains emerge [11]. This delay reflects the need for complementary investments in organizational redesign, human capital, and institutional adaptation – investments that are costly, time-consuming, and uncertain in outcome.

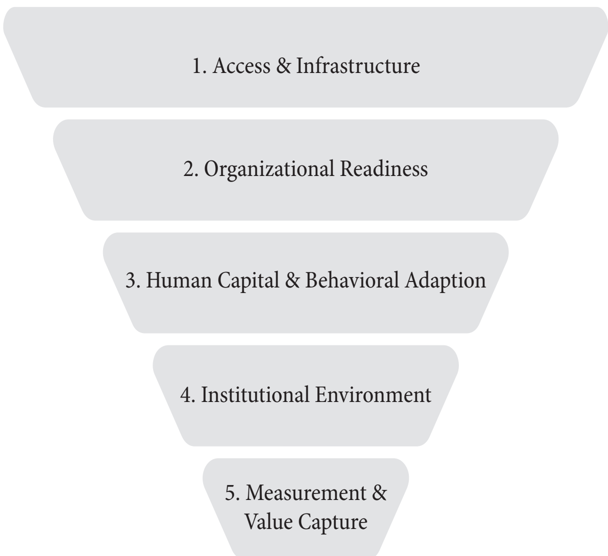
To explain how AI's theoretical productivity potential translates – or fails to translate – into measured economic gains, we use a conceptual framework – the productivity funnel. The funnel metaphor captures the progressive narrowing of technological potential as it passes through successive constraints at the levels of technology access, organizational capacity, human capital, institutional environment, and statistical measurement. At each stage, a portion of AI's potential productivity contribution is filtered out, leaving only a fraction visible in aggregate statistics. The framework is illustrated in Figure 1.

We distinguish five stages, three of which can be operationalized with available firm-level data, and two of which remain primarily conceptual but are essential for interpreting aggregate productivity patterns and cross-country heterogeneity.

The first stage concerns access and digital infrastructure – the availability and affordability of digital technologies, connectivity, and data. While AI capabilities are increasingly commoditized through cloud platforms and open-source tools, access remains uneven across firms and economies. Small and medium-sized enterprises, particularly in CEE economies, often face barriers related to digital infrastructure, data availability, and the fixed costs of AI adoption [23]. Without basic access and digital readiness, subsequent stages become irrelevant. However, access alone does not translate into productivity gains; it simply determines whether a firm enters the funnel.

The second stage, organizational readiness, captures a firm's capacity to integrate AI into existing workflows,

Figure 1: Productivity Funnel



Source: Authors' illustration

decision processes, and managerial structures. We argue that this stage represents the critical bottleneck in the productivity funnel – the point where most firms become trapped. AI adoption frequently disrupts established routines, creating coordination costs and requiring the redesign of roles, responsibilities, and incentive systems [4]. Empirical evidence suggests that firms with stronger management practices and organizational flexibility realize significantly greater productivity gains from digital technologies [9]. Organizational readiness – reflected in standardized processes, quality management systems, and formalized routines – provides the absorptive capacity necessary to convert technological access into operational efficiency. Firms lacking such readiness may adopt new technologies without capturing commensurate productivity gains. We term this situation the complementarity trap.

The third stage addresses human capital and behavioral adaptation. AI changes task composition rather than simply substituting for labor, meaning that productivity gains depend critically on workers' ability to interpret, validate, and act upon AI outputs [3]. Training and skill development are often cited as essential complements to technology adoption. However, our framework suggests that human capital investments are necessary but not sufficient: skill upgrading yields productivity returns primarily when embedded within organizationally mature firms that can effectively deploy new capabilities and manage the transition costs associated with process change. In the absence of organizational readiness, training may support longer-term adjustment without translating into immediate productivity improvements. Moreover, behavioral mechanisms, such as increased job insecurity, cognitive offloading, and disruption to established workflows, can offset potential efficiency gains during early adoption phases [17], [15], [6].

The fourth stage concerns institutional environment – regulatory conditions, labor market flexibility, and competitive dynamics that shape how firm-level productivity gains scale to the aggregate level. Even when firms successfully adopt and integrate AI, weak intellectual property protection, rigid labor markets, or limited competitive pressure can prevent productivity leaders from expanding and laggards from restructuring [1].

The fifth and final stage is measurement and value capture – the extent to which efficiency improvements are captured by standard productivity metrics. Many AI-enabled gains take intangible forms such as improved quality, faster response times, and enhanced risk management, which remain statistically invisible in conventional productivity measures [25], [2]. While these two stages are not directly operationalized in our firm-level analysis, they inform our interpretation of cross-country heterogeneity and the measured productivity paradox.

Building on this framework, we formalize the complementarity trap as a relational phenomenon: it is not simply that organizationally weak firms are unproductive in general, but rather that the productivity return to organizational readiness increases with the level of AI diffusion in the environment. This is a complementarity effect, consistent with the broader literature on technology–organization interactions [7].

The productivity funnel framework, combined with the complementarity trap mechanism, generates clear empirical predictions about which firm-level capabilities condition the translation of AI diffusion into productivity gains. The theoretical framework implies that the productivity effects of AI diffusion depend critically on the presence of complementary firm-level capabilities. These considerations motivate the following empirically testable hypotheses:

- Hypothesis 1 (Core: Organizational Readiness)

H1: Productivity gains from AI diffusion materialize primarily in firms with high organizational readiness, i.e., firms with formalized processes and solid managerial practices.

- Hypothesis 2 (Secondary: Skills)

H2: Firm-level skill investments strengthen the association between AI diffusion and firm productivity, amplifying productivity gains in environments with higher AI diffusion.

Data and Methodology

This section describes the data sources, variable construction, and empirical strategy used to test the hypotheses developed in Section 3.

Data

The analysis uses firm-level data from the World Bank Enterprise Surveys (WBES), which provide harmonized cross-sectional information on firm characteristics, business practices, innovation activity, and performance. The surveys cover formal firms with five or more employees and are nationally representative by sector and firm size. The sample is restricted to firms in four Central and Eastern European economies: Serbia, Croatia, Czechia, and Romania1. These economies are characterized by relatively low but heterogeneous levels of AI diffusion, making them suitable for examining differences in AI adoption environments at early stages of diffusion.

Basic firm-level variables include firm age, sector affiliation, and firm size class. The dataset also includes indicators related to firms' digital engagement and business practices, such as website presence, online sales activity, internet connectivity constraints, quality certification, provision of formal training, and reported innovations in the last three years.

To capture the AI adoption environment in which firms operate, the analysis incorporates external measures of AI diffusion, defined at the country × firm size-class level as the share of firms using at least one AI technology extracted from Eurostat [14]. This measure captures the AI adoption environment in which firms operate, rather than firm-specific AI use.

Methodology

Our empirical strategy is designed to assess whether artificial intelligence (AI) diffusion is associated with higher firm productivity on its own, or whether productivity gains materialize only in the presence of complementary firm-level organizational and human capital capabilities. Guided by the theoretical framework, the analysis focuses on two firm-level complements emphasized in the literature: organizational readiness and workforce skills.

Firm productivity is measured as the logarithm of value added per worker. Value added is constructed using

1 Serbia (417 firms, year 2024), Croatia (456 firms, year 2023), Czechia (248 firms, year 2024), and Romania (919 firms, year 2023)

firm-level information on sales, intermediate inputs, and employment, following standard practice in the productivity literature. This measure captures cross-firm differences in labor productivity while allowing for comparability across sectors and countries.

Given the absence of firm-level information on AI adoption in the World Bank Enterprise Surveys, AI diffusion is treated as a contextual, environment-level variable. It is measured at the country–firm size class level and reflects differences in AI adoption environments rather than firm-specific AI use. Identification therefore relies on variation in AI diffusion across country–size environments combined with firm-level variation in organizational readiness and skills within those environments.

