Adopting Fast and Slow: Cross-Country Evidence on Business Adoption of Artificial Intelligence

Elwyn Davies, David Francis, Filip Jolevski,
Gaurav Nayyar, Katherine Stapleton and Shu Yu
World Bank[1]

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Abstract

This paper presents ten stylized facts on the use of Artificial Intelligence drawn from nationally representative surveys of 4,205 firms in seven economies: India, Jordan, Kenya, Mexico, Nigeria, Thailand, and the United States. The findings indicate a fast trend in the adoption of AI by firms across the world. Evidence suggests that AI is used for a wide range of business tasks and functions, consistent with it being a General-Purpose Technology. While AI adoption rates of firms nearly tripled between 2024 and 2025, suggesting a fast diffusion, the diffusion of sophisticated use cases remains more slowly and highly concentrated. The early evidence shows little impact on labor markets in developing economies, while in contrast layoffs and hiring freezes due to AI are more common in the U.S. Looking forward, firm managers expect AI adoption to positively affect their employment levels and productivity over the next three years.

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1 Introduction

Cross-country adoption data suggests that Generative AI (GenAI) has been diffusing around the world faster than other technologies since the launch of ChatGPT in 2022 (Chatterji et al. 2025; Appel et al. 2025). Nevertheless there remains a significant knowledge gap on the extent of firm-level adoption of AI, how the technology is being used by different types of firms, and its impacts on the firms adopting it. While some studies have directly estimated the share of firms using AI through surveys, efforts so far have focused on the U.S. and a handful of high-income countries (McElheran et al. 2025, Bonney et al. 2026, Yotzov et al. 2026, Eurostat 2026), and results largely depend on the scope of AI under consideration, who the respondents are (e.g., senior executives vs. frontline workers), the sample coverage, and the weighting scheme (Li et al. 2026). This knowledge gap is particularly acute for developing countries, where to date there is very little empirical evidence on how AI is being adopted or its impacts.

This paper aims to address this knowledge gap by shedding new light on how firms around the world are adopting AI. It presents ten findings with new and early evidence on AI adoption from nationally representative surveys of 4205 firms in seven countries: the U.S., Thailand, Mexico, Nigeria, India, Jordan, and Kenya. It shows that the use of AI has grown rapidly in firms around the world, with developing countries seeing nearly the same growth rate in adoption as in the U.S. In the six developing economies surveyed, usage of AI has increased from 1 percent in 2020 to 27 percent by 2025, just behind the U.S.'s level of 40 percent in 2025. The diffusion of AI among firms has been faster than seen for other key technologies, with the adoption curve far steeper for AI than was seen previously for email or websites. The most common technologies used are AI chatbots and other generative forms of AI (AI used to generate images, sounds, video, or larger pieces of text). Other forms of AI technologies, such as AI agents, AI for workflow automation or decision support, and AI for autonomous physical machine movement, remain less used. The rapid pace of diffusion could reflect the already high adoption rates of the internet and other enabling digital technologies, as firms with higher adoption of other digital technologies are more likely to adopt AI.

AI is used for a wide range of such business tasks, ranging from finding information to controlling business or production processes. Among those firms that do use AI, the task with the highest share of firms using AI is finding information. By contrast, the task with the lowest share of firms using AI is coding or software. The propensity to use AI is notably higher in the surveyed developing countries than in the U.S. when it comes to using AI for finding information, translation, and customer or external interactions. The difference suggests that AI plays an important role in further closing language, information, or communication barriers facing firms in developing countries. In terms of business functions, the the highest proportion of AI-using firms use the technology for marketing, sales, and product development (64 percent of AI-using firms in the U.S. and just under 60 percent of AI-using firms in surveyed developing countries), followed by research and development. The second-most frequently cited business function among AI users is research and development. The results are also consistent with AI being a general-purpose technology (GPT): in both the U.S. and surveyed developing countries, there are sizeable and nearly equivalent proportions of firms using AI for several (four or more) business functions.

Although AI has diffused fast, more sophisticated use cases of AI have spread more slowly, and remain limited and highly concentrated. This study constructs an index of AI sophistication, consisting of the following components: (1) whether a firm adopts any AI technology; (2) whether a firm adopts AI agents, AI process automation, or AI-driven robotics; (3) whether a firm uses them for more advanced tasks (such

as coding); (4) the number of business functions AI is used for; and (5) whether a solution is customized (either internally or externally). The results show that firms in the surveyed developing countries deploy AI technology in a less sophisticated way than firms in the U.S. The composite AI sophistication index in the U.S. is about 70 percent higher than in the surveyed developing countries, with a similar gap found across all components of the index. Sophisticated AI adoption is also highly concentrated in large firms.

In terms of the characteristics of firms adopting AI, AI adoption and AI sophistication are higher for firms with higher innovation activity and higher prior digital use. For example, firms with a history of innovation through the introduction of new products or services are 17 percentage points more likely to use AI, while those investing in R&D are 13 percentage points more likely to do the same. Firms where more than half of workers use computers are 35 percentage points more likely to have adopted AI. These findings reinforce earlier evidence that firms that were more technologically sophisticated before AI use took off have adopted GenAI at much higher rates than less technologically sophisticated firms. The surveys also ask which reason, among seven, is their main constraint for not using AI or not increasing use. Across both groups—AI adopters and AI non-adopters—a lack of knowledge is the most highly cited constraint.

The surveys also provide early evidence on the labor market implications of AI by asking firms if they have laid off workers due to AI, frozen hiring, reassigned workers or started hiring new workers. In the U.S., 16 percent of firms report layoffs due to AI adoption, and in the surveyed developing countries, this is lower at 7 percent. Nevertheless, roughly a quarter of US firms and 13 percent of firms in the surveyed developing countries report slowing or freezing hiring due to AI adoption. Conversely, firms that have adopted AI are also more likely to hire and reassign their workers. The share of firms hiring new workers due to AI is higher in developing countries than in the US, with 21 percent of firms in the surveyed developing countries hiring workers due to AI adoption, which is four times the level observed in the U.S. Despite uncertainty about the future, firms generally expect AI adoption to positively affect their employment levels and productivity over the next three years.

This paper contributes to the existing literature on firm-level AI adoption in several ways. First, it adds new evidence to the literature measuring the extent and types of firm-level AI adoption in the US or advanced economies. For instance, in the U.S., McElheran et al. (2025) show that adoption among U.S. manufacturing firms ranged from 13 to 23 percent in 2021, depending on the definition of AI used. More recently, the Census Bureau's Business Trends and Outlook Survey reports that 18 percent of U.S. firms used AI during November 2025–January 2026 (Bonney et al. 2026. A survey of senior executives using a broad definition of AI reports a U.S. firm adoption rate of 78 percent (Yotzov et al. 2026), while Hartley et al. (2026) found that 38 percent of U.S. workers reported having adopted an LLM as of December 2025. This paper's finding that 40 percent of U.S. firms (with five or more employees) had adopted AI falls somewhere in the middle of these other estimates.

This paper also contributes to the literature on cross-country AI diffusion. Some international surveys have been conducted to enable cross-country comparisons of firm-level AI adoption. For instance, OECD (2025) found that between 2020 and 2024, the share of businesses with 10 or more employees using AI increased from 6 percent to 14 percent across member countries. Eurostat (2026) carried out harmonized enterprise surveys and showed that 20 percent of EU enterprises used at least one AI technology in 2025, with adoption rates ranging from 5 percent to 42 percent across member states. Yotzov et al. (2026) conducted executive surveys with comparable questions across four countries and reported much higher adoption rates than Eurostat (2026), with the highest at 78 percent in the U.S. and the lowest at 59 percent in Australia.

Our study contributes to this line of research by broadening the cross-country comparison beyond high-income countries to include developing economies as well.

