n° 2025-15 December 2025

WORKING PAPERS

Adoption of AI by Firms: Determinants and Impacts

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Version: 19 November 2025

Abstract

This chapter provides an up-to-date overview of evidence on firms' adoption of Artificial Intelligence (AI). We revisit the main conceptual drivers of AI uptake discussed in the literature and summarize global trends in AI diffusion. We then examine the firm characteristics associated with adoption—including the distinction between in-house development and external acquisition—and highlight how patterns differ between general AI and generative AI technologies (GenAI). Next, we review the emerging literature on the productivity effects of AI, distinguishing non-experimental firm-level studies from recent experimental and quasi-experimental evidence on task-level impacts. As a case study, we draw on recent firm-level data from Germany to investigate how adoption decisions correlate with firm size, age, R&D intensity, human capital, location, and strategic orientation, and how these patterns vary across stages and types of AI adoption.

1. Introduction

Artificial intelligence (AI) is rapidly transforming the way firms operate, compete, and innovate. By enabling machines and algorithms to process complex and unstructured data, make predictions, and generate content or decisions, AI technologies have opened new possibilities for automation, product development, and strategic decision-making. The past decade has seen a sharp rise in the deployment of AI tools across a wide range of sectors, driven by advancements in machine learning, the proliferation of data, and growing computational capacity. Generative AI (GenAI), in particular, has further expanded the scope of applications, enabling firms and workers to automate tasks previously thought to require human judgment, creativity, or skills.

Understanding how AI adoption unfolds across firms is critical for anticipating its broader economic impacts. Patterns of diffusion, adoption strategies, and productivity effects vary significantly across industries, firm sizes, and organizational structures. These differences have implications for competition, workforce dynamics, and inequality, and they are increasingly shaping policy debates on innovation, digital infrastructure, and labor markets.

This chapter provides an overview of recent evidence on AI adoption by firms. We review the main conceptual drivers of AI adoption discussed in the literature and summarize global trends in AI diffusion. We also examine which firm characteristics are associated with AI uptake, the distinction between in-house development and external acquisition, and how patterns differ between general AI and GenAI technologies. In addition, we assess whether early adopters differ systematically from those adopting later. As a case study, we exploit recent firm-level data from Germany to investigate how adoption decisions correlate with firm size, age, R&D intensity, human capital, location, and strategic orientation, and how these patterns vary across different types and stages of AI adoption.

The findings reviewed confirm that AI adoption has expanded steadily across countries and over time, with particularly rapid growth in digitally intensive sectors and among firms with strong absorptive capacity. Adoption is more likely among larger, younger, and more innovative firms, and this pattern is even more pronounced for GenAI, which appears to favor firms with a highly skilled workforce, active R&D engagement, and international exposure.

Finally, we review the emerging literature on the productivity effects of AI adoption, distinguishing between non-experimental firm-level studies and recent experimental or quasi-experimental evidence focused on task-level impacts. While observational studies often link

AI use to higher firm productivity, especially for firms with strong digital foundations, experimental studies highlight substantial performance gains from GenAI tools at the task level, particularly for lower-skill workers. Taken together, the evidence suggests that AI is becoming a widely adopted general-purpose technology, but its benefits remain unequally distributed across firms, sectors, and skill levels.

2. Drivers of AI adoption in firms

According to the latest OECD definition of AI, "an AI system is a machine-based system that, for explicit or implicit objectives, infers, