AI Adoption in Developing Countries:

Lessons from the Adoption of other Advanced Digital Technologies

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Abstract

This paper examines how firms in developing countries adopt and productively use artificial intelligence (AI) based technologies. It draws on evidence from the FAT (Firm Adoption of Technology) survey on the diffusion of earlier advanced digital technologies, which covers more than 20,000 firms across countries at different income levels, together with new evidence on AI adoption among firms in Romania. The cross-country evidence shows that advanced digital technologies diffuse more slowly and are used less intensively in lower-income countries, with intensive use more strongly associated with productivity than adoption alone. The evidence from Romania shows that AI adoption remains limited and concentrated among larger, more productive, better-managed, and technologically advanced firms, providing little evidence of technological leapfrogging. AI adoption is associated primarily with worker reassignment rather than displacement or net employment reduction. The findings highlight the need to narrow the dual gap—adoption and use—with measures that support building complementary digital, managerial, organizational, and workforce capabilities to accelerate the diffusion of AI technologies. Not addressing these gaps will prevent developing countries from capturing the anticipated productivity gains from AI.

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"We stand at the threshold of perhaps the most consequential economic transformation since the Industrial Revolution." Agrawal et al. (2025b) (pp.1)

1 Introduction

The Artificial Intelligence (AI) revolution promises the largest economic transformation since the industrial revolution - which combined the introduction of several general purpose technologies (GPT), such as combustion engines or electricity. AI can perform tasks that normally require human intelligence — such as understanding language, recognizing patterns, making decisions, learning from data, and solving problems. As a GPT, AI is expected to greatly transform societies with the development and diffusion of multiple applied technologies that integrate AI capabilities.

From an economic development perspective, the transformational impact of AI will depend on the types of AI based technologies developed, but more importantly, on the speed of adoption and use in developing countries. Data on the diffusion and adoption of AI technologies across firms in developing countries remains scarce, but based on evidence from recent decades, the lessons suggest that developing countries could struggle to reap the benefits of the AI revolution. Developing countries have struggled to rapidly adopt new technologies, and while technologies are arriving faster to developing countries, the intensity of their use is diverging (Cirera et al., 2026; Comin and Mestieri, 2018). In the words of David Landes, rather than the *Unbound Prometheus* (Landes, 1969), *Prometheus* has never fully arrived to developing countries.

This paper takes stock of lessons from a cross-country dataset of more than 20,000 firms in developed and developing countries that measures the adoption and use of advanced technologies, and combines it with a new dataset for Romania that explores the adoption and use of AI technologies. Specifically, the paper tries to shed some light on the following questions: i) how fast are firms in developing countries likely to adopt and use AI technologies? ii) What are the key barriers that may impede the adoption and use of AI?, and iii) who are the likely adopters and what is the expected impact?

To address these questions, the starting point is to understand how AI, as embodied in GPT, differs from other digital technologies and GPTs more generally. Understanding their benefits and costs of adoption help us to predict the pattern of adoption (Agrawal et al., 2023). Agrawal et al. (2025a) characterize the main benefits of AI technologies as providing a large reduction in the costs of prediction, and, therefore, reducing the amount of missing information needed for decision making. This has important implications to study the patterns of adoption across firms, sectors and countries. Primarily, we should expect that

both the development of AI technology applications and their adoption and use is higher in tasks where prediction and information plays a more important role. Planning, risk management, managing supply chains, marketing and demand forecast, or HR, are some of these functions where improving predictions can help firms improve decision-making. Indeed, these are the areas where existing technologies, such as ERP and CRM, are being rapidly augmented by AI.

In addition to the potential benefits, adoption depends largely on the potential costs of adoption, not only reflected by the prices of the technologies - i.e. purchasing the licenses or applications needed to use them- but more importantly by the additional adjustments and investments that firms must implement to integrate these technologies and fully take advantage from their use. Bresnahan and Greenstein (1996) and Agrawal et al. (2023) label these costs "co-invention costs." Bresnahan et al. (2002) continuing a large innovation literature emphasize the role of organizational complementarities in the adoption of ICT technologies (Brynjolfsson et al., 2002; Brynjolfsson and Hitt, 2000). In the case of AI, Agrawal et al. (2024) find that productivity-enhancing AI might not be adopted when there are multiple decision-makers due to the potential lack of coordination between decision-makers. What is important of this literature is the emphasis that there are complementary factors needed to fully reap the benefits of these technologies; adopting these technologies without the right organizational structure is not sufficient.

The quality of management and firm organization is a critical determinant of firm productivity and growth (Ichniowski and Shaw, 2009; Bloom and Van Reenen, 2007). However, existing empirical work measuring the quality of management and organization in developing countries suggests large gaps in good management practices in developing countries. High-skilled professionals can implement management practices that are more conducive to raising productivity, for example, by introducing better incentives to workers that increase their performance (Lazear, 2000). A key challenge for developing countries is finding these professionals who can identify and integrate new technologies and make firms grow and compete in international markets. In addition to lower quality management practices (Bloom et al., 2012), firms in developing countries face a scarcity of high-skilled professionals and higher hiring costs (Hjort et al., 2022). As a result, one should expect more difficulties in firms in developing countries in taking advantage of AI technologies.

A more important consideration in assessing the adoption, use, and impact of AI is how AI, as a general-purpose technology, is likely to reshape complementarities across technologies. Firms use a large number of technologies in different tasks. Some of the existing technologies are going to be augmented with the integration of AI with significant impacts on the productivity of these technologies within each task. For example, AI can change the

productivity of technologies used for supply management - SRM - by significantly increasing the technological capabilities to identify suppliers and price changes. But it is also possible that AI changes the relationship across different business functions and technologies. Following the previous example, by increasing the complementarities with production planning and the decisions on how to use and purchase inputs.

In order to better predict the speed of adoption and the effects of AI technologies, in the next section, we present a framework to understand adoption and the complementarities across different technologies.

2 A framework to understand the impact of AI technologies

We model a firm whose production requires performing a set of tasks - business functions - indexed by f. Each business function combines labor, capital, and technology to produce an intermediate output according to a constant elasticity of substitution (CES) production function. Output at the business function level is given by:

$$Y_{ft} = e^{\gamma_f s_{ft}} \left[(1-\alpha_f)^{\frac{1}{\sigma_f}} L_{ft}^{\frac{\sigma_f - 1}{\sigma_f}} + \alpha_f^{\frac{1}{\sigma_f}} K_{ft}^{\frac{\sigma_f - 1}{\sigma_f}} \right]^{\frac{\sigma_f}{\sigma_f - 1}} \tag{1}$$

where s_{ft} is the sophistication of the most-widely used technology in the business function f and time t. γ_f is the rate of technological progress in the technologies in each business function. $e^{\gamma_f s_{ft}}$ captures Hicks-neutral technological progress: adopting more sophisticated technologies raises the productivity of all inputs used within the business function.

In this setup, capital and labor can be substitutable in each business function ($\sigma_f > 1$) but they do not need to be perfectly substitutable as in many task-based production functions. This elasticity of substitution can vary across business functions. Technology is Hicks-neutral at the business function level.[1]

We can then aggregate the outputs from the different business functions to the firm-level output, specified as:

$$Y_t = \left[\sum_f \xi_f (Y_t)^{\frac{1}{\sigma(x^{AI})}} Y_{ft}^{\frac{\sigma(x^{AI})-1}{\sigma(x^{AI})}} \right]^{\frac{\sigma(x^{AI})}{\sigma(x^{AI})-1}} \tag{2}$$

[1]It is easy to introduce the notion of automation by making technology biased towards capital (or capital embodied technology) by making α_f an increasing function of s_{ft}. Also, it is possible to differentiate between different types of labor/occupations i.e., skilled vs. unskilled) and model capital-skill complementarities or skilled-biased technical change.

where ξ_f represents the importance of business function f in overall production, and $\sigma(x^{AI})$ is the elasticity of substitution across business functions. We allow this elasticity to depend on the firm's AI capabilities, x^{AI}. This captures the idea that AI may improve not only the productivity of individual business functions but also the coordination among them.

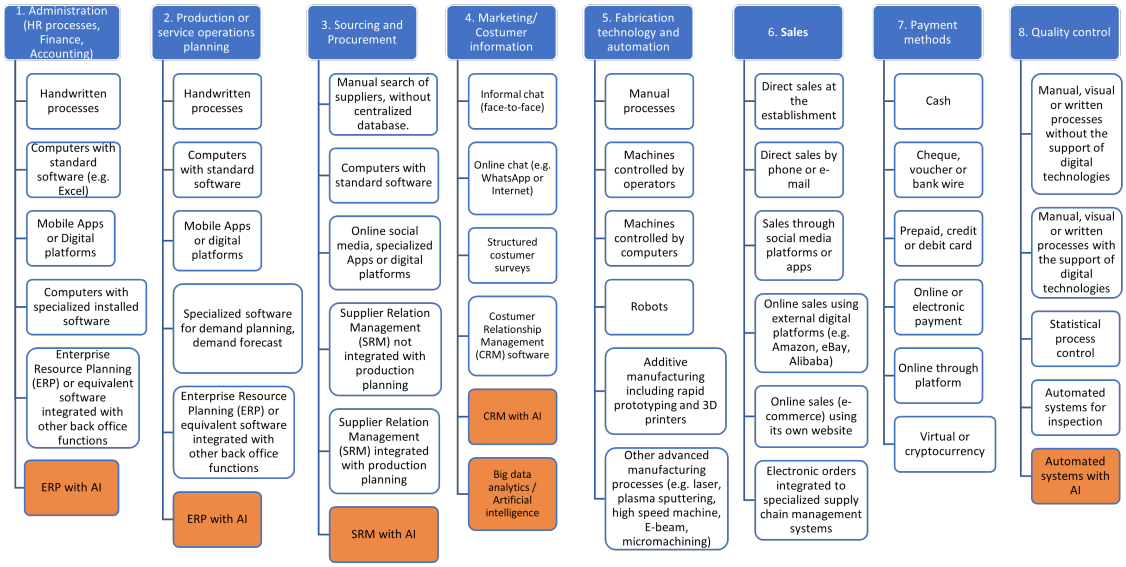
Within this framework, there are three key channels through which AI can increase productivity. The first channel is technology upgrading within business functions. For some business functions, AI can improve the capabilities of existing technologies and increase the sophistication of technologies employed withing business functions (i.e. higher levels of s_{ft}). These improvements raise the productivity of labor and capital employed in that business function by enabling more accurate prediction, better information processing, and more effective decision-making.[2]

Figure 1 shows how AI can be added to technologies - orange cells in the grid - in existing business functions that are common across firms in different sectors and are related to management and administration. Rather than replacing conventional digital technologies, AI primarily augments their functionality by expanding their ability to process information, generate predictions, and automate decisions. For example, AI augmented ERP, expands the functionalities of traditional ERP in production planning by making reactive planning with better informed data-driven automation. This can reduce costs by reducing inventory waste, minimizing downtime through predictive maintenance, and accelerating the speed and accuracy of decision-making. In other words, businesses can plan production better and more accurately when using this technology. Similar augmentation of the capabilities occur for supply chain management, quality control or targeted marketing. [3]

[2]Note also that if the productivity improvements achieved by AI in a business function are large, one could think that γ_f is not constant (i.e. productivity gains from AI are much larger than those brought by previous technologies.