Finally, this paper contributes to the literature on the labor market effects of AI. Hui, Reshef and Zhou (2024), Teutloff et al. (2025) and Brynjolfsson, Chandar and Chen (2025) all document displacement effects of AI for certain groups of workers. Conversely, Humlum and Vestergaard (2025), using Danish administrative data, find null effects on earnings and hours, while Hartley et al. (2024) find no statistically significant declines in job openings or employment in exposed occupations. Firm-level European evidence also points to productivity gains without short-run labor replacement (Aldasoro et al. 2026), and Hampole et al. (2025) find positive employment effects of firm-wide adoption masking substantial occupational heterogeneity. By directly asking firms whether they have laid off workers due to AI, this paper provides evidence on job impacts without relying on a causal identification strategy. Our finding that a small subset of firms laid off workers or paused hiring due to AI is consistent with displacement effects, while our finding of new hiring among firms that have adopted AI highlights the complex nature of labor market impacts, with both new demand and displacement.

The remainder of the paper is organized as follows. Section 2 describes our survey instrument and sampling strategy, followed by the implementation process and results. The sections after this present ten findings of the AI survey, with Section 3 highlighting the use of AI among businesses, Section 4 discussing the enabling conditions for AI adoption and Section 5 presenting the labor market implications of AI adoption to date as well as firms' expectations for AI's future impact on productivity and employment. Section 6 concludes.

2 Data

The primary data source for this study is new data collected through follow-up modules to the World Bank Enterprise Surveys (WBES). These modules focus on the usage of AI by private sector firms and were administered in 7 countries (see Table 1). The selection of countries was such that at least one country from each lending region of the World Bank was chosen and where a recent WBES survey was completed. In addition to countries with World Bank lending, the United States was included as benchmark country. The survey was conducted in two further countries, Türkiye and Malaysia, but without reaching the survey sample target. These two countries are therefore not included in the analysis in this paper.[2]

The survey instrument was designed to capture the adoption of AI technologies, the tasks and use cases, how the technology was sourced, current labor impacts as well as the expectations of employment and productivity impacts. Questions in the survey are based on those in earlier survey instruments, including the Eurostat survey on ICT usage and e-commerce in enterprises, which has included questions on AI usage since 2021[3] and the United States Census Bureau's Business Trends and Outlook Survey (BTOS). In

[2] The target for each country was set at 360 establishments. In Türkiye, 161 establishments were sampled, and in Malaysia, 180 establishments. Although Jordan missed the target by two firms (358 respondents), the country was still included in the analyzed sample. The collected microdata for both Türkiye and Malaysia are available through the World Bank website.

[3] This survey was conducted in 27 EU member states as well as in several EU candidate countries (e.g. Türkiye, Serbia and Albania).

addition, the survey instrument includes measures of technology use within specific business functions, derived from the Firm-level Adoption of Technology (FAT) survey (Cirera et al. 2020, 2026). The questions on expectations have been based on the methodology developed by the Atlanta Fed to measure business uncertainty (Altig et al. 2022) and used by the World Bank during COVID-19 to measure uncertainty around the world (Avalos, Barrero et al. 2025), with language on the AI adoption scenarios of more and less rapid adoption adapted from Karger et al. (2026).

The adoption of AI is determined by a set of questions asking about the use of specific AI technologies. Respondents are asked whether they use any of the following AI technologies: machine learning (e.g., deep learning), AI chatbot, AI agents performing tasks directly, AI technologies generating pictures, videos, speech or audio, or larger pieces of text, AI technologies automating different workflows or assisting in decision making, and AI technologies enabling the physical movement of machines via autonomous decisions based on surroundings. The questions were accompanied by examples of each technology. A firm that responds yes to any of these uses is considered an AI adopter and is asked a more extensive set of questions. This approach was chosen (rather than a single yes or no question about the use of AI technologies) to avoid biases in understanding what technologies qualify as AI or not. The entirety of the survey instrument is available online and was translated into all the official languages of the surveyed countries.[4]

The survey was conducted as a follow-up to the World Bank Enterprise Surveys (WBES). The WBES are nationally representative surveys administered to top managers or business owners of establishments eliciting information about the business. The standardized methodological approach [5] and consistent survey instrument allows for comparability across economies. The universe of inference for the WBES includes establishments that are formally registered with the relevant authority and that have five or more workers. The WBES includes all manufacturing sectors and a majority of services sectors.[6] To be eligible for the WBES, establishments must also have been in operation for at least one fiscal year and cannot be fully government owned. The WBES survey is administered primarily face-to-face in the local language. In each country, the survey target was at least 360 firms. In three countries, India, Mexico and Nigeria, a higher target was set (see Table 1).[7]

Since the follow-up survey was administered to a subset of establishments, a second degree of sampling using sectoral stratification was implemented in order to oversample establishments deemed to be in likely AI intensive sectors. The grouping of AI intensive sectors was based on sectors with high degrees of exposure in the task-based measures of Gmyrek et al. (2025) or with the highest AI adoption rates in the Eurostat ICT survey. AI intensive sectors are defined as pharmaceutical manufacturing, computer, electronics, and electrical equipment manufacturing, the manufacturing of motor vehicles and other transport equipment, water and air transport, publishing, telecommunications, and professional activities.

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[4] See https://www.enterprisesurveys.org/en/enterprisesurveys for more details.

[5] Details on the methodology are available here: https://www.enterprisesurveys.org/content/dam/enterprisesurveys/documents/methodology/Sampling_Note-Consolidated-2-16-22.pdf

[6] The two digit ISIC Rev. 4 codes include 10-33, 41-43, 45-47, 49-53, 55-56, 58, 61-62, 69-75, 79, and 95.

[7] Higher sample sizes were chosen in these countries due to a relatively lower cost of surveying relative to the other surveyed countries. In Nigeria, all firms interviewed as part of the original WBES (1,043 firms) were targeted, while India and Mexico had increased targets falling short of the original WBES sample size (respectively 10,479 and 1,322 firms).

To account for this additional level of stratification, the sampling weights are adjusted so as to preserve the representativeness of the original survey universe. This adjustment is constructed by chaining the baseline sampling weights with a second-stage adjustment factor. Consequently, the weights can be represented by the following:

$$wt = wt_ES \times \frac{N_h}{n_h} \quad (1)$$

where N_h is the total number of completed interviews in stratum h in the baseline World Bank Enterprise Survey, while n_h is the number of completed interviews in the follow-up survey, and wt_ES is the sampling weights in the baseline survey which is the inverse of the probability of selection.

The surveys were administered between January and May, 2026. The follow-up survey was administered to the same respondent of the baseline survey (i.e. the top manager or business owner) over the phone with a duration of about 20 minutes. In the end, 4,205 establishments across 7 countries were sampled. An overview of the sample is presented in Table 1, alongside with the World Bank income classifications.

Table 1. The list of surveyed countries

Economy	Region	Income Group	Sample Size	Survey Dates
India	South Asia	Lower Middle	1,355	March – April 2026
Jordan	Middle East and North Africa	Lower Middle	358	April – May 2026
Kenya	Sub-Saharan Africa	Lower Middle	360	March – April 2026
Mexico	Latin America and Caribbean	Upper Middle	603	January – March 2026
Nigeria	Sub-Saharan Africa	Lower Middle	777	January – March 2026
Thailand	East Asia and Pacific	Upper Middle	360	March – April 2026
United States	North America	High	392	January – February 2026
		TOTAL	**4,205**	

Notes: Income classifications as of FY2026 (calendar year 2024). Additional surveys were conducted in Türkiye (161 firms and Malaysia (180 firms), but not included in this paper due to the low response rate.

The sample contains a heterogeneous distribution of establishments and is representative of the formal private sector in each economy. The average firm employs 71 full-time permanent workers, defined as workers who work a full shift for one year or more at the firm. The average age of the interviewed firms is roughly 23 years old. Use of digital technology is widespread, with 85 percent of firms having a website or social media presence and 89 percent using text messaging applications (see Appendix Table A1).

3 The use of AI among businesses

Finding 1. Adoption of AI technologies increased rapidly over time – but with large differences across countries

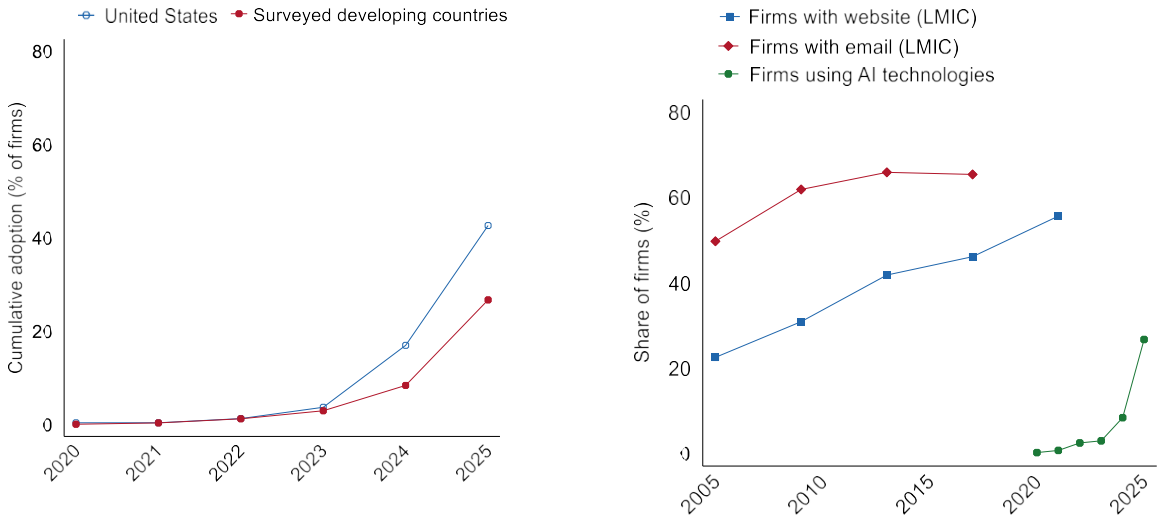
Adoption of generative artificial intelligence among firms has risen sharply as the technology has become more accessible to non-technical users. Figure 1(a) shows that in developing economies, on average share of firm usage of AI has increased from 1 percent in 2020 to 27 percent by 2025. In the U.S., AI adoption has surpassed 40 percent of firms in the same period, showing a divergence between the U.S. and the average developing economies. The pace is notably faster when compared with other technologies of the 21st century, as shown in Figure 1.b, where website and email usage has increased steadily over time. Adoption

of a website or social media took about 15 years to double from 23 to 56 percent. Conditional on the availability of basic digital infrastructure – computers, internet, and electricity – the marginal cost of adopting AI is relatively low, where earlier technologies required investments in physical and human capital.

Figure 1. Adoption of AI technologies over time

(a) Adoption of AI technologies (use of at least AI technology)

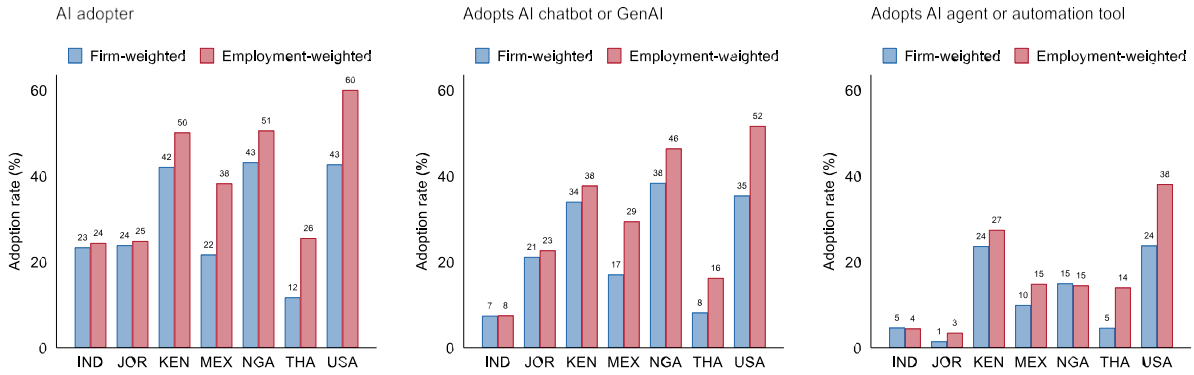
(b) Comparison with earlier technologies



Notes: Based on the question "When did this business first start using any AI technologies? (month and year)" (ai_b5a). The curves for earlier technologies in panel (b) are derived from cross-sectional data from the WBES, averaging across all low- and middle-income countries. The curve for AI adoption in panel (b) is derived based on the surveyed developing countries (excluding the United States; LMIC).

Adoption of AI by firms varies across countries. Figure 2 shows adoption rates by country. Notably, in some countries, such as Nigeria, more than 40 percent of firms (50-60 percent when employment-weighted) use AI, while in others, such as Thailand, only 12 percent do so. In the United States, the birthplace of generative AI, 43 percent of firms use it, comparable to the level seen at the top end of the surveyed developing countries. Differences between the United States and the other surveyed economies are larger when firm-level responses are weighted by business size, measured by the number of employees. The adoption rate in the United States is 60 percent, compared with around 50 percent in Kenya and Nigeria, and a quarter in India, Jordan, and Thailand.

Figure 2. AI adoption by country



Notes: The firm-weighted averages apply the sampling weights from the WBES follow-up survey on AI adoption. The employment-weighted averages multiply the sampling weights by the stated number of employees at the time of the baseline WBES survey.

There are several important caveats to note when comparing these figures across countries. First, the universe of the formal private sector is quite divergent across countries due to the presence of informality. The formal private sector captures a much smaller segment of the economy in developing economies than in advanced economies. For example, informal sector output in the United States amounts to about 8 percent of GDP, while in Nigeria is over half (Elgin et al., 2021).[8] That means that the composition of the sample in developing economies likely contains the more productive part the distribution of firms. Adoption rates among informal firms are likely lower.[9]

Furthermore, various biases can affect responses, including social desirability bias, question wording bias, and uninformed response bias. Social desirability bias stems from the respondent's desire to present themselves as a more advanced or innovative firm. [10] Question wording bias deals with the fact that artificial intelligence is a broad concept that respondents do not always have a common understanding of.[11]

[8] In Nigeria specifically, using the latest census done by the National Bureau of Statistics, which includes both formal and informal businesses, the universe of the World Bank Enterprise Survey comprises only 12 percent of all businesses operating in the country. In other developing countries, such as Mozambique for example, for every formal business, there are 9 informal ones operating (Jolevski and Aga, 2019). Not only do lower income economies have large informal sectors, but the informal sector in general is less productive than the formal counterparts (La Porta and Shleifer, 2014; Aberra et al., 2022).

[9] Informal businesses tend to be less sophisticated in their use of digital products (Islam and Jolevski, 2019). In Zambia in 2019, for example, only 6 percent of informal businesses had a website or social media presence, as opposed to 57 percent of the firms in the World Bank Enterprise Survey (Jolevski et al., 2025). A logical extrapolation of these patterns of the differential adoption of technologies between informal and formal firms would imply that the estimates for the lower- and middle-income economies are overstated given that the universe of inference is comprised of formal firms which are the best performing and the more technological integrated firms, hence more likely to use artificial intelligence.

[10] This pattern is analogous to responses to questions on firm innovation, which are documented to suffer from this bias, with differences seen across countries (Cirera and Muzi, 2020).

[11] In-depth semi-structured interviews reveal that there is no uniform understanding of what artificial intelligence is (Jolevski and Torre, forthcoming).

Given the fast evolution of this technology [12] and the unclear terminology, the bias may go in both directions. Lastly, uninformed response bias refers to respondents – in this case top managers or business owners – not always being aware of how technology is used by their employees in the workplace. It is possible that some workers use artificial intelligence without the managers' knowledge, hence biasing the estimates downwards.[13]

Finding 2. Chatbots and generative forms of AI remain the most used technology

The most common technologies used are AI chatbots and other generative forms of AI (AI used to generate images, sounds, video, or larger pieces of text), which are adopted by 35 percent of firms in the surveyed developing countries and by 21 percent of firms in the United States. Other forms of AI technologies, such as AI agents, AI for workflow automation or decision support, and AI for autonomous physical machine movement, remain less used, by 14 percent of firms in the surveyed developing economies and by 35 percent of firms in the United States.

The use of chatbots and generative forms of AI has been facilitated by their online access. More than four out of five firms in both the surveyed developing economies (83 percent) and in the United States (87 percent) that use of AI depend on online platforms to access AI technologies. Almost nine out of ten (89 percent in both the surveyed developing countries and the United States) firms using AI chatbots are using chatbots that are readily available. Among the surveyed developing countries, 41 percent of firms using chatbots uses the chatbot for a specific business function and 23 percent uses a chatbot that was customized for the establishment.

Finding 3. AI is used for a wide variety of tasks and business functions

AI adoption can be understood in terms of both the tasks AI performs—or augments—and the business functions those tasks serve. Business tasks are specific activities, while business purposes are the broader goals firms seek to achieve, such as communicating with customers, reducing costs, improving quality, or reaching new markets (Agrawal et al., 2022). How a firm organizes tasks can change how firms organize work and shape their workforces (Acemoglu and Restrepo, 2019). How firms use AI also depends on both market needs and their existing capabilities. For example, a firm operating in a multilingual market may use AI for translation depending on customer needs and the language skills of its workers.

AI is used for a wide range of such business tasks, ranging from finding information to controlling business or production processes (Figure 3).[14] Among those firms that do use AI, the task with the highest share of firms using AI is finding information, with 76 percent of firms in the U.S. and 92 percent in the surveyed developing countries. The task with the lowest share is coding or software, which is about 20 percent in

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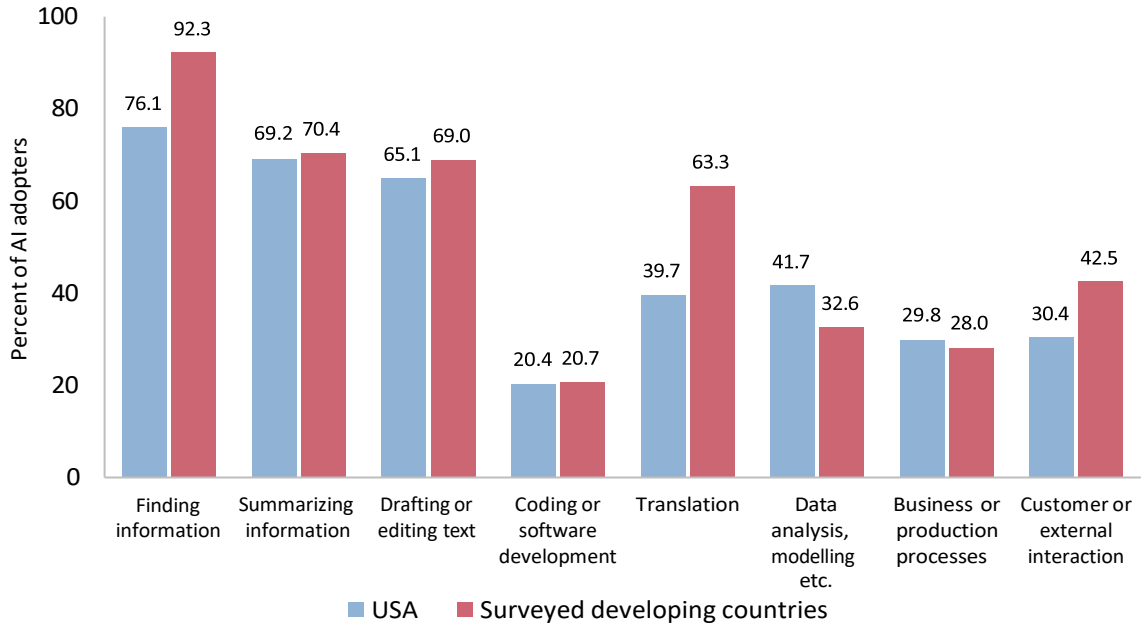
[12] By the time of the composition of this paper in July 2026, a simple google search automatically uses artificial intelligence to summarize the output of the search. It is unclear whether in the eyes of the respondents this would count as usage of artificial intelligence.

[13] Labor force surveys are a more appropriate way to address the issue of uninformed response bias (Bick et al., 2024; Hartley et al., 2024). Recent studies indicate that over a quarter of daily messages sent on ChatGPT from individual accounts are work-related (Chatterji et al., 2025), further pointing out to likely underreporting of use of AI by firms.

[14] Business tasks are oriented toward specific business needs and functions. Tasks, such as using AI to find information, can span across several business functions, including marketing and supply chain management. Certain essential business functions are common across nearly all firms: virtually all firms must manage their inputs and supplies—including purchasing decisions—and therefore the adoption of advanced technologies such as AI in these functions can be a marker of sophistication (Cirera et al. 2026).

both the U.S. and the surveyed developing countries. In most cases, the U.S. and the surveyed developing countries do not differ much in their propensity to use AI for specific tasks, with the rate higher for less technical, less sophisticated, or less autonomous tasks. However, the propensity to use AI is notably higher in the surveyed developing countries than in the U.S. when it comes to using AI for finding information, translation, and customer or external interactions. The difference suggests that AI plays an important role in further closing language, information, or communication barriers facing firms in developing countries.

Figure 3. AI use by tasks



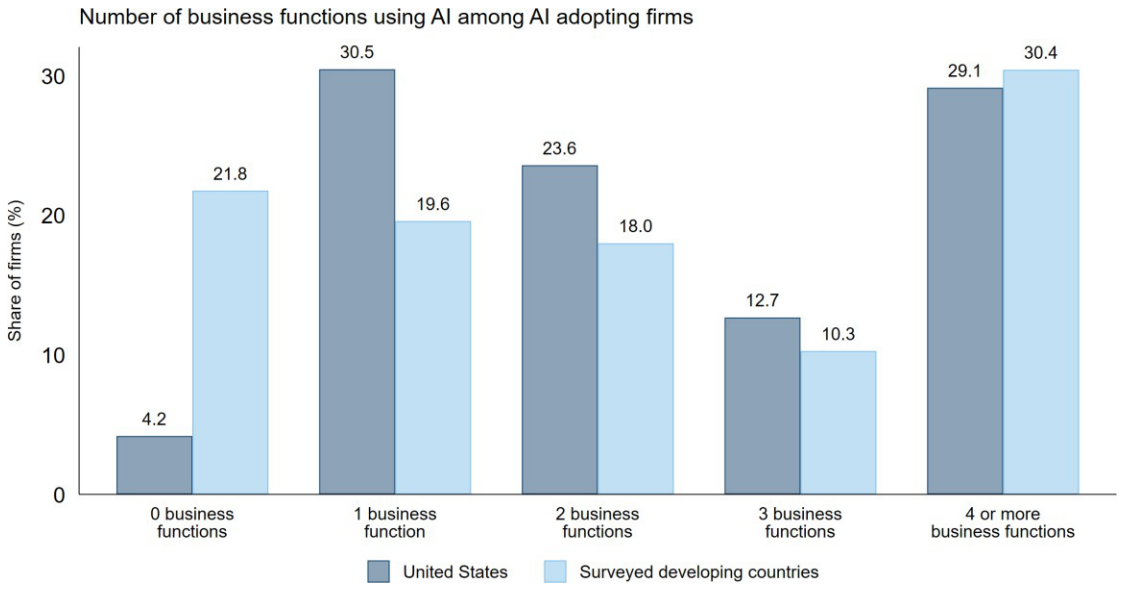
Notes: Bars show the percentage of AI adopting firms that report using AI for each task.

The survey measures AI use across seven distinct business functions. These include research and development; marketing, sales, and product development; sourcing, procurement, and supply chain management; business administration; strategic decision making; compliance; and quality control. Across these business functions, the highest proportion of AI-using firms use the technology for marketing, sales, and product development (64 percent of AI-using firms in the U.S. and just under 60 percent of AI-using firms in surveyed LMICs). The second-most frequently cited business function among AI users is research and development (55 percent of AI-using firms in the U.S. and 51 percent of AI-using firms in LMICs). While similar proportions of AI-using firms use the technology for these functions both in the U.S. and in the surveyed LMICs, there are noticeable departures between the two groups on two business functions that involve business functions that affect directly how workers organize and go about their daily operations: namely, in business administration (which includes HR) and strategic decision making. In both business functions, AI-using firms in the group of surveyed LMICs lag substantially behind AI-using firms in the U.S. Over 44 percent of American AI-using firms employ the technology in business administration, and almost a third of AI-using firms in the U.S. use AI in strategic decision making. These proportions are 29 percent and 23 percent, respectively, among AI-using firms in the surveyed LMICs.

AI technologies can be used across many business functions simultaneously, and the relative number of business functions for which firms use AI can further indicate the degree of firms' integration into their

work. Similarly, it is possible that firms employ AI technologies, such as chatbots, without orienting those tasks toward a specific business function. Figure 3 shows the proportions of AI-using firms based on the number of business functions for which the firms use these technologies. Three patterns emerge. First, AI use without a designated business function is much more common among AI-using firms in the surveyed LMICs. An average of 22 percent of AI-using firms in these countries report no business functions for which AI is used. This rate is less than 5 percent of AI-using firms in the U.S. A second pattern is that, perhaps unsurprisingly, a smaller proportion of firms use AI across increasing numbers of functions. In the U.S., 31 percent of firms use AI in one of the selected business functions; 24 percent in two functions; and 13 percent in three functions. Among AI users in surveyed developing countries, these proportions are 20 percent of firms use AI for one identified function, 18 for two, and 10 for three. This trend highlights a third pattern: in both the U.S. and surveyed developing countries, there are sizeable and nearly equivalent proportions of firms that use AI for several (four or more) business functions. An average of approximately 30 percent of firms in both the U.S. and in surveyed developing countries report such varied use.

Figure 4. Number of business functions using AI (among AI adopting firms)



Notes: Bars show the distribution of the number of business functions in which AI is used among firms that have adopted AI. The sample is restricted to AI adopting firms. Surveyed developing countries exclude the United States, Türkiye, and Malaysia. Estimates use normalized survey weights.

Finding 4. Larger gaps are visible when looking at more sophisticated uses of AI technology

The adoption of AI does not equal productive use. There are large differences between adopting firms with respect to the sophistication of use: some businesses only use online platforms to find information, while other firms have customized platforms that support workflows directly. This is in line with findings from earlier technologies, where firms in developing countries often do not use the most sophisticated technology that is available (Cirera, Comin & Cruz 2026). To study more sophisticated uses of AI technology, an index of AI sophistication is constructed, consisting of the following components: (1) whether a firm adopts any AI technology; (2) whether a firm adopts AI agents, AI process automation, or

AI-driven robotics; (3) whether a firm uses them for more advanced tasks (such as coding); (4) the number of business functions AI is used for; and (5) whether a solution is customized (either internally or externally). All indices start from whether a firm adopts any AI technology (a dummy equals 1 if adopted, and zero otherwise) as the base and then add the weighted components that are counts of use, tasks, functions, or sourcing choices.[15] Each component that counts is normalized to a 0–1 scale before being summed, so dimensions are approximately comparable in magnitude.

The results in Table 2 show that firms in the surveyed developing countries deploy AI technology less sophisticatedly than firms in the U.S. The composite AI sophistication index in the U.S. is about 70 percent higher than in the surveyed developing countries, with a similar gap being found across all components of the index. Moreover, the adoption gap is also observed within countries, between small firms and medium and large firms. In the surveyed developing countries, the level of AI sophistication among small firms is about three-fifths of that among medium and large firms, with the largest gap observed in the use of advanced AI technologies and sourcing solutions. A wider sophistication gap between small firms and medium and large firms is observed in the U.S. The within-U.S. gap between firms of different sizes is larger than the level observed among medium and large firms across country groups.

Table 2. Elements of AI technology sophistication

Component / Index	Surveyed developing countries			United States		
	All firms	Small (5-19)	Medium and large (20+)	All firms	Small (5-19)	Medium and large (20+)
(1) Adoption of any AI technologies (binary, 0 or 1)	0.28	0.24	0.37	0.43	0.33	0.61
(2) Use of AI agents, AI process or AI robotics (count, 0-3)	0.16	0.12	0.24	0.32	0.16	0.61
(3) Use for more advanced tasks (count, 0-3)	0.24	0.19	0.35	0.39	0.25	0.66
(4) Use for more business functions (count, 0-7)	0.75	0.61	1.02	1.07	0.76	1.68
(5) Sourcing (count, 0-3)	0.26	0.19	0.41	0.55	0.33	0.97
Composite index	0.51	0.41	0.72	0.86	0.59	1.37

Notes: The table reports data on formal firms with 5 or more employees in the manufacturing, construction, and services sectors. Firm size is based on the number of employees, with a small firm having 5–19 employees and medium and large firms having 20 or more employees. The AI sophistication index = component (1) + component (2)/3 + (component (3)/3+ component (4)/7)/2 +component (5)/3. Component (1) is a dummy that equals 1 if adopted, and zero otherwise. Components (2)-(5) are numerical variables (count). Component (3) covers the "Use for more advanced tasks", which includes the use of AI for coding and software development (ai_b3a4), for data analysis, modelling and simulation (ai_b3a6) and for controlling business or production processes (ai_b3a7). Component (5) captures "Sourcing of customized solutions", including whether a firm used commercial AI software (ai_b6a3), whether a firm paid for AI use (ai_b6b) and whether a firm used custom-built solutions (ai_b6a4).Surveyed developing countries exclude the United States as well as Türkiye and Malaysia, and are averaged across countries, so each country carries a total weight of one.

[15] The AI sophistication index = component (1) + component (2)/3 + (component (3)/3+ component (4)/7)/2 +component (5)/3

4 Enablers of AI adoption

Finding 5. Adoption depends on firm characteristics – including firm size and age

Even though adoption of AI has been widespread, certain patterns emerge in terms of the characteristics of the businesses that are more likely to use AI, and those that use it in a more sophisticated way. Early evidence from developed economies show that AI adoption is systematically higher for larger, more productive, and higher paying firms (Yotzov et al., 2026). In China, larger firms, firms with pre-AI talent pool, and service sector-oriented firms are more likely to adopt generative AI (Li et al., 2026).[16] These patterns from relatively wealthier economies warrant an examination of whether firms in developing economies follow the same pattern or some differences exist.

Table 3. The determinants of firm characteristics on AI adoption

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable	AI adoption	AI adoption	AI adoption	AI sophistication	AI sophistication	AI sophistication
Sample	All countries	US only	Surveyed developing countries	All countries	US only	Surveyed developing countries
Medium (20-99 workers)	14.10***	28.61	10.96***	32.28**	80.49	22.86**
	(3.84)	(9.43)	(2.64)	(11.71)	(23.34)	(8.02)
Large (100+ workers)	21.96***	28.04	19.69**	60.09***	85.54*	53.33**
	(5.80)	(4.62)	(7.68)	(17.90)	(10.81)	(22.76)
Mature age (10-19 years)	-6.08	-44.46***	-2.56	-2.45	-56.56*	2.50
	(4.43)	(0.22)	(3.46)	(6.71)	(8.94)	(6.46)
Old age (20+ years)	-4.71	-26.78**	-2.59	-2.767	-32.50	0.18
	(3.64)	(0.60)	(3.31)	(5.03)	(7.46)	(5.13)
Country dummies	Yes	No	Yes	Yes	No	Yes
Sector dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3873	366	3507	3873	366	3507
R squared	0.151	0.217	0.143	0.158	0.231	0.149

Notes: Robust standard errors clustered at the strata level are reported in parentheses. Employment size "5 to 19" (small firms) and age group "Young (0-9)" are the omitted reference groups. Coefficients are reported in percentage points. All regressions include sector dummies. Country dummies are included except in the US-only specifications. Surveyed developing countries exclude the United States as well as Türkiye, and Malaysia. Estimates are obtained using normalized survey weights (with weights adding to one for each country) and the OLS estimator. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Firm size is strongly and positively associated with AI adoption, as shown in Table 3. Relative to small firms, medium sized businesses in developing economies (column 3) are 11 percentage points more likely to have adopted AI, while large firms 20 percentage points. While the coefficients are not significant in the U.S. alone, the statistically significant monotonic pattern in the coefficients on size for developing economies shows consistency in the adoption patterns with evidence from high income economies. This pattern is further amplified when examining the sophisticated usage of AI.

[16] In a subset of listed firms in China, Li et al. (forthcoming) further show that the likelihood of GenAI adoption is higher among more capital-intensive firms and those with higher R&D intensity.

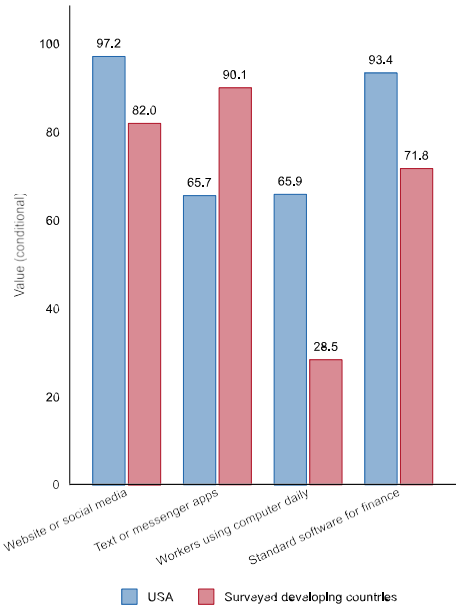
While the findings for the U.S. are consistent with other data from the literature (Yotzov et al., 2026) with respect to firm age, the pattern does not hold for developing economies. Younger firms in the U.S., those that have started in the last 10 years, show greater usage of AI relative to older firms. In developing economies, the coefficient on age is very small and insignificant, indicating a divergence in adoption patterns with high income economies. There are a couple of possibilities, which require further examination, that could be behind this difference: (1) competitive pressure where more developed markets are exposed to higher churn, while lower income economies have less turnover (Aga and Francis, 2017); or (2) infrastructure access in developing economies may be concentrated with older firms.

Finding 6. AI adoption is facilitated by firms already having access to and using digital technologies

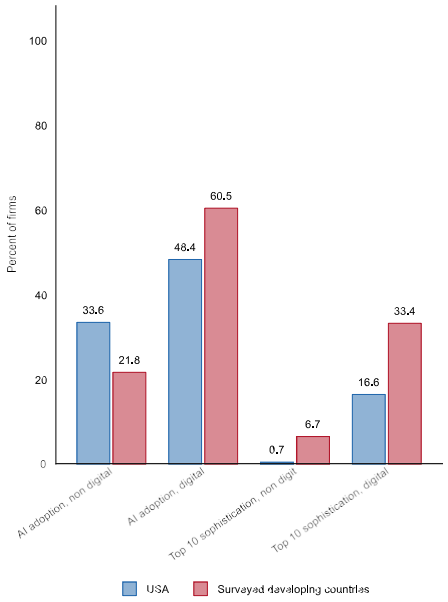
The surveyed firms also have high levels of digital readiness, which could explain their high AI adoption rates. In the U.S., 97 percent of firms report using a website or social media, while this value is 82 percent for firms in the surveyed developing countries, as shown in Figure 5(a). Firms in the surveyed developing countries also report high rates of usage of text or messenger apps, although use is somewhat lower in the USA. The share of firms using a computer daily is also high in the U.S. at 66 percent, while it is lower in developing countries at 29 percent. The share of firms using standard software for finance is also high in all surveyed countries. Firms with higher digital technology adoption are also more likely to adopt AI. Figure 5(b) reports AI adoption and top 10 AI sophistication by digital business status, where digital business is defined as having more than 50 percent of workers using computers daily. AI adoption rates are around 50 percent higher for digital businesses than non-digital businesses in the U.S. and nearly three times higher in developing countries. Top 10 AI sophistication is also substantially higher in digital businesses, while top AI sophistication is very low for non-digital businesses.

Figure 5. Digital readiness and AI adoption outcomes

(a) Digital readiness measures



(b) AI adoption and sophistication by digital readiness



Notes: Panel (a) shows four firm level digital readiness measures. For workers using computers daily, the bar reports the average share of workers using a computer in daily work activities; the other measures are reported as percentages of firms. "Value (conditional)" means that each bar is calculated within the corresponding country group. Panel (b) reports AI adoption and top 10 AI sophistication by digital business status, where digital business is defined as having more than 50 percent of workers using computers daily. Surveyed developing countries exclude the United States, Türkiye, and Malaysia. Estimates use normalized survey weights.

Finding 7. Innovation and firm capabilities spur adoption and sophistication in developing economies

Innovation and firm capabilities matter for firms' adoption of AI. The history of past innovation is associated with higher AI adoption (Table 4). Specifically, firms with a history of innovation through the introduction of new products or services are 17 percentage points more likely to use AI, while those investing in R&D are 13 percentage points more likely to do the same. In line with the earlier result on digital readiness, firms where more than half of workers use computers are 35 percentage points more likely to have adopted AI. These findings reinforce earlier evidence that firms that were more technologically sophisticated before AI use took off—in terms of their adoption of complementary technologies like cloud computing—have adopted generative AI at much higher rates than less technologically sophisticated firms.

There are other complementary factors that matter for firms' AI adoption. Stronger management capabilities (as measured by the adoption of structured managerial practices) and better market access (as measured by export status) are positively associated with the adoption and sophisticated use of AI.

Table 4. Determinants of AI adoption,surveyed developing countries only (coefficients x100)

Dep var=AI adoption	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Uses text, SMS, or WhatsApp	7.37								
	(5.55)								
More than half of workers use computers		35.18***							
		(4.99)							
Introduced new product or service			17.17***						
			(5.13)						
Spent on R&D				13.29**					
				(5.33)					
Above median management practices					17.76***				
					(4.44)				
Has loan or line of credit						4.80			
						(2.89)			
Has checking or savings account							9.80		
							(5.67)		
Labor productivity (log)								1.18*	
								(0.62)	
Exporter									15.78***
									(3.77)
Country dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3813	3756	3813	3813	1736	3813	3813	3793	3813
R squared	0.067	0.156	0.086	0.071	0.093	0.067	0.066	0.067	0.074

Notes: The dependent variable is an indicator for whether the firm has adopted AI, multiplied by 100. Each column reports a separate regression using the explanatory variable shown in the corresponding row. The sample is restricted to surveyed developing countries and excludes the United States as well as Türkiye and Malaysia. All regressions include country and sector dummies and use normalized survey weights (with weights adding to one for each country). Estimates are obtained using the OLS estimator. Robust standard errors clustered at the strata level are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 5. Determinants of AI sophistication,surveyed developing countries only (coefficients x100)

Dep var=AI sophistication	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Uses text, SMS, or WhatsApp	8.02***								
	(1.13)								
More than half of workers use computers		21.93***							
		(4.78)							
Introduced new product or service			12.29**						
			(4.40)						
Spent on R&D				0.82					
				(5.96)					
Above median management practices					9.83*				
					(5.39)				
Has loan or line of credit						0.20			
						(2.25)			
Has checking or savings account							3.77		
							(3.70)		
Log labor productivity								1.53**	
								(0.54)	
Exporter									6.55
									(6.45)
Country dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3813	3756	3813	3813	1736	3813	3813	3793	3813
R squared	0.007	0.076	0.024	0.001	0.041	0.001	0.001	0.005	0.004

Notes: The dependent variable is an indicator for whether the firm is in the top 10 percent of the AI sophistication index within its country, multiplied by 100. The index is defined in the code and combines AI technologies, AI tasks and business functions, and AI sourcing or customization. Each column reports a separate regression for surveyed developing countries only, excluding the United States as well as Türkiye and Malaysia. All regressions include country and sector dummies and use normalized survey weights. Estimates are obtained using the OLS estimator (with weights adding to one for each country). Robust standard errors clustered at the strata level are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

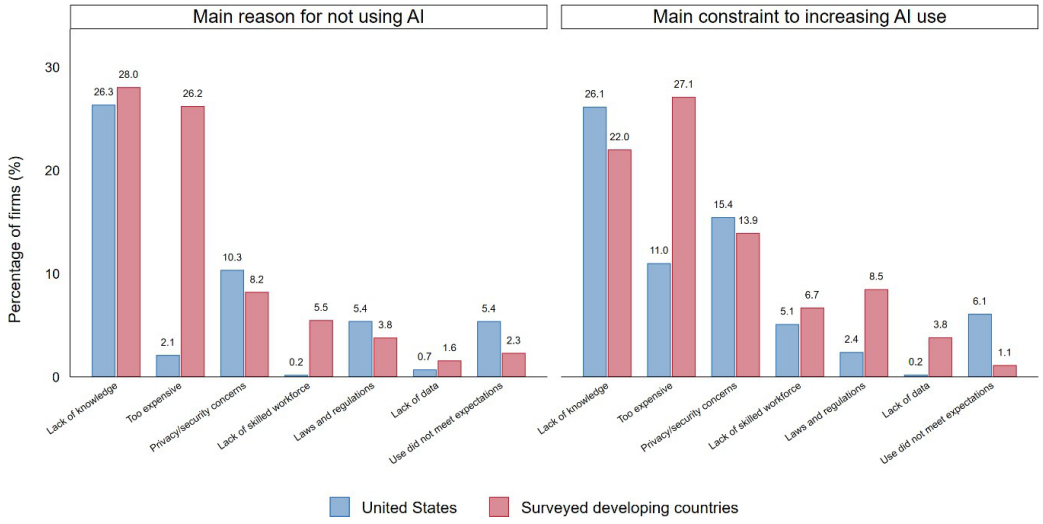
Specifically, a firm that ranks above the median in terms of the adoption of managerial practices is 17 percent more likely to adopt an AI technology than a firm ranking below the median. Financial access tells a muted story. Neither having a loan nor a line of credit, nor having a checking or savings account, is significantly associated with AI usage. This is suggestive that the marginal cost of AI adoption is low enough that access to formal credit is not a binding constraint.

Factors that matter for firms' adoption of AI also matter for the use of more sophisticated types and ways of using AI. As shown in Table 5, more productive firms with stronger innovation capacity, digital readiness, and management practices are more likely to use AI in a sophisticated way. Unlike the results from the simple adoption of AI, using text, SMS, or WhatsApp is associated with an 8 percent higher likelihood of using AI in a sophisticated way.

Finding 8. Lack of knowledge and limited information remain important constraints

For non-AI-using firms, the survey asks which reason, among seven options, is their main constraint for not using AI. Among AI-using firms, the survey asks about which of these constraints is the main reason they do not increase their AI use.Across both groups—AI adopters and AI non-adopters—a "lack of knowledge" is the most highly cited constraint on average. This can include knowledge of the functionality of AI but also how firms may choose to deploy AI. Among firms in the surveyed developing countries, the cost of AI being "too expensive" is reported as a substantial constraint to adopt AI or increase its use. This is less of a constraint for firms in the U.S. percentIn the U.S., the second-most-cited reason for not adopting AI are concerns around privacy and data concerns (reported by 10.3 percent of firms in the U.S., against 8.2 in the surveyed developing economies). percent percent.

Figure 6. Main constraint to increasing use of AI and main constraint for not using AI



Notes. The left panel is restricted to firms that have not adopted AI and reports their main reason for not using AI. The right panel is restricted to firms that have adopted AI and reports their main constraint to increasing AI use. Bars show percentages within each country group. Surveyed developing countries exclude the United States, Türkiye, and Malaysia. Estimates use normalized survey weights.

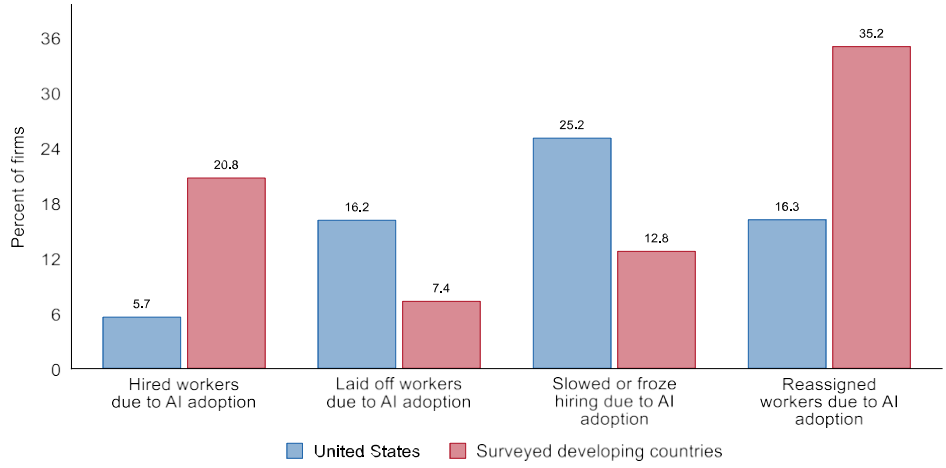
5 Labor market impacts and expectations

Finding 9. Job impacts are (and expected to be) not that large

Despite broader claims about AI's potential to displace workers, only a subset of firms adopting AI report that they have laid off workers.[17] In the U.S., 16.2 percent of firms report layoffs due to AI adoption, and in the surveyed developing countries, this is lower at 7.4 percent. Nevertheless, roughly a quarter (25.2 percent) of US firms and 12.8 percent of firms in the surveyed developing countries report slowing or freezing hiring due to AI adoption. Some firms also re-assigned workers after AI adoption, but it is more common in the surveyed developing countries (35.2 percent of firms) than in the U.S. (16.3 percent of firms). More importantly, 20.9 percent of firms in the surveyed developing countries hired workers due to AI adoption, which is four times the level observed in the U.S.