Organizational readiness is proxied by quality certification, which reflects the presence of formalized processes, standardized routines, and managerial practices that may facilitate the integration of new technologies into production and organizational workflows. Quality certification serves as an observable indicator of the absorptive capacity emphasized in Stage 2 of the productivity funnel. Workforce skills are proxied by a firm-level indicator of formal employee training, capturing investments in human capital that may complement the effective use of advanced technologies such as AI, corresponding to Stage 3 of the funnel.

To account for baseline digital capabilities (Stage 1 of the funnel), the analysis includes a Digital Infrastructure Index constructed by summarizing three binary indicators: website presence, online sales activity, and internet access constraints. The index ranges from 0 to 3 and is included as a control capturing general digital readiness rather than AI-specific adoption. It is not standardized, allowing more advanced and less prevalent digital practices – such as online sales – to contribute proportionally more to measured productivity differences.

The baseline empirical specification is given by:

$$\ln(VA/L)_{i,c,s,k} = \beta 1 Zi + \beta 2 AIc,s + \beta 3(Zi \times AIc,s) + \gamma Xi + \delta c + \delta s + \delta k + \varepsilon i,c,s,k$$

where ln(VA/L) is a log function of value added per employee, i indexes firms, c countries, s firm size classes and k sectors. Zi denotes firm-level organizational readiness (proxied by quality certification), while AIc,s captures AI diffusion in the corresponding country–size environment, and the interaction term $Z_i \times$ AIc,s captures the complementarity effect central to Hypothesis 1. Xi is a vector of firm-level controls, including Digital Infrastructure Index, training, process innovation, and firm age. Country, sector and size-class fixed effects account for unobserved heterogeneity at these levels. Standard errors are computed using heteroscedasticity-robust estimators.

Given the cross-sectional nature of the data and the aggregated measurement of AI diffusion, estimated coefficients are interpreted as conditional associations rather than causal effects. Inference therefore focuses on marginal effects of firm-level characteristics evaluated at different levels of AI diffusion observed within the sample.

Main Findings

This section presents evidence on how firm-level complementarities affect productivity outcomes in environments characterized by differing levels of AI diffusion. Across the sample of four Central and Eastern European economies, the results indicate that AI diffusion alone is not systematically associated with higher firm productivity. Instead, productivity differences emerge primarily through complementarities between AI-intensive environments and firm-level organizational readiness.

The dependent variable is ln(Value Added per Employee).

Table 1 presents the baseline estimates of the relationship between AI diffusion, organizational readiness, and firm productivity. Column (1) reports pooled OLS estimates that do not account for structural heterogeneity across countries and sectors. Column (2) introduces country fixed effects, absorbing cross-country differences in productivity levels and institutional environments. Column (3) further incorporates sector fixed effects, ensuring that identification relies on comparisons among firms operating within the same country and industry.

The pooled specification in Column (1) suggests a large positive association between AI diffusion and productivity; however, this effect disappears once fixed

Table 1: AI Diffusion, Organizational Readiness, and Firm Productivity

Dependent variable: ln(Value Added per Employee)

Variables	(1) Pooled OLS	(2) + Country FE	(3) + Country & Sector FE
AI diffusion	9.452*** (1.083)	0.096 (1.209)	-0.757 (1.128)
Quality certification	-0.022 (0.113)	0.046 (0.077)	0.073 (0.073)
AI × Quality certification	-1.020 (1.199)	0.743 (0.791)	1.688** (0.757)
Digital infrastructure	0.279*** (0.050)	0.141*** (0.032)	0.091*** (0.030)
Training	0.036 (0.079)	0.121** (0.054)	0.100* (0.051)
Process innovation	0.688*** (0.125)	-0.049 (0.073)	-0.024 (0.072)
Firm age	-0.002 (0.003)	0.003 (0.002)	0.003* (0.002)
Size controls	Yes	Yes	Yes
Country fixed effects	No	Yes	Yes
Sector fixed effects	No	No	Yes
Observations	2,040	2,040	2,040
Adjusted R^2	0.144	0.674	0.707

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Heteroscedasticity-robust standard errors reported in parentheses. Joint F-tests strongly reject the null that country and sector effects are zero ($p < 0.001$), supporting the inclusion of both dimensions of fixed effects.

effects are introduced, indicating that the naive relationship is driven primarily by cross-country and cross-sector differences. The sharp attenuation of the AI coefficient after introducing only country fixed effects suggests that cross-country structural factors – such as institutional quality, technological ecosystems, and macroeconomic conditions – play an important role in shaping the observed association between AI diffusion and productivity. These results indicate that the productivity implications of AI diffusion are highly context-dependent, which is in line with the productivity funnel presented in Section 3.