[3]There are other potential applications of AI that can reduce costs. These range from enhanced IT security or fraud prevention, to Research and development or the maintenance of machines and equipment. Furthermore, AI can enhance significantly the level of automation and efficiency of robotics, increasing the quality of products and reducing refuse costs. AI can *de facto* expand the capabilities of existing technologies in the use of information for prediction and decision making.

Figure 1: AI in General Business Functions



A second channel through which AI can affect productivity is when the intensive use of AI helps in the integration between the different business functions in the firm and and help eliminate bottlenecks; *de facto* increasing the elasticity of substitution between the different functions. These complementarities can arise from the fact that improved information and decision making in the technology used in one business function can increases the efficiency and capabilities in other technologies used in other business functions. For example, a more precise quality control process can expand the benefits of using SRM technologies for supply chain management given the increased accuracy and inventory control.

A third potential channel can occur if by increasing output, AI, change the importance of the different business functions if production is non-homothetic ($\xi_f(Y_t)$). Certain functions may become more important as production increases (e.g., business administration and production planning) while others may become less important. If the functions that become more important with Y_t are those where the productivity gains brought by AI are largest, then this will give an extra boost to productivity.

Summing up, AI can impact productivity, performance and employment through various channels. A first direct channel is via expanding the capabilities of existing technologies and making them more productive. A second channels depends on the potential complementarities between technologies in different business functions. The third channel is via potentially altering the importance of different tasks in production. However, all of these effects are conditional to the speed of adoption and use of AI technologies in developing countries. Skill bottlenecks, technology costs or lack of complementary factors and organizational capabilities are likely to delay adoption and use of some of these technologies, resulting in potentially

large productivity differences between adopters and non-adopters.

In what follows, we use the Firm Adoption of Technology (FAT) survey dataset[4]—and draw some lessons from the adoption of other advanced technologies. We start by describing the speed of technology diffusion in developing countries in the last two decades and measure and characterize the technological gap in developing countries. Then we use existing data to explore some of the channels discussed in the framework above.

3 What we know about the diffusion of technologies in developing countries and the technology gap

The potential benefits from AI described in the previous section are conditional to the successful adoption of AI based technologies. However, the adoption and use of advanced technologies in developing countries is lagging significantly compared to high income countries. Specifically:

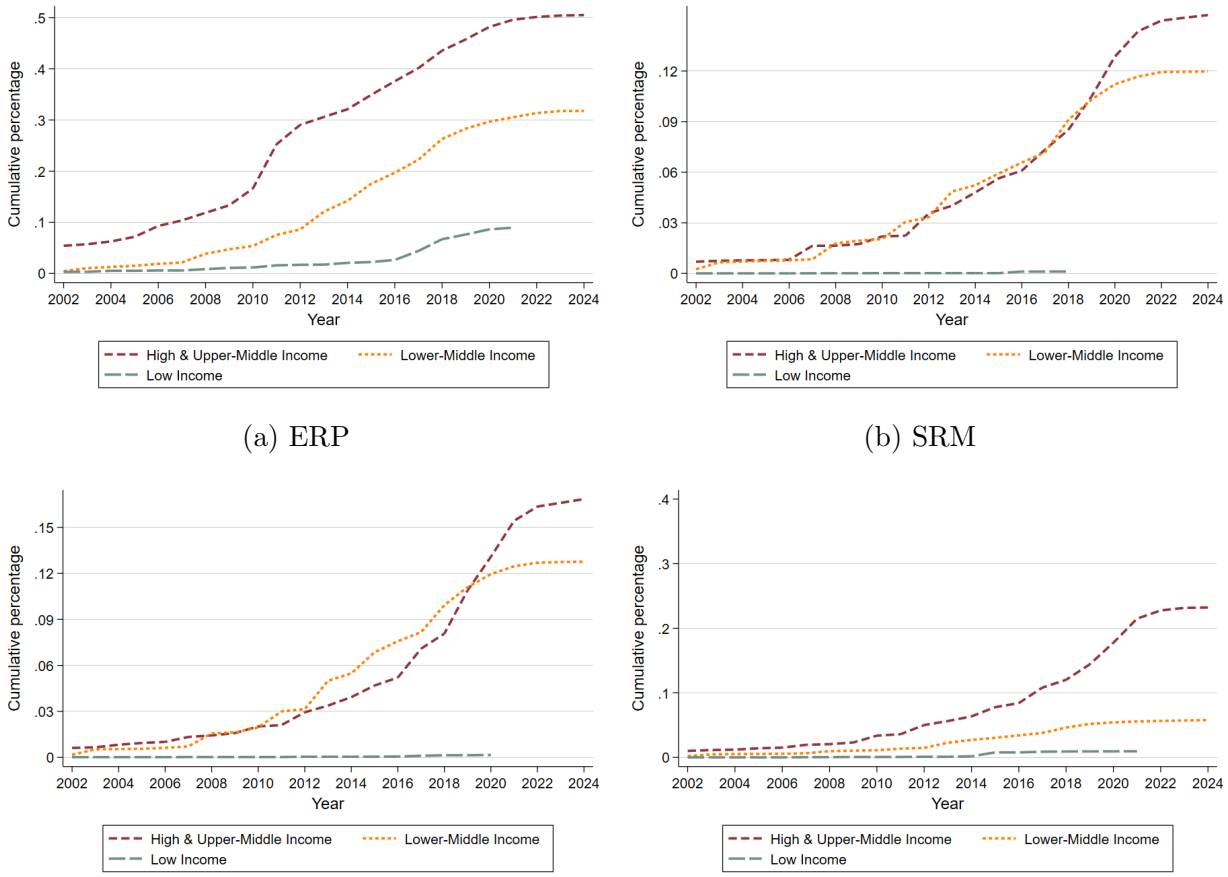
3.1 The diffusion of digital technology in developing countries

The speed of diffusion of digital technologies in developing countries is slower than in higher income countries

There are long adoption lags for advanced digital technologies, especially in low-income countries. Adoption of off-the-shelf digital technologies is lower and slower in low income countries, and these are mature technologies with a reasonable availability of suppliers to support diffusion, even in low income countries. The diffusion gap is most significant for ERP where less than 10% of firms in low income countries have adopted this technology (Figure 2).

[4]See Cirera et al. (2026) for the details of the survey design and method.

Figure 2: Diffusion Curve by Income Group



(a) ERP

(b) SRM

(c) CRM

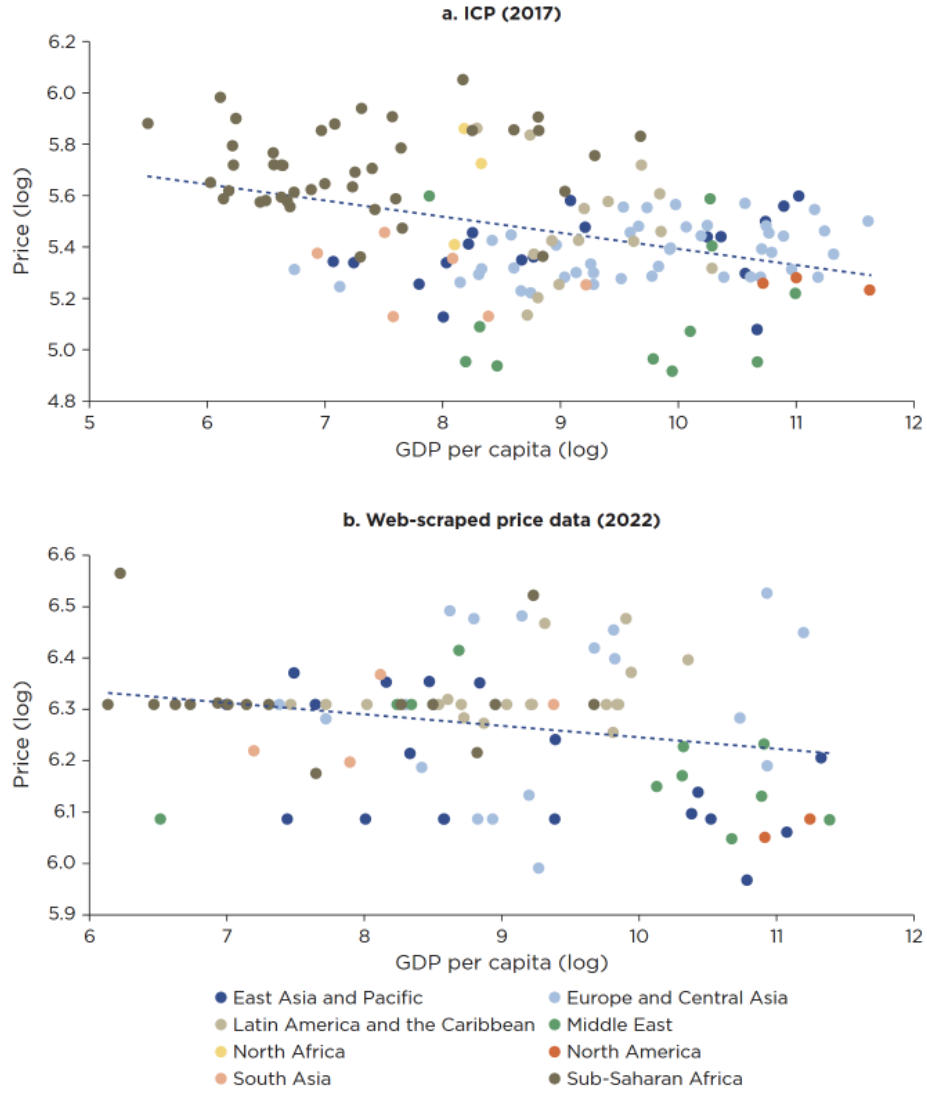
(d) Advanced Quality Control

Note: This figure shows the diffusion of advanced technologies—Enterprise Resource Planning (ERP), Supplier Relationship Management (SRM), Customer Relationship Management (CRM), and Advanced Quality Control (AQC)—by country income groups. The X-axis indicates the years of adoption of advanced technology while the y-axis presents the cumulative share of firms that had adopted the technology by each year. All estimates are weighted using sampling weights.

While slow diffusion is the result of different factors, Cruz et al. (2024) suggests that digital technologies are disproportionately expensive in developing countries. Examining item-level price data from the International Comparison Program (ICP) to identify digital versus nondigital goods in the machinery and equipment and other products categories enables a more detailed understanding of digital goods prices. Figure 3 shows a negative relationship between the price of software and per capita gross domestic product (GDP). A similar picture emerges in panel (b) when using a web scrapping methodology. Although these higher prices are not the only binding constraint, they play a role in slowing diffusion. When thinking about accelerating the adoption of AI technologies in developing countries it is important to ensure that the costs are not much larger than in developed economies. In addition to import costs, country specific costs that can be large. For example, most

standard ERP packages in Cambodia are not translated to Khmer, which increases the costs of using the technology since firms require hiring workers that can manage the software in english.

Figure 3: Correlation cost of software and income per capita



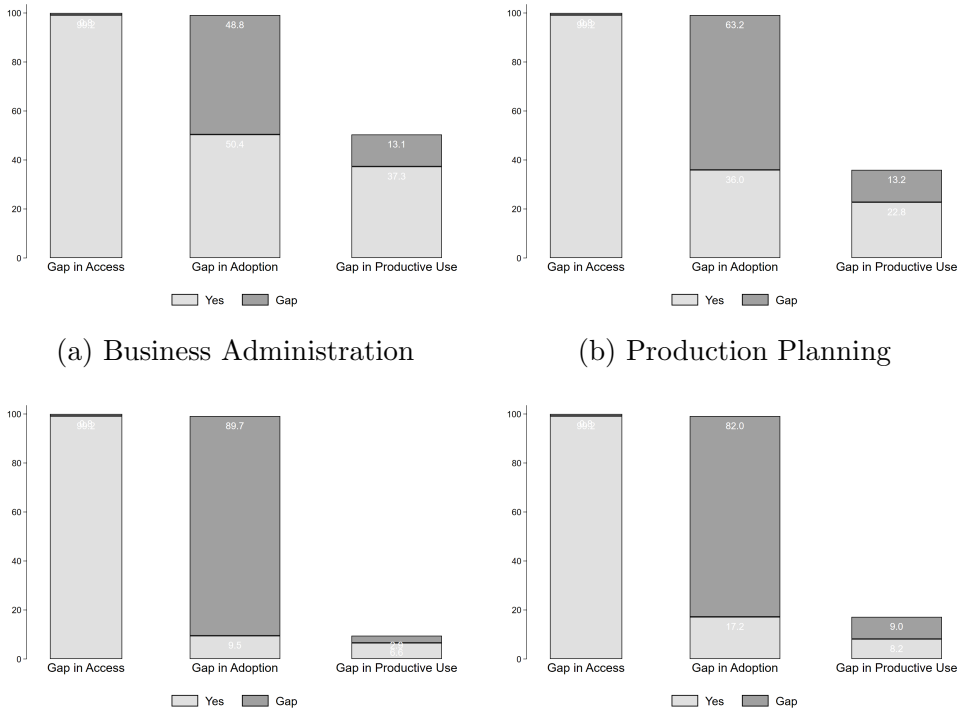
Source: Cruz et al. (2024) Note: Estimates based on 2017 ICP data on software, 2022 web-scraped software price data from Microsoft online store, and World Bank data on GDP per capita for 2017 and 2022. The 2022 web-scraped software price data are obtained for 91 countries, which include 16 in Sub-Saharan Africa. The 2017 ICP software price data are obtained for 147 countries, which include 42 Sub-Saharan African countries. Prices are in US dollars at market prices. GDP = gross domestic product; ICP = International Comparison Program; IFC = International Finance Corporation.

3.2 Intensive use of advanced digital technology

In addition to slow diffusion, a key technology gap relates to the lack of intensive use of advanced digital technologies

The technology more intensively used in a business function is not necessarily the most sophisticated technology that has been adopted. Even in cases where firms have incurred in the costs of investing in these technologies, they are often underutilized. These gaps between adoption and use - MAX-MOST gaps (Cirera et al., 2026) - are persistent and strongly associated with productivity both across establishments and countries. Figure 4, Figure 5 and Figure 6 show graphically these gaps by income region and for four different business functions. The first bar represents the gap to access to digital infrastructure - connection to internet and having computers - and it is almost universal for high-income and upper middle incomes, but with significant gaps in low income countries. The second bar show the gap in adoption of advanced digital technologies, which increases at lower income per capita. The third and final bar is the gap in use of advanced digital technologies that have been already adopted. In some cases, this gap in intensive use of firms that have adopted and incurred some of the costs of adoption can be significant. Adoption does not ensure that firms use advanced technologies productively.

Figure 4: Digitalization Gap in Core General Business Functions, High and Upper-Middle Income Countries



(a) Business Administration

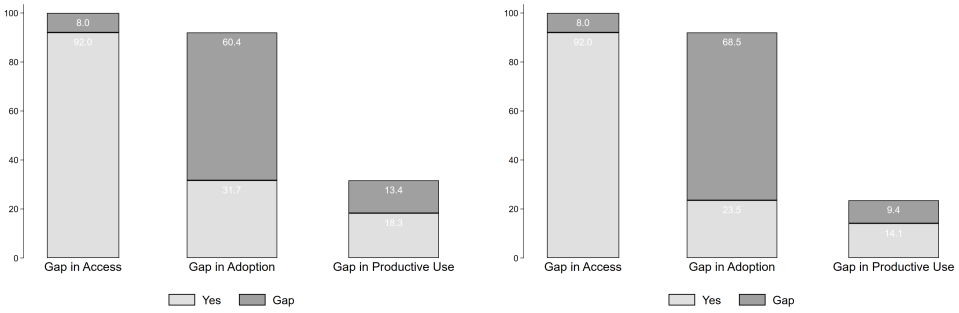
(b) Production Planning

(c) Supply Chain Management

(d) Quality Control

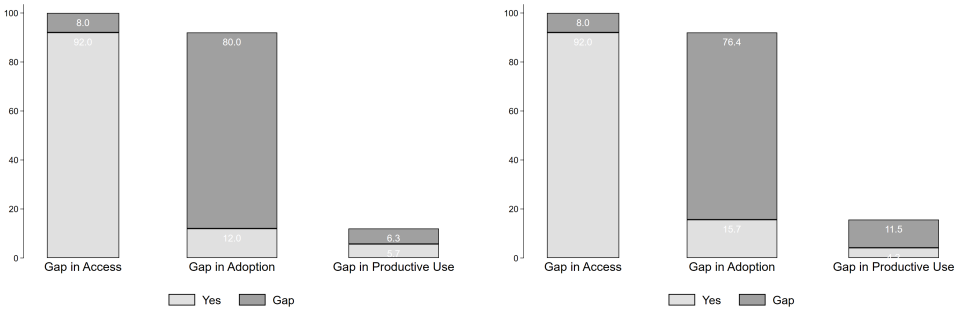
Note: This figure shows the share of firms with access to basic digital technologies, those adopting advanced digital technologies, and those intensively using advanced digital technologies across four core business functions in high-income and upper-middle-income countries. The four core general business functions include Business Administration, Production Planning, Supply Chain Management, and Quality Control Inspection. All estimates are weighted using sampling weights.

Figure 5: Digitalization Gap in Core General Business Functions, Lower-Middle Income Countries



(a) Business Administration

(b) Production Planning

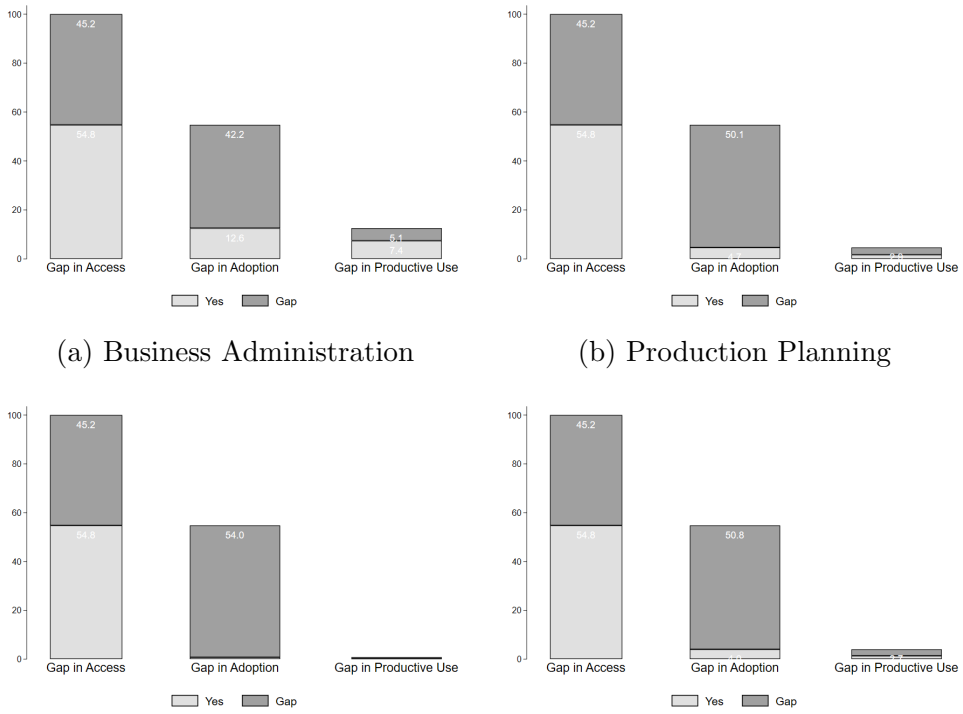


(c) Supply Chain Management

(d) Quality Control

Note: This figure shows the share of firms with access to basic digital technologies, those adopting advanced digital technologies, and those intensively using advanced digital technologies across four core business functions in lower-middle income countries. The four core general business functions include Business Administration, Production Planning, Supply Chain Management, and Quality Control Inspection. All estimates are weighted using sampling weights.

Figure 6: Digitalization Gap in Core General Business Functions, Low Income Countries



(a) Business Administration

(b) Production Planning

(c) Supply Chain Management

(d) Quality Control

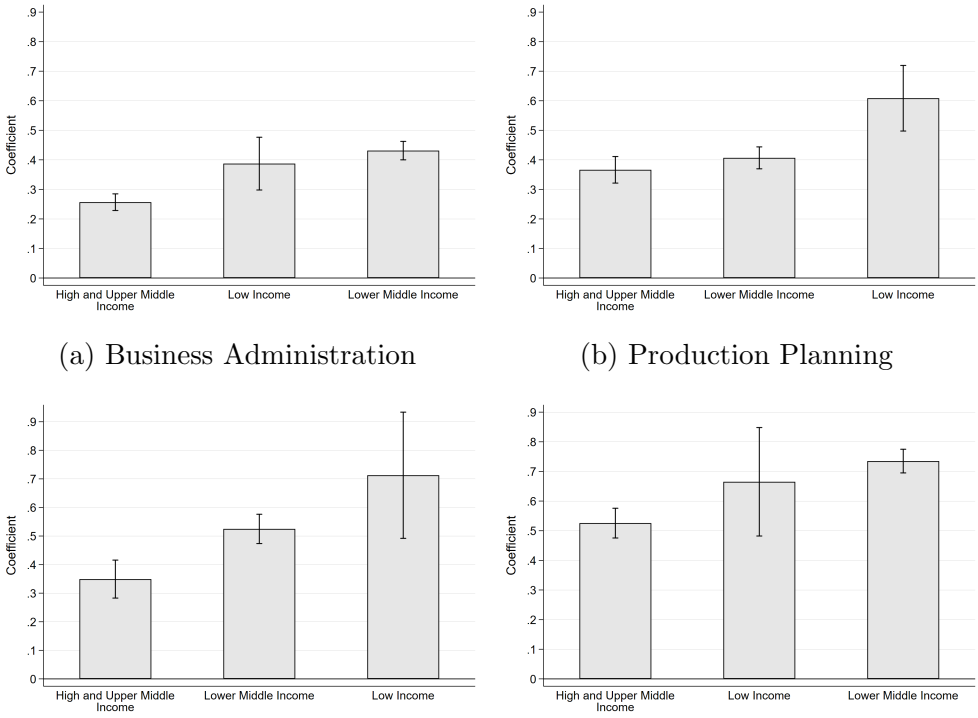
Note: This figure shows the share of firms with access to basic digital technologies, those adopting advanced digital technologies, and those intensively using advanced digital technologies across four core business functions in low-income countries. The four core general business functions include Business Administration, Production Planning, Supply Chain Management, and Quality Control Inspection. All estimates are weighted using sampling weights.

3.3 The gap between technology adoption and use

The gap in use is larger in relative terms in low income countries

While adoption of advanced technologies is lower in low income countries and as a result the gap in use of these technologies is lower as a share of total firms, the relative share of firms that adopt these technologies and do not use them intensively is larger in low and lower middle income countries, characterizing an incomplete digitalization Cirera et al. (2024). A lower share of firms adopt in these regions, but from those a significant share do not use these technologies intensively.

Figure 7: Incomplete Digitalization for Core General Business Functions by Income Group



(a) Business Administration

(b) Production Planning

(c) Supply Chain Management

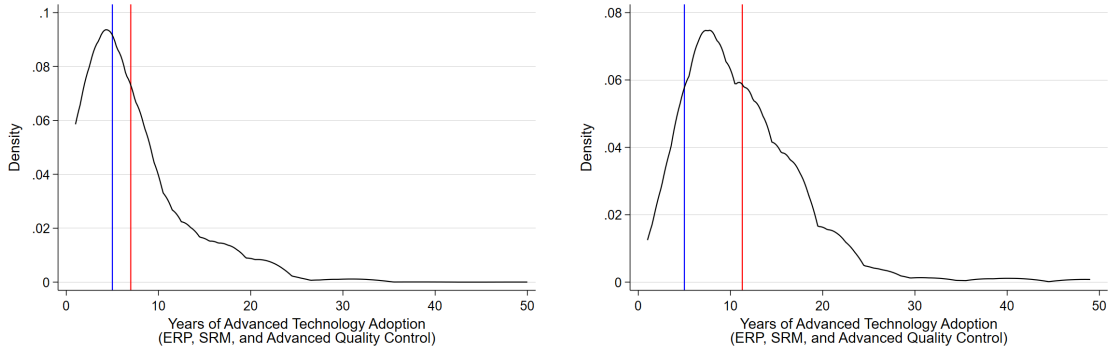
(d) Quality Control

Note: This figure shows the extent of incomplete digitalization for four core general business functions by country income groups. Incomplete digitalization is measured as the share of firms that intensively use advanced digital technologies among those that have adopted these technologies. Four core general business functions include Business Administration, Production Planning, Supply Chain Management, and Quality Control Inspection. All estimates are weighted using sampling weights.

The gap in use is persistent over time, especially in lower income countries

One potential explanation for the gap in use of advanced technologies could be associated to the need for learning and integration of new technologies within the firm. For example, adopting an ERP system will require some system integration and training of users within the firm, which would take time and could explain these MAX-MOST gaps as temporary. Figure 8 shows the number of years since an advanced technology was adopted in cases where this technology is not the most frequently used. The figure suggest long time lags of under-utilization. The blue vertical line indicates 5 years since adoption and the blue line shows the average. For higher and upper middle income countries the average is around 7 years and for lower middle and low income countries the average is around 11 years. The MAX-MOST gap appears to be persistent, especially in lower income countries, and not a temporary process of learning and integration within the firm.

Figure 8: Years since adoption of advanced technologies



(a) High and Upper-Middle Income (b) Lower-Middle and Low Income

Note: This figure shows the distribution of the number of years since the adoption of advanced digital technologies. The sample is restricted to the firms that have adopted such technologies but do not use them intensively. All estimates are weighted using sampling weights.

The evidence on this large and persistent gap in the use of advanced digital technologies suggests that accelerating the diffusion of AI technologies will require a concerted effort in both adoption and use, and a greater understanding of the bariers to effectively use these technologies once adopted.

3.4 Technology adoption and productivity

There is a strong positive association between technology sophistication and productivity, especially for measures of MOST (use)

There is a strong positive association between technology sophistication and both productivity and profit rates across establishments (See columns 1-4 in Table 1). The association between productivity and technology sophistication is stronger when country fixed effects are excluded, reflecting the strong association between these variables across countries. Decomposing $\overline{S}_j$ into MAX_j and $MOST_j$, we find a much stronger association between the measures of establishment performance –labor productivity, Solow residuals and profit rates– and $MOST_j$ than with MAX_j. This finding suggest that there are two technology upgrading processes, adoption and use, that differ in how they relate to productivity dynamics. Adoption seems to have a weaker impact when it comes to productivity than effective use.

Table 1: Productivity and Sophistication

	ln(Sales per worker)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
K_j	0.22***	0.25***	0.22***	0.25***	0.43***	0.27***	0.23***	0.22***
	(0.02)	(0.03)	(0.02)	(0.03)	(0.04)	(0.06)	(0.03)	(0.02)
H_j	0.25**	0.67***	0.28***	0.71***	1.13***	0.64***	0.68***	0.25**
	(0.11)	(0.12)	(0.11)	(0.12)	(0.43)	(0.20)	(0.13)	(0.11)
$\bar{S}_j$	0.50***	0.63***			1.00***	0.70***	0.59***	0.52***
	(0.04)	(0.05)			(0.13)	(0.06)	(0.06)	(0.05)
$MOST_j$			0.44***	0.73***				
			(0.05)	(0.06)				
MAX_j			0.09*	-0.03				
			(0.05)	(0.06)				
$\bar{S}_j * D(RichCountry)$								-0.08
								(0.10)
N	13128	13128	13128	13128	828	6074	6226	13128
R-squared	0.40	0.23	0.41	0.25	0.57	0.32	0.19	0.40
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	No	Yes	No	No	No	No	No
Data	All	All	All	All	Agri.	Manu.	Serv.	All

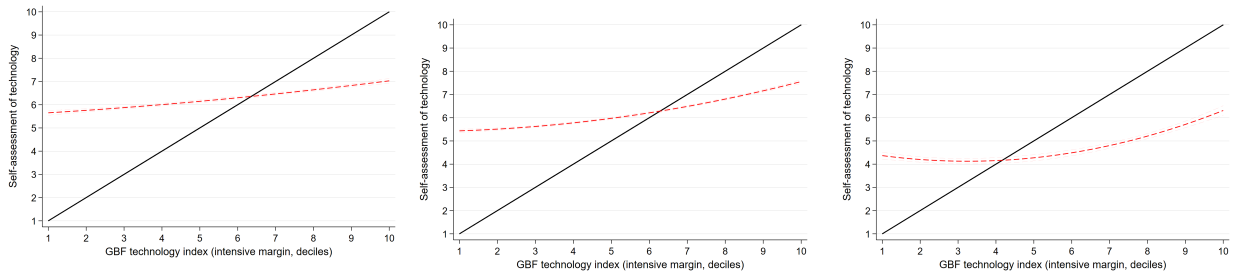
Source: Cirera et al. (2026). Note: $\overline{S}_j$ is the simple average of MAX_j and $MOST_j$. $D(RichCountry)$ is a dummy variable equal to 1 for high-income countries (South Korea, Poland, and Croatia) and 0 otherwise. Agri., Manu., and Serv. denote the agriculture, manufacturing, and services sectors, respectively. *, ** and *** denote 10%, 5% and 1% significance respectively.

3.5 Role of overconfidence in technology adoption and use

A key barrier to both adoption and use is overconfidence

One key factor that slow downs adoption and use of advanced technologies is managerial misperceptions arising from overconfidence. Overconfidence in firms abilities reduces incentives to adopt more advanced technologies. If managers think they have high levels of technology sophistication compared to peers, they are not likely to invest in upgrading their technology. To measure this potential overconfidence bias, the FAT survey asks firms to self-evaluate their level of technology sophistication compared to other firms in the same sector in their own country. Figure 9 shows how firms evaluate their technology sophistication with respect to other firms vis-a-vis their actual sophistication level as measured in the survey. Above the 45-degree line, the perceived level of technology is greater than their actual level, and the opposite below the 45-degree line. The red dotted line draws a quadratic fit across the different points. The line suggests that for most firms, especially the ones with lower sophistication scores, this overconfidence is larger. This bias, which is a mix of reference group neglect (Camerer and Lovallo, 1999), where agents tend to undervalue their competitors or the Dunning-Kruger effect where those less competent think they are more competent, translates into low incentives to upgrade, especially among the firms more distant from the technological frontier.

Figure 9: Overconfidence in general business function technology by income group



(a) High and Upper-Middle Income

(b) Lower Middle Income

(c) Low Income

Note: This figure illustrates the relationship between firms' self-assessed technological level and their actual level of technology adoption, as measured by the GBF intensive margin, across country income groups. In the FAT survey, firms are asked to rate their technological level relative to similar firms in their country on a scale from 1 to 10. The vertical axis reports these self-assessments, while the horizontal axis shows firms' decile rank based on the GBF intensive margin. All estimates are weighted using sampling weights. FAT = Firm Adoption of Technology; GBF = General Business Function.

The evidence from adoption and use patterns of advanced digital technologies over the past two decades points to a slow and unequal diffusion of AI-based technologies in developing countries. Accelerating that diffusion requires closing two distinct gaps. The first is the adoption gap: firms in developing countries need access to AI technologies at interna-

tionally competitive prices, and managers need credible information on adoption benefits to overcome behavioral barriers to uptake. The second is the use gap: firms must deploy these technologies intensively, which requires restructuring organizational processes and upgrading management practices. Failure to address both gaps carries a stark cost — given the substantial productivity gains AI technologies promise, inaction risks deepening productivity divergence both within and across countries.

4 The Adoption of AI technologies. Lessons from Romania.

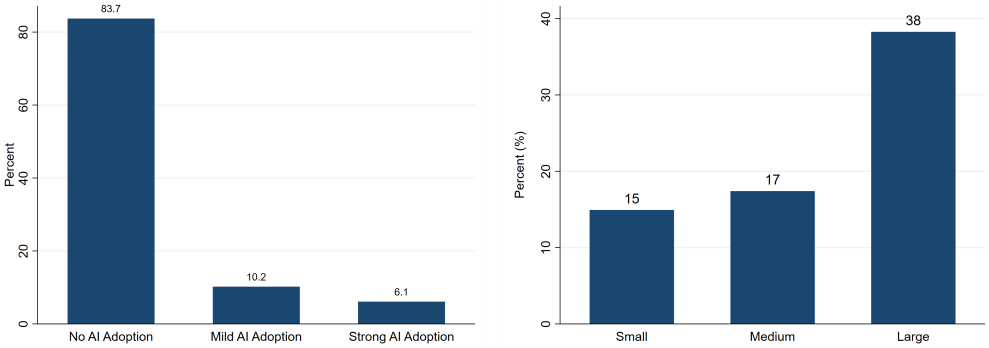
While the previous section summarizes what we have learned from previous advanced digital technologies, in this section we describe the results from a sample of 1,516 Romanian firms that were interviewed for the Firm Adoption of Technology (FAT) survey in Romania. The survey, complements the measurement of AI adoption and use embedded in existing technologies as shown in Figure 1 with questions for other more general uses of AI. Given the diversity in potential adoption and use of AI, we define 2 different levels of AI adoption. First, we define mild AI adoption when a firm declares that makes any use of AI. [5] Second, we define strong AI adoption when a firm uses any of the AI augmented technologies in the grid (Figure 1).

4.1 Adoption and use of AI in Romania

AI adoption in Romanian firms is still limited and uneven, with a significant gap between small/medium and large firms. Figure 10 shows the percentage of firms adopting AI in Romania for the two measures of AI - mild (any) and strong (technology in the grid) adoption. About 16% of firms adopted any AI technologies for their business operations and around 10% of firms mildly adopt AI for some type task, while 6.1% of firms adopt AI to use in general business functions. Interestingly, 68.3% of firms that use AI in GBFs and 32.6% of all AI adopters are not necessarily aware that they are using AI and they respond "NO" to a generic question on AI use. Figure 10 panel (b) shows that large firms are approximately more than two times more likely to adopt AI than SMEs, which is consistent with the patterns in the adoption of other technologies.

[5] The survey asks several questions related to the use of AI directly. This variable is one when the manager responds yes to any type of use.

Figure 10: AI Adoption by Intensity and Firm Size

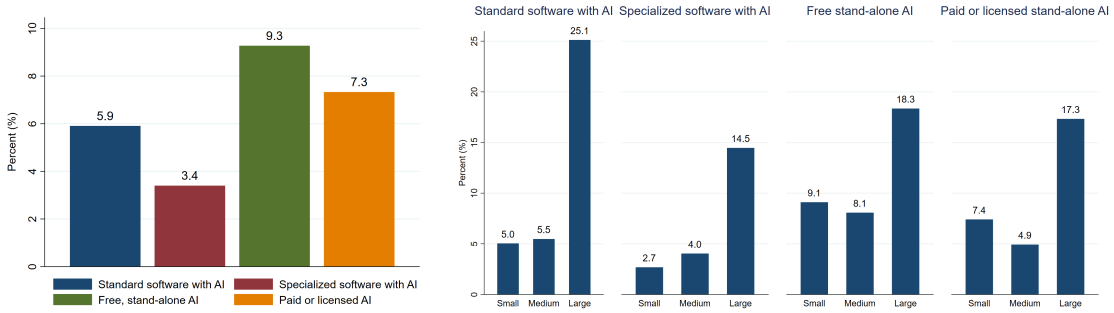


(a) Intensity of AI adoption (b) AI adoption by firm size

Note: This figure show the share of firms using AI and share by firm size. Panel (a) shows the shares of firms adopting AI in Romania under two definitions of AI adoption: mild and strong AI adoption. Mild AI adoption refers to firms that use AI but not in core general business functions, while strong AI refers to firms that use AI in one or more core general business functions. Panel (b) reports AI adoption rates by firm size. Sample is restricted to firms in Romania. All estimates are weighted using sampling weights.

Another proxy to understand the intensity in the use of AI for those that answer generically that they adopted and use AI, is by the understanding the type of software they use. Figure 11 shows that most firms use low cost versions of AI, either free versions 9.3% of firms or standard software like excel or word with AI, 5.9% of firms. Only 7.3% used paid versions of AI, and 3.4% versions in specialized software.

Figure 11: Types of AI Technology Adoption by Firm Size

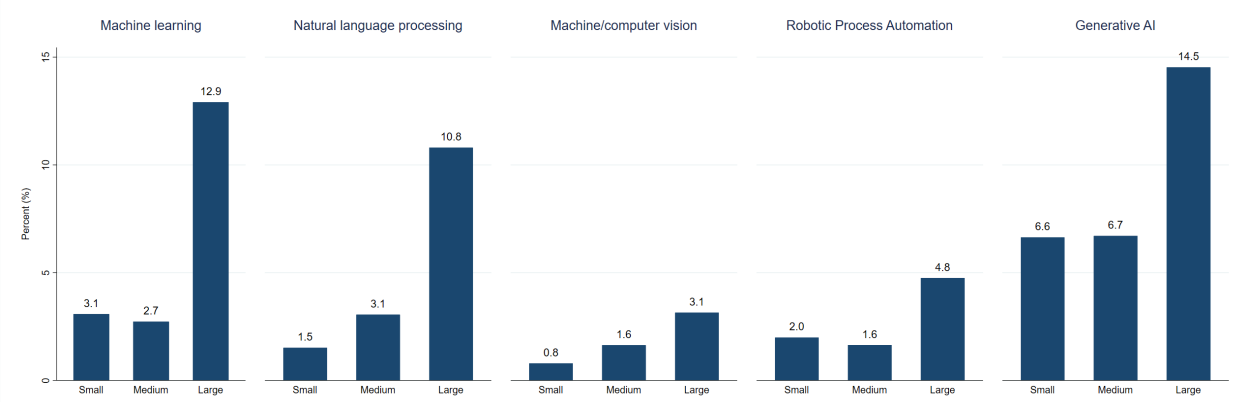


(a) AI type (b) AI type by size

Note: This figure shows the share of firms using different types of AI and by firm size. Panel (a) presents the share of firms using four types of AI including standard software with AI, specialized software with AI, free and stand-alone AI, and paid or licensed AI. Panel (b) reports the corresponding shares by firms size. The sample is restricted to firms in Romania. All estimates are weighted using sampling weights.

When looking at what is type of AI function, excluding augmentation of existing technologies, the main application is generative AI, followed by machine learning and natural language processing (Figure 12). Very few firms use AI for more advanced applications such as computer/machine vision or robotic processes and automation.