The survey results suggest that the reported job displacement effects among firms adopting AI is currently limited and less pronounced in the surveyed developing countries, compared to the U.S. figures. This limited displacement could reflect the overall lower rate of exposure of current employment tasks to AI technologies (Huang et al. 2026), but also the overall less sophisticated use of AI in the surveyed developing countries (as highlighted before) or possible lags in employment adjustment following adoption. The higher percentages of reassignment and new job hirings due to AI could reflect that AI is creating new tasks or boosting demand for tasks that can now be done more productively, in line with expected labor reinstatement and productivity effects (Acemolgu & Restrepo 2019).

Figure 7. Reported employment adjustments after AI adoption, among firms adopting AI



Notes: Bars show the percentage of AI adopting firms reporting each employment adjustment due to AI adoption. These questions were asked only to firms that had adopted AI. Surveyed developing countries exclude the United States, Türkiye, and Malaysia. Estimates use normalized survey weights.

[17] In the survey, firms were asked the following question: "In three years, what change in the number of employees do you expect due to the adoption of AI technologies?" by choosing from the following options: 1) hired workers due to AI adoption, 2) laid off workers due to AI adoption, 3) slowed or froze hiring due to AI adoption, and 4) reassigned workers due to AI adoption.

Finding 10. The outlook remains highly uncertain, but firms are optimistic

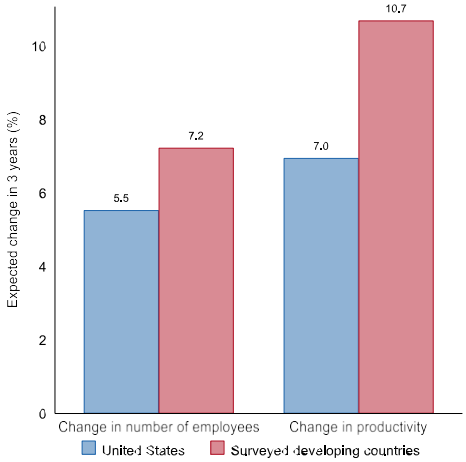
Firms surveyed reported a wide range of expectations about the potential impacts of AI on their businesses' productivity under different scenarios.

Firms tend to be optimistic on both the employment and productivity impacts of AI (Figure 8). The survey asked firms to respond to the following question: "In three years, suppose you keep your current workforce size, what change in output do you expect due to the adoption of AI technologies?" This question was asked under three scenarios: a most likely scenario, a less rapid scenario, and a more rapid scenario, to measure the uncertainty around these expectations. [18] Under the most likely scenario, firms in the surveyed developing countries expected productivity to increase by 10.7 percent and employment by 7.2 percent, which are higher than the expected increases observed in the U.S. (respectively, 7.0 and 5.2 percent).

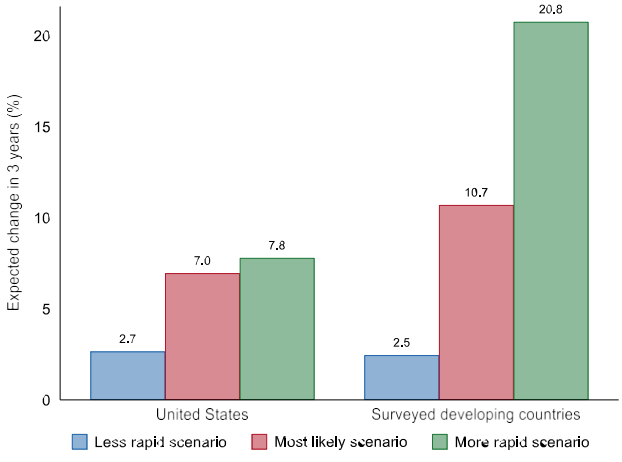
However, uncertainty around these expectations are high, as highlighted by the range of responses given across the three scenarios. Firms in the United States expect that a rapid development scenario of AI could result in productivity gains of about 8 percent in the following three years, while a less rapid scenario would yield gains of 3 percent. Firms in the surveyed developing countries report wider ranges, with the most rapid scenario resulting in a productivity increase of 21 percent and a less rapid scenario yielding an increase of 2 percent, on average. The variance in expectations could be driven by different factors, for example differences in firms' familiarity with AI technologies, but also due to differences in beliefs about the economic effects of highly capable AI systems (e.g., Karger et al. 2026; Markridis 2026).

Figure 8. Expected changes in employment and productivity in 3 years.

(a) Expectations of employment and productivity changes



(b) Expectations of productivity among the three scenarios



Notes: In panel (a), the change in productivity represents the most likely scenario.

[18] Among respondents providing answers to these questions, 85.7 percent of respondents in the United States and 78.9 percent of respondents among the surveyed developing countries gave responses that were consistent in the sense that the productivity expectations in the more rapid scenario were higher than those in the most likely scenario and the productivity expectations of the less rapid scenario were lower than those in the most likely scenario.

6 Conclusion

Utilizing a set of nationally representative surveys of 4,205 firms (in the formal sector with five or more employees) in seven economies, ten stylized facts are presented. AI adoption has spread quickly worldwide but unevenly across economies. Chatbots and generative tools are the dominant form of AI use and adoption spans a wide range of business tasks and functions. Sophisticated use of AI tends to be more prevalent in relatively higher income economies, with larger, more digitally-ready, and more innovative firms driving complex usage. This early evidence indicates that, thus far, labor market effects appear modest, with a focus on reassignment and hirings as opposed to displacement. Despite uncertainty and the rapid development of the technology, firms remain optimistic about the impact on productivity and employment.

This paper provides the initial assessment of AI's impact on firms and labor markets in the three years since its mass access to technology. The contributions of this study are threefold: (1) it is among the first studies which contains comparable firm-level data across different regions and income groups, further adding to the growing literature on the impact of AI on firm behavior; (2) provides an early analysis of the differential impact AI has across developing countries when compared to the United States; and (3) builds on the growing literature that examines the early impact of AI on labor markets, with a focus on the impact in developing economies. These findings carry importance for policymakers, as they provide an initial assessment of the state of integration of AI in the private sector, as well as the early trends of the impact this technology has on broader labor markets. For developing economies in particular, the findings illustrate the potential for targeted policies as the sophisticated use of AI is correlated with characteristics that are lacking in developing economies – including around digital readiness, firm capabilities and innovative capacities (Belacin et al., 2025).

As highlighted by the responses by firms, much uncertainty exists in how firms will behave in the future, both due to how adoption and firms' behavior will change over time, and due to the rapid evolution of the technology. Given the fast adoption of AI by many firms, and the slow sophistication in how this technology is used, this paper looks into the heterogeneity of firms, which opens more questions than it provides answers to. More research is needed not just around whether firms are adopting, but also around the intensive margin of use, including how the technology gets embedded into business processes and the actual adoption of the technology by workers (including the incentives around adoption), as well as the implications for firm organization. Specifically for developing economies, more research is needed to understand adoption and use of AI technologies within informal and micro-sized business establishments, which represent the lion's share of employment and firms in many economies. As the development of AI continues to progress, these questions, along with many more that will emerge over time, will be critical to understand how the technology is changing firms and labor markets.

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Appendix. Additional Table

Table A1. Sample description of firms interviewed as part of the AI follow-up

Variable	Mean	S.D.	Minimum	Maximum
Variables from original WBES survey				
Number of workers	71.0	142.1	1.0	3500.0
Age	22.6	17.5	0.0	168.0
Revenue per worker (USD, 2009)	55336.6	107109.1	6.4	1803247.1
Variables from follow-up survey				
Share of businesses using text messaging apps	0.893	0.310	0.000	1.000
Share of businesses with website or social media presence	0.845	0.362	0.000	1.000
Share of workers using computers daily	0.291	0.277	0.000	1.000

Note: Cells show unweighted averages, pooled across all surveyed countries (excluding Türkiye and Malaysia). S.D. = standard deviation.