Given the strong joint significance of both country and sector effects, Column (3) represents our preferred specification and serves as the basis for the main interpretation of results, presented below.

AI diffusion on its own is not significantly associated with firm productivity once structural heterogeneity is accounted for. Similarly, organizational readiness – proxied by quality certification – does not exhibit a statistically significant relationship with productivity in isolation.

In contrast, the interaction between AI diffusion and organizational readiness is positive and statistically significant ($\beta = 1.69$), indicating that the productivity advantage associated with formalized managerial practices increases with the level of AI diffusion. Evaluated at the highest observed level of AI diffusion in the sample (approximately 10%), the estimates suggest a productivity differential of roughly 17% for certified firms relative to their non-certified counterparts. This finding supports Hypothesis 1 and points to the importance of complementary organizational capabilities in translating technological diffusion into performance gains. Rather than operating as a standalone productivity driver, AI appears to generate value primarily in firms equipped with structured processes that facilitate effective technology integration.

With respect to workforce capabilities, training enters the specification with a modest positive association with productivity; however, the interaction between AI diffusion and training is not statistically significant. This result provides no evidence that skills investments alone are sufficient to unlock productivity gains from AI diffusion at this early stage of technological adoption. Hypothesis 2 is therefore not supported.

Among the control variables, baseline digital infrastructure emerges as a robust predictor of productivity, underscoring the importance of general digital readiness independent of AI-specific complementarities. Given the additive construction of the index, the estimates imply that adopting one additional basic digital capability – such as website presence, internet connectivity, or online sales – is associated with approximately a 9% higher level of value added per worker.

Process innovation, by contrast, is not statistically significant and enters with a negative coefficient, a pattern consistent with short-run adjustment costs associated with organizational change. This mechanism is explored further in Section 6.

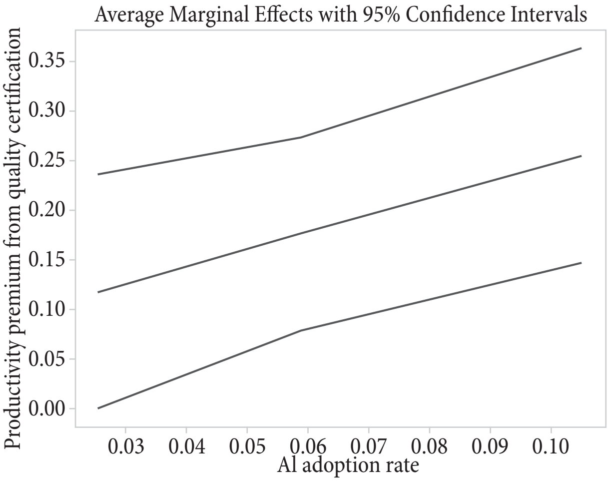
To illustrate the interaction between AI diffusion and organizational readiness, we compute *marginal effects* of quality certification at different levels of AI diffusion. The productivity premium associated with certification increases monotonically with AI diffusion, rising from approximately 12% in low-AI environments (25th percentile) to nearly 26% in high-AI environments (75th percentile) within our sample. All marginal effects are statistically significant, except that the one at 25th percentile is significant only at 10% significance level.

Table 2: Marginal Effects of Quality Certification at Different Levels of AI Diffusion

AI diffusion (percentile)	Marginal Effect	Standard Error
25th (low AI diffusion)	0.118*	(0.060)
50th (median AI diffusion)	0.176***	(0.050)
75th (high AI diffusion)	0.255***	(0.055)

Notes: Marginal effects are based on robust standard errors. AI diffusion rates correspond to selected values from the observed distribution in the sample. *** p < 0.01, ** p < 0.05, * p < 0.10.