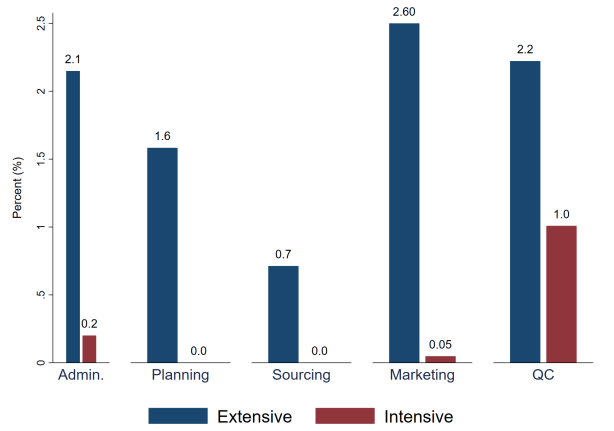
Figure 12: Adoption of AI Applications by Firm Size



Note: This figure show the share of firms using different AI applications by firm size. The sample is restricted to firms in Romania. All estimates are weighted using sampling weights.

A stronger measure of the adoption and use of AI technologies is related to their use in general business functions. Figure 13 show the frequencies of adoption and intensive use of AI augmented technologies. Adoption remains very low and intensive use of these AI applications, minimal. Adoption is below 3% for all business functions, and higher share in marketing and client relationship with a mere 2.6% using CRM. Regarding, intensive use, this is minimal. Only 0.2% of firms use ERP augmented with AI in business administration, and 1% AI augmented quality control.

Figure 13: AI Adoption for General Business Functions: Extensive and Intensive Margins

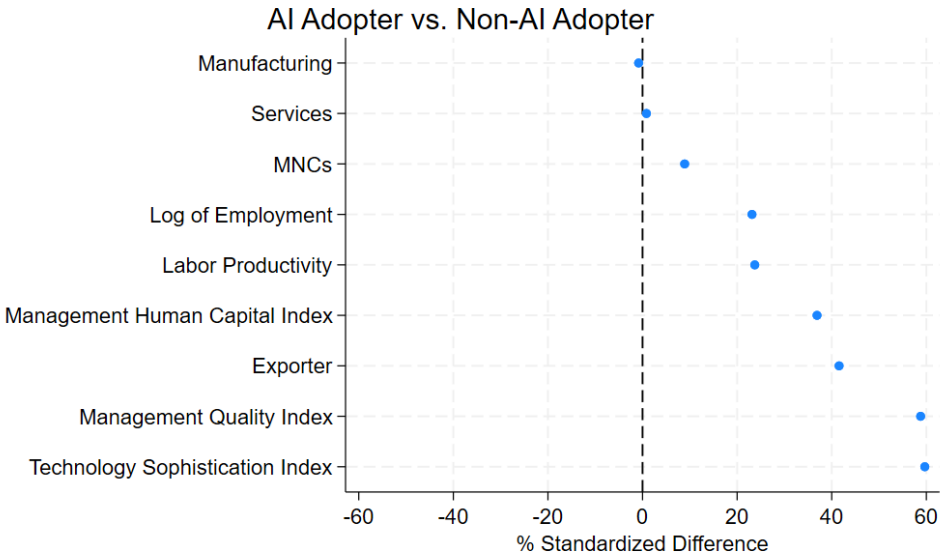


Note: This figure shows the extensive and intensive margin of AI technology adoption across selected general business functions. Sample is restricted to firms in Romania. All testimates are weighted using sampling weights.

4.2 What type of firms are more likely to adopt AI?

What type of firms are more likely to adopt AI technologies? Figure 14 shows a balance plot with the standardized differences between the two groups - adopters vs non-adopters - to better understand what firm characteristics are more correlated with AI adoption. While the sector of activity does not appear to be correlated with AI adoption, adopters have 20% larger standardized differences in firm size and labor productivity, and for exporters 40% higher standardized differences. The differences are even larger for adopters in terms of the level of management quality and technology sophistication. Overall, these are all correlates with good performance, and emphasize the role of managerial and technological capabilities in adoption.

Figure 14: Balance of Firm Characteristics by AI Adoption Status



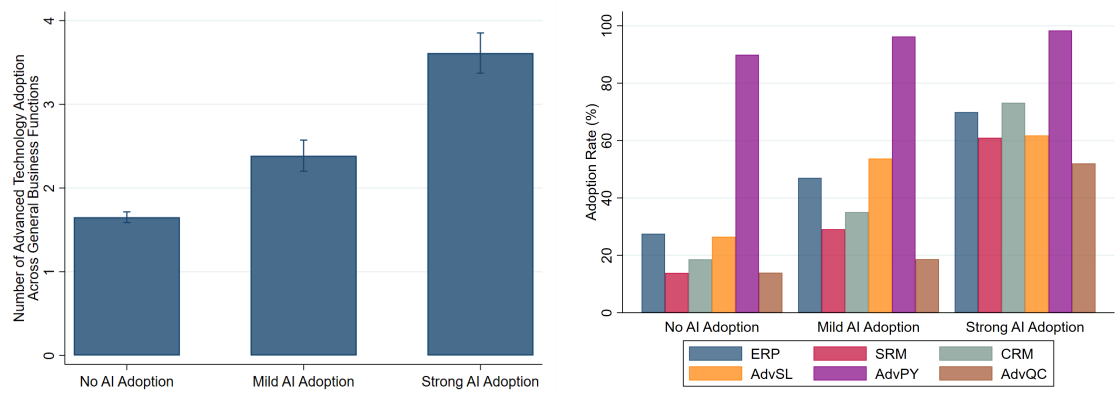
Note: This figure presents the % of standardized differences in characteristics of AI adopters and Non-AI adopters. Sample is restricted to those adopting AI in Romania. All estimates are weighted by the sampling weight.

4.3 AI and technological capabilities

One important question is to what extend firms can leapfrog with AI technologies and jump from more basic technologies to advanced technologies. The evidence of leapfrogging is very thin and mainly concentrated in a handful of technologies: mobile phones vs landlines, or some ICT technologies such as mobile money. Rather than leapfrogging, there is heterogeneity in the speed of diffusion of technologies across firms and countries, and as the previous section suggests, firms that have larger technological capabilities are more likely to adopt AI technologies.

To illustrate this point, Figure 15 shows the average number of advanced technologies in GBFs for each AI adoption group: non-adopters, mild adopters (any use) and strong adopters (use in GBFs). On average, strong adopters have adopted more than 3 other advanced technologies and mild adopters more than two advanced technologies. Panel (b) shows the shares of firms for each group an advanced technology. While advanced digital payment methods is high for all groups, given that adoption and use of these technologies are very much conditional to existing financial infrastructure, other advance technologies such as ERP, SRM, CRM and advanced quality control inspection are much more likely to be adopted by AI strong adopters. In some cases, AI technologies are just extensions of existing technologies, and, therefore, this result should not be surprising - for instance a firm using ERP for a few years will find it easier to upgrade the software and use AI capabilities. But also shows the importance of accumulating technological capabilities for upgrading.

Figure 15: AI Adoption and Adoption of Advanced Digital Technologies



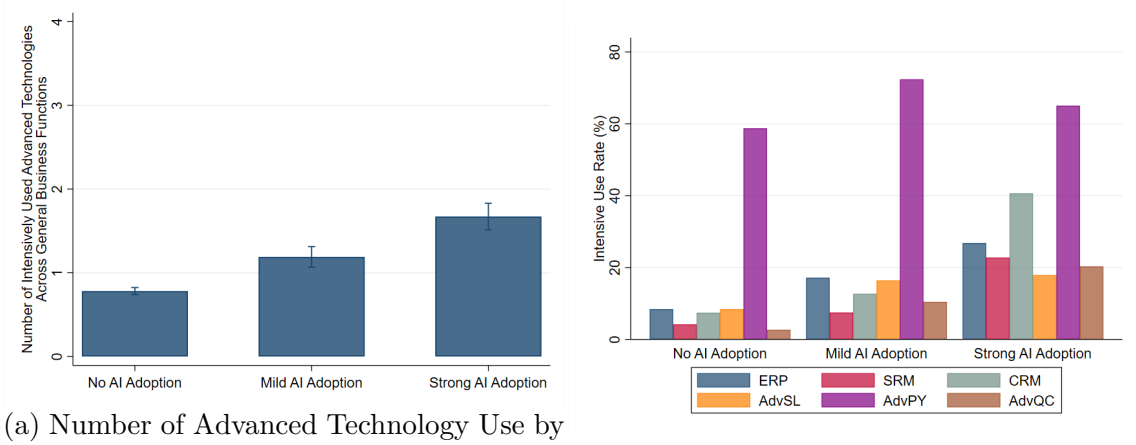
(a) Number of Advanced Technology Adoption by AI Levels

(b) Advanced Technology Adoption by AI Levels

Note: This figure shows the adoption of advanced digital technologies by AI adoption level such as no AI adoption, mild AI adoption, and strong AI adoption. Panel (a) shows the predicted number of advanced technologies adopted by AI adoption. Panel (b) shows the share of firms adopting advanced digital technologies—ERP, SRM, CRM, Advanced Sales, Advanced Payment, and Advanced Quality Control—by AI adoption. All estimates are weighted using sampling weights.

A similar picture emerges when using intensive use rather than adoption. Figure 16 shows the average number of advanced technologies in GBFs intensively used for each AI adoption group. The numbers of technologies decrease given the existing MAX-MOST gap described in the previous section, but AI strong adopters use intensively more advanced technologies, with the exception of advanced digital payments.