Figure 2: Average Marginal Effects



Source: Authors' calculations

Figure 2 plots average marginal effects of quality certification on productivity evaluated at selected levels of AI diffusion. The upward-sloping relations illustrates the core finding: the incremental productivity premium associated with quality certification rises systematically with AI diffusion, consistent with a complementarity effect. The widening confidence intervals at higher AI diffusion levels reflect reduced sample density in high-AI environments.

Discussion

Our findings provide support for the hypothesis that organizational readiness conditions the productivity effects of AI diffusion. By contrast, the hypothesis that workforce training acts as a direct complement to AI diffusion is not supported in the pooled sample and is rejected in its original form. At the same time, additional exploratory evidence suggests that training may play a more context-specific and transitional role, particularly during periods of organizational change and among medium-sized firms, rather than functioning as a general-purpose complement to AI adoption. We discuss these findings in more detail in the following paragraphs.

AI diffusion and organizational readiness

The results indicate that artificial intelligence (AI) diffusion does not translate into higher firm productivity in isolation, but instead conditions the productivity returns to organizational readiness. In the baseline specification, neither AI diffusion nor organizational readiness – proxied by quality certification – exhibits a statistically significant association with productivity on its own. By contrast, the interaction between AI diffusion and organizational readiness is positive and statistically significant, implying that the productivity premium associated with formalized processes and managerial practices increases as AI diffusion in the surrounding environment rises. This pattern suggests that AI acts less as a direct productivity-enhancing input and more as a catalyst that amplifies existing organizational capabilities. This finding is also consistent with evidence that AI adoption may disproportionately benefit organizationally advanced firms, thereby reinforcing productivity dispersion rather than reducing it [5].

This finding is consistent with the broader productivity paradox literature, which emphasizes delayed and uneven productivity responses during periods of major technological transition. As argued by David [12], productivity gains often lag behind technological adoption as firms redirect resources toward experimentation, learning, and organizational reconfiguration. In the context of AI, Brynjolfsson, Rock, and Syverson [10] describe this dynamic as a J-curve, whereby adjustment costs and coordination frictions initially offset potential efficiency gains. From this perspective, the absence of a positive association between AI diffusion and productivity in isolation reflects early-stage diffusion dynamics rather than technological failure.

The results further suggest that organizational readiness constitutes a binding constraint in translating AI diffusion into measurable productivity gains. Quality certification captures a set of formalized routines, standardized processes, and managerial practices that facilitate coordination and workflow redesign. In more AI-intensive environments, these organizational features appear to enable firms to better absorb new technologies and reorganize production accordingly. This interpretation aligns with evidence that advanced technologies tend to reinforce existing organizational capabilities rather than compensate for their absence, thereby contributing to heterogeneous productivity outcomes across firms.

By contrast, the lack of significant interaction between AI diffusion and workforce training indicates that generic skill investments are insufficient to unlock AI-related productivity gains at that stage. While training is an important input, the results suggest it is not a substitute for deeper organizational structures that support experimentation, coordination, and sustained process change when it comes to AI adoption. One possible explanation is that training-related productivity benefits in AI-exposed environments may follow a J-curve pattern, whereby learning, adaptation, and coordination costs initially offset potential efficiency gains. In early stages of AI diffusion, training may thus support longer-term organizational adjustment without translating into immediate productivity improvements, rendering its interaction with AI diffusion statistically insignificant in cross-sectional data.

The findings also point to a hierarchy of complements, in which foundational digital infrastructure as well as training are associated with higher productivity on its own, while AI-related gains require a higher level of organizational maturity. This pattern is consistent with cross-country evidence showing that small open economies often experience delayed productivity responses to AI due to limited scale, managerial depth, and complementary capabilities [18]. As AI diffusion remains shallow, firms continue to operate at the lower segments of the productivity funnel, where foundational digital adoption precedes more advanced organizational transformation.

Finally, the results resonate with emerging behavioral explanations of delayed productivity gains from AI. Organizational change associated with new technologies can generate uncertainty, increased verification demands, and coordination costs, which may suppress measured productivity in the short run even when technical capability is present. Organizational readiness may mitigate these frictions by providing clearer processes, decision rules, and accountability structures that stabilize expectations and support learning. From this perspective, the AI productivity paradox is best understood as a translation problem rather than a technological one, in which organizational bottlenecks delay the conversion of technological potential into realized productivity gains.

Skills, process innovation, and firm size: exploratory evidence

While the main analysis focuses on complementarities between organizational readiness and AI diffusion, an additional exploratory regression points to a more nuanced role of skills and organizational change at specific stages of firm development – particularly, among medium-sized firms. In the analyzed sample of countries, medium-sized firms represent a strategic backbone of the private sector, bridging small, resource-constrained enterprises and large incumbents, and playing a central role in employment generation, productivity growth, and structural upgrading.

In the exploratory regression shown in Table 3, we find evidence that training is positively associated with productivity primarily when firms report process innovations in the last three years. Predicted margins indicate that firms undertaking process changes without accompanying training experience lower productivity levels, consistent with short-run adjustment and implementation costs (J-curve), whereas training appears to mitigate these transitional productivity losses.

Table 3: Skills, Process Innovation, and Organizational Readiness: Exploratory Evidence

Variable	Coefficient	Std. Error
Training	-0.0025	0.0903
Process innovation	-0.4736**	0.2170
Training x Process innovation	0.5598**	0.2484
Digital Infrastructure Index	0.1142*	0.0611
Quality certification	0.1738**	0.0884
Firm age	0.0013	0.0023
Country fixed effects	Yes	
Sector fixed effects	Yes	
Firm size-class fixed effects	Yes	
Observations	540	
Adjusted R2	0.76	

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Importantly, this pattern is not observed among small or large firms. For small firms, limited organizational scale and resource constraints may restrict the effectiveness of both training and process change, while for large firms, more established routines and internal capabilities may dampen the marginal productivity effects of incremental training during periods of organizational change. Medium-sized firms, by contrast, often occupy a transitional position in which organizational complexity increases, but formalized routines and managerial structures are still being developed. In this context, training may play a more salient role in facilitating the absorption of new processes and preventing short-run productivity disruptions.

The observed pattern among medium-sized firms is also consistent with a growing body of research emphasizing psychological and behavioral mechanisms during periods of organizational transition. Even when technical capabilities are present, organizational change can generate short-run productivity losses if it increases perceived job insecurity, time pressure, or role ambiguity, which may reduce experimentation, initiative, and knowledge sharing—precisely the behaviors required for effective process redesign [6, pp. 486-489], [17, pp. 4-7]. In addition, organizational change often reallocates effort from production toward coordination, verification, and risk management, increasing adjustment and supervision costs that are not immediately reflected in higher measured productivity [10, pp. 7-10], [15, pp. 15-16].

At the same time, the results of our exploratory regression should be interpreted cautiously. The process innovation indicator in the data captures a broad range of organizational and technological changes and does not specifically identify AI-related process adoption, although it can be a part of it. As such, these findings are best understood as suggestive evidence on the role of skills in managing organizational transition, rather than as direct evidence of AI-related productivity complementarities.

Taken together, the results underscore an important distinction between episodic capability investments, such as training during periods of organizational change, and more persistent forms of organizational readiness. While the former may help firms navigate organizational adjustment costs – particularly among medium-sized firms – the latter emerges as the key factor enabling sustained productivity gains in more AI-intensive environments.

Implications for Early-Stage AI Diffusion Environments

The findings carry important implications for economies at early stages of AI diffusion, such as those examined in this study. In such contexts, policy strategies that emphasize technology adoption, infrastructure, or pilot projects alone are unlikely to generate measurable productivity gains in the short run. Instead, the results suggest that the binding constraint lies in firms' absorption capacity – the organizational, managerial, and procedural capabilities required to translate AI exposure into effective changes in production and decision-making.

AI policy should be understood less as a narrowly defined technology policy and more as an enterprise transformation agenda. Interventions that support organizational redesign, managerial capability development, and the integration of AI into core workflows are likely to be more consequential than standalone investments in software or equipment.