Figure 16: AI Adoption and Intensive Use of Advanced Digital Technologies



(a) Number of Advanced Technology Use by AI Levels

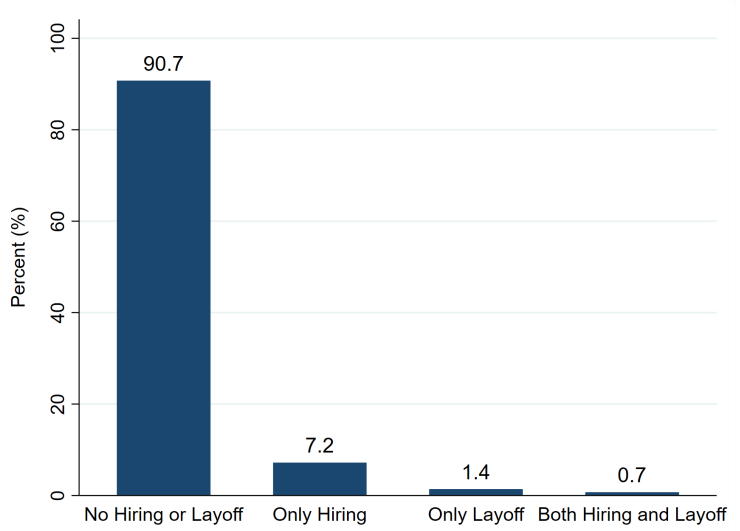
(b) Advanced Technology Use by AI Levels

Note: This figure shows the intensive use of advanced digital technologies by AI adoption level such as no AI adoption, mild AI adoption, and strong AI adoption. Panel (a) presents the predicted number of advanced digital technologies used intensively by firms across AI adoption levels. Panel (b) shows the share of firms intensively using advanced digital technologies—ERP, SRM, CRM, advanced sales, advanced payment, and advanced quality control systems—by AI adoption level. All estimates are weighted using sampling weights.

4.4 Expected employment impact

One concern of these technologies is whether the adoption of AI technologies displaces workers. The survey asks directly the managers that adopt some type of AI technologies what changes they have implemented when it comes to the labor force, both in terms of hiring and training. As mentioned above, there is hardly any application of AI directed to automate tasks, so most of the adoption applications are for tasks where AI technologies are worker/skill augmented. Also, most firms adopt AI mildly and, therefore, we expect very small impacts on jobs via the automation channel. This is partially confirmed by the data (Figure 17), which suggests that most AI adopters do not hire or layoff workers after adoption - 90.7% neither hire nor layoff any workers. In the case of 0.7% of firms, they both hire and layoff workers, and 1.4% lays off workers. The second most frequent category is to hire workers with 7.2% firms. This suggests minimal effects in the demand for labor, consistent with the low adoption and intensive use of AI technologies, and lack of automation.

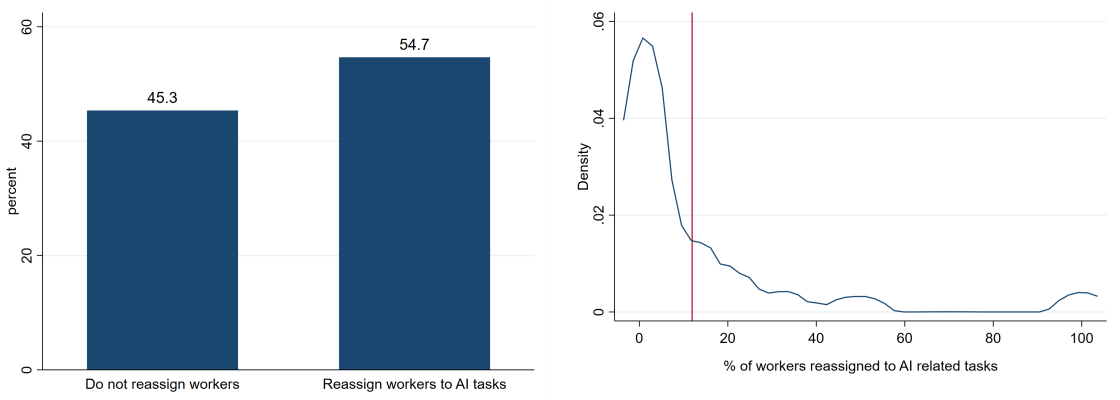
Figure 17: Hiring and Layoff Responses among AI-Adopting Firms



Note: This figure shows the share of AI-adopting firms by hiring and layoff status over the reference period. Firms are classified into four mutually exclusive categories: no hiring or layoff, hiring only, layoff only, and both hiring and layoff. The sample is restricted to firms that adopted AI in Romania. All estimates are weighted using sampling weights.

One potential explanation for the very small changes at the extensive margin of employment is that most of the action occurs at the intensive margin, with within firm reassignments of tasks and responsibilities. Indeed, Figure 18 shows that this is the case. Around 55% of firms that adopted AI reassign workers across tasks. Panel (b) shows the extend of this reassignment for AI adoption firms. While there is a large variance, these reassignments usually involve a significant amount of workers, around 12% is the average. This suggests that while employment effects are small, they mostly occur within firms and by resigning workers to AI related tasks.

Figure 18: Reassignment of Workers among AI-Adopting Firms

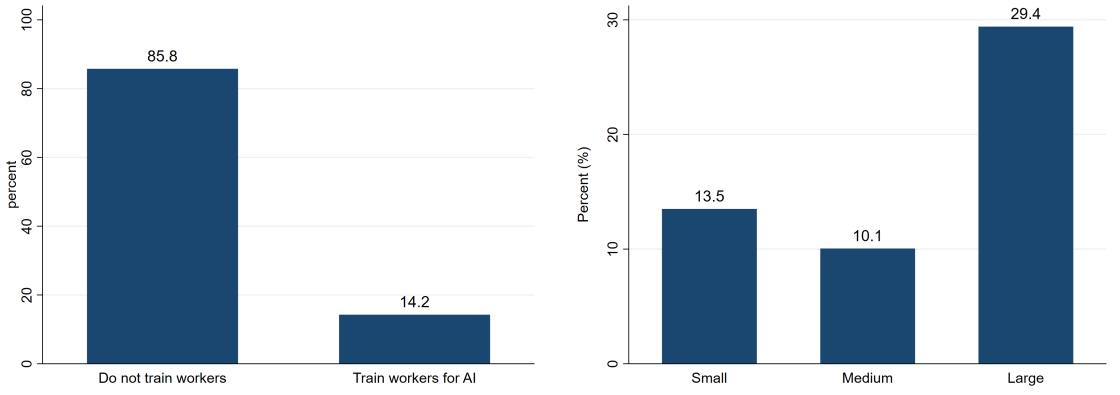


(a) Reassignment (b) % of reassigned workers

Note: This figure shows the share of AI adopting firms reassigning workers after the adoption of AI in Panel (a) and the distribution of the share of assigned workers in Panel (b). The sample is restricted to AI adopting firms in Romania. All estimates are weighted using sampling weights.

Another dimension of AI employment adjustment is training. Firms can keep the same workforce allocation by training workers to conduct AI related tasks. Figure 19 shows that in most cases, however, there is no formal specific training. Only 14% of firms that adopt AI offer some formal training, and the probability of doing training is much larger in large firms, 29.4%, which is consistent with the well known fact that larger firms are more likely to offer training to workers.

Figure 19: Training Workers among AI-Adopting Firms



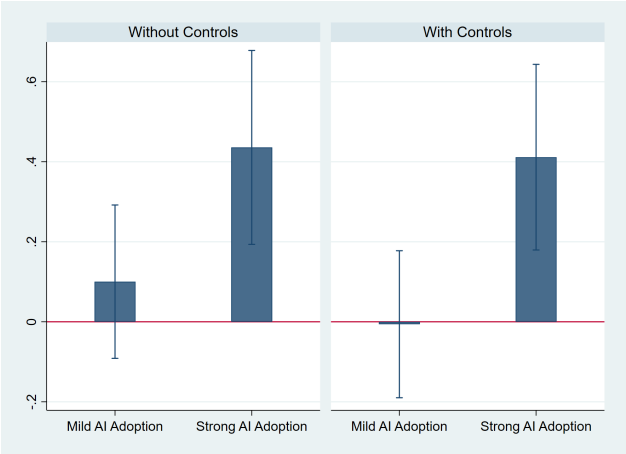
(a) Training of workers (b) Training of workers by size

Note: This figure shows the share of AI-adopting firms that provide AI-related training to workers in Panel (a) and the corresponding shares by firm size in Panel (b). The sample is restricted to AI-adopting firms in Romania. All estimates are weighted using sampling weights.

4.5 The productivity effect of AI-augmented technologies

In section 2, the framework suggests three channels through which AI is likely to affect productivity. The first channel is the direct effect on productivity via improving the functionalities and capabilities of existing technologies. Although we cannot identify causality given the cross-section nature of our data, Figure 20 shows the unconditional (left) and conditional (right) correlation of labor productivity and the type of AI adoption vis-a-vis non-adopters. Both figures show that only strong AI adoption is correlated with higher productivity.

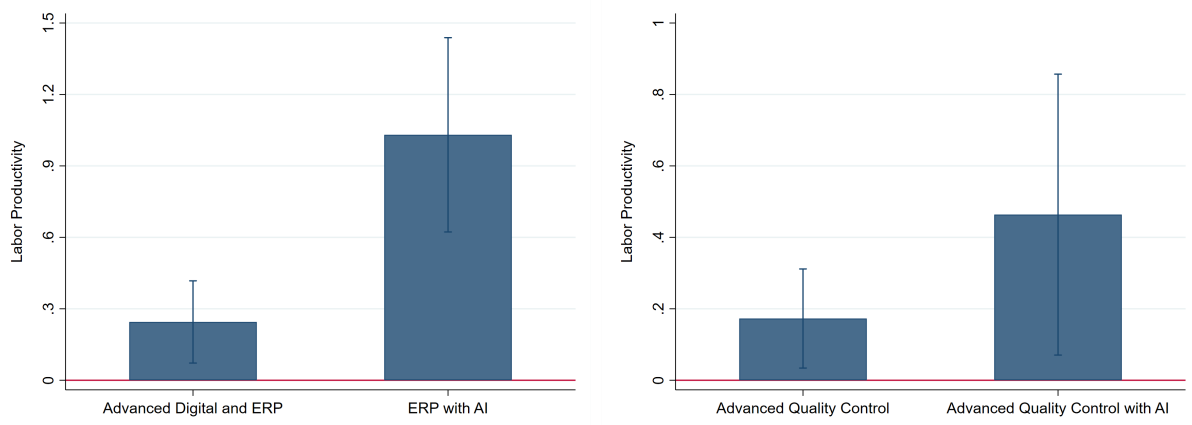
Figure 20: Relationship with Productivity: Mild vs. Strong AI Adoption



Note: This figure presents the estimated association between AI adoption and log labor productivity. Panel (a) reports the estimated coefficients from regressions without control variables, while Panel (b) reports the estimates after controlling for firm characteristics. AI adoption is measured using two indicators: mild AI adoption and strong AI adoption, with firms that do not adopt AI serving as the reference group. Vertical bars denote 95 percent confidence intervals. All estimates are weighted using sampling weights.

Furthermore, Figure 21 shows the correlation with labor productivity at the business function level between adopters of ERP and advanced quality inspection with and without AI augmentation. The figure shows a positive productivity premium vis-a-vis other technologies in the business function, but significantly larger for those using AI augmented ERP and quality control. Given the low incidence of AI adoption in the business functions, the standard errors are large, but for business administration the AI augmented ERP correlation is significantly larger than non-AI ERP.

Figure 21: AI Premium in Business Administration and Quality Control



(a) Business Administration (b) Quality Control

Note: The figure shows the estimated coefficients and 95 percent confidence intervals for advanced digital technology and advanced digital technology with AI controlling for sector, size, and region. Firms using manual and basic digital technologies serve as the reference group. Panel (a) reports the estimates for business administration, while Panel (b) reports the estimates for quality control. The sample is restricted to firms in Romania. All estimates are weighted using sampling weights.

4.6 Technology complementarities

Does using several advanced technologies have an additional productivity premium? The second channel outlined in the framework is related to the potential positive complementarities of adopting and using several advanced technologies at the same time, which can even increase with AI. In practical terms this would translate into a larger effect on productivity or performance from having several technologies than the sum of the individual effects. This view is consistent with the literature on innovation and organizational complementarities, which argues that the returns to innovation depend on implementing different types of innovation and on the existence of complementary technologies or organizational practices (Athey and Stern, 1998; Ballot et al., 2015; Cassiman and Veugelers, 2006; Milgrom and Roberts, 1995).

Testing for these complementarities is difficult in the context of many potential technologies. We follow the supermodularity approach used in Ballot et al. (2015) and Cassiman and Veugelers (2006), both estimating separate performance effects for all combinations of two dummy variables and test whether the coefficient of the interaction of two variables (union) is significantly larger than the sum of coefficients for individual variables. Table 2 attempts to measure this potential complementarities in the case of two advanced technologies - ERP and advanced quality control inspection. Firms are classified into four mutually exclusive groups: neither ERP or advanced quality control, only ERP, only advanced quality control, and both ERP and advanced quality control. We assess the complementarity between these

Table 2: Complementarities between ERP and Quality Control

Dep. Var: ln(Sales/Worker)	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	All	Manufacturing	Services	High and Upper-Middle Income	Lower-Middle Income	Lower Income
Only ERP	0.641***	0.643***	0.644***	0.604***	0.660***	0.609***
	(0.024)	(0.029)	(0.037)	(0.043)	(0.030)	(0.133)
Only Adv. QC	0.245***	-0.076	0.374***	-0.143	0.340***	1.753***
	(0.048)	(0.065)	(0.069)	(0.090)	(0.057)	(0.273)
Both ERP and Adv. QC	0.659***	0.756***	0.629***	0.592***	0.681***	-0.221
	(0.033)	(0.043)	(0.049)	(0.065)	(0.038)	(0.446)
Test: Both ERP and Adv. QC - Only ERP - Only Adv. QC	-0.227***	0.188**	-0.389***	0.130	-0.319***	-2.583***
	(0.057)	(0.077)	(0.085)	(0.109)	(0.069)	(0.518)
Sector FE	YES	YES	YES	YES	YES	YES
Size Group FE	YES	YES	YES	YES	YES	YES
Region FE	YES	YES	YES	YES	YES	YES
Observations	22,790	10,365	11,157	5,952	15,217	1,621
R-squared	0.414	0.493	0.397	0.268	0.353	0.281

Note: The table presents the regressions of labor productivity on indicators for only ERP, only Advanced Quality Control, and both of these technologies, controlling for sector, size, and region fixed effects. The results are weighted using sampling weights.

two technologies by examining whether the coefficient of both ERP and advanced quality control is larger than the sum of the coefficients of only ERP and only advanced quality control.

The results indicate complementarities among advanced technologies may not be universal. In manufacturing, the estimated joint productivity premium is significantly larger than the sum of the individual premiums, which is consistent with complementarity between production planning and quality control. A positive relationship also appears among firms in high- and upper-middle-income countries, although the estimated difference is not statistically significant. By contrast, the test is negative for the full sample, services, lower-middle-income countries, and low-income countries. These heterogeneous patterns suggest that adopting multiple technologies does not automatically generate additional productivity gains. Complementarities may depend on whether the technologies are relevant to interconnected production processes and whether firms possess the managerial, technical, and organizational capabilities needed to integrate them effectively.

5 Conclusions and policy implications

The diffusion of AI technologies can generate significant opportunities to raise firm productivity in developing countries. AI can improve the capabilities of existing technologies within business functions, facilitate coordination across functions, and alter how firms allocate tasks

and organize production. However, the realization of these gains depends not only on access to AI technologies, but also on firms' ability to integrate them into their operations and use them intensively. The evidence presented in this paper suggests that this transition is unlikely to occur automatically or uniformly across firms and countries.

The evidence from the FAT survey regarding other advanced digital technologies offers several important lessons. First, technologies such as ERP, SRM, CRM, and advanced quality control have diffused more slowly in lower-income countries. Second, adoption does not necessarily translate into productive use. Many firms that have acquired advanced technologies continue to rely primarily on less sophisticated alternatives, and this gap between adoption and intensive use can persist for many years. Third, the intensive use of advanced technologies is more strongly associated with productivity than their mere adoption. These findings suggest that conventional measures of technology adoption may overstate the extent of meaningful digital transformation.

The evidence also points to the importance of firm capabilities. Technology upgrading is more common among firms with stronger management practices, greater technological sophistication, higher productivity, and better access to skilled workers. Managerial misperceptions and overconfidence can present an additional obstacle: firms that overestimate their technological capabilities may have little incentive to upgrade. Taken together, these results suggest that the key constraint is often not simply access to technology, but the capacity to identify an appropriate technology, reorganize production around it, train workers, and use it effectively.

The results from Romania provide an early illustration of how these patterns may carry over to AI. AI adoption remains limited, particularly when adoption is defined as the intensive use of AI-augmented technologies in core business functions. Many firms use free and standard AI-enabled software, while relatively few integrate specialized AI applications into production, administration, supply-chain management, marketing, or quality control. AI adopters also tend to be larger, more productive, better managed, and more technologically advanced than non-adopters. This provides little support for the proposition that AI will automatically allow less capable firms to leapfrog earlier stages of digital transformation. Instead, AI adoption appears to build on capabilities accumulated through the adoption and use of previous digital technologies.

The Romanian evidence further suggests that the initial labor-adjustments associated with AI occur primarily within firms rather than through large changes in total employment. Most AI-adopting firms report neither hiring nor laying off workers because of AI. Worker reassignment is considerably more common, however, indicating that AI may initially change the allocation of tasks and responsibilities rather than the number of jobs. At the same time,

relatively few adopters provide formal AI-related training, especially among smaller firms. This combination of task reallocation and limited training raises concerns that firms may not yet be making the complementary workforce investments required to realize the full productivity benefits of AI.

The productivity results should be interpreted cautiously because the data are cross-sectional and more capable firms select into AI adoption. Nevertheless, the patterns are consistent with the conceptual framework developed in this report. Mere experimentation with AI is not systematically associated with higher productivity, whereas the use of AI within core business functions is associated with stronger firm performance. AI-augmented ERP and quality-control technologies also exhibit a larger productivity premium than comparable technologies without AI capabilities. These findings suggest that the returns on AI depend on the extent of its integration into production and management processes, rather than on whether a firm simply adopts the AI.

These results have several implications for policy. First, policy makers should distinguish among access, adoption, and intensive use. Policies that incentivize the acquisition of AI applications - via subsidies or cheap finance - may have limited effects especially if firms lack the managerial, organizational, technological, and workforce capabilities required to use them productively. Support programs should therefore combine access to technology with technical assistance, management upgrading, and worker training.

Second, AI adoption is part of a broader process of digital capability accumulation. For many firms in developing countries, particularly small firms, the immediate priority needs to be to establish foundational digital systems, improve data collection and management, and adopt advanced technologies. These investments can provide the data and organizational foundations needed for subsequent AI integration. AI policies should therefore complement rather than displace broader digital-transformation policies.

Third, information and demonstration programs may help address managerial misperceptions and uncertainty about the benefits of new technologies. Firm's benchmarking, technology-extension services, and carefully designed pilot programs can help managers identify capability gaps and assess relevant AI use cases. Because the benefits and implementation requirements of AI differ across business functions and sectors, such support needs to be based on firm diagnostics rather than on a uniform technology package.

Fourth, policies need to address the different firm capabilities to adopt and use AI. Larger and more capable firms are likely to benefit first. Smaller firms may require access to affordable software and local-language applications, additional technical assistance, and training programs. However, support should be conditional on credible implementation and use plans to avoid subsidizing technologies that remain underutilized.

Finally, workforce policies should focus not only on potential job displacement but also on task transformation. The early evidence suggests that worker reassignment and changes in responsibilities may precede significant changes in employment. Training systems should therefore help workers and managers develop the technical, analytical, and organizational skills needed to work effectively with AI. At the same time, governments should strengthen data governance, cybersecurity, and accountability so that productivity gains do not come at the expense of privacy, security, or job quality.

The findings in this paper are subject to some limitations. The direct evidence on AI comes from a cross-sectional survey of Romanian firms and should not be interpreted as representative of all developing countries or as establishing causal effects. AI technologies are also evolving rapidly, and both their costs and capabilities may change faster than those of earlier digital technologies. Longitudinal data, comparable surveys from countries at different income levels, and experimental evaluations of programs supporting AI adoption will be needed to establish how firms move from experimentation to intensive use and how this transition affects productivity, employment, wages, and firm growth.

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