At the same time, policymakers should recognize that weak or delayed productivity responses are consistent with transitional dynamics and adjustment costs rather than evidence of AI's ineffectiveness. In early-stage environments, sustaining policy commitment requires acknowledging that productivity gains may materialize only after complementary organizational investments have been made and diffusion has reached sufficient scale. Escaping the complementarity trap thus requires a shift in policy focus – from accelerating technology adoption toward building the organizational foundations that enable firms to capture value from AI diffusion.

Limitations

This study has several limitations that should be acknowledged when interpreting the results.

First, the empirical strategy relies on cross-sectional firm-level data combined with externally measured AI diffusion at the country–size level. While the inclusion of extensive fixed effects and firm-level controls mitigates some sources of confounding, the estimates should be interpreted as conditional correlations rather than causal effects of AI diffusion or organizational readiness on productivity.

Second, AI diffusion is measured at an aggregated level, as firm-level AI adoption data are not available in the WBES. The AI diffusion indicator from Eurostat captures the share of firms using at least one AI technology at the country × firm size-class level, and therefore reflects the broader technological environment rather than firm-specific AI inputs. While this measurement choice aligns with the conceptual framing of AI as an environmental or contextual factor, it limits within-cell variation and constrains the precision with which AI exposure can be identified.

Third, organizational readiness is proxied by quality certification, which captures formalized processes, routines, and managerial practices but does not fully encompass the multidimensional nature of organizational capabilities. Certification may not reflect informal practices, leadership quality, or firms' adaptation capacities. The results should thus be understood as relating to a specific dimension of organizational readiness rather than to organizational capacity in a broader sense.

Fourth, the analysis focuses on a set of early-stage AI-adopting Central and Eastern European economies, and its findings should not be extrapolated mechanically to highly AI-intensive economies, where adoption, complementary investments, and learning effects may follow different trajectories. Moreover, the sample is limited to four countries, which constrains cross-country variation and may limit the generalizability of findings to other CEE economies.

Taken together, these limitations also point to promising directions for future research, including panel-based analyses that would allow for examination of productivity dynamics over time and firm-level measurement of AI adoption as such data become increasingly available. Another promising avenue for future research is the integration of psychological and behavioral mechanisms into models of AI-driven productivity.

Concluding Remarks

This paper examines why the diffusion of AI has not yet translated into proportional productivity gains in early-stage adoption environments in Central and Eastern Europe. Rather than interpreting weak outcomes as technological failure, it reframes the AI productivity paradox as a structural and transitional phenomenon shaped by organizational, managerial, and institutional constraints.

The analysis introduces a productivity funnel perspective, conceptualizing productivity gains as the result of a multi-stage translation from technological potential to realized output. Within this framework, we identify a complementarity trap: firms adopt AI but fail to capture productivity gains due to insufficient organizational readiness. As AI diffusion increases, the productivity gap between organizationally prepared and unprepared firms widens.

In contrast, generic skill investments and baseline digital infrastructure appear insufficient to unlock

AI-related productivity gains at this stage. However, our exploratory analysis within medium-sized firms points to complementarities between skill development and the successful implementation of process innovations, potentially including AI transformations. These findings suggest a clear hierarchy of complements: digital capabilities raise productivity broadly, skills support adjustment, but organizational readiness remains the binding constraint for AI-driven gains.

The results carry important implications for economies such as Serbia, where productivity gains remain concentrated in basic digital adoption and AI-related complementarities have yet to emerge at scale. Policies narrowly focused on AI adoption or pilot projects are therefore unlikely to deliver short-term productivity growth. Instead, AI policy should be embedded within a broader enterprise transformation agenda emphasizing organizational redesign, managerial capability development, and adaptive human capital.

Despite data and methodological limitations, the central message is clear: the AI productivity paradox reflects delayed, uneven, and conditional gains rather than technological disappointment. Productivity growth depends less on the speed of AI adoption than on firms' ability to escape the complementarity trap by widening the productivity funnel – primarily through organizational and human capital transformation.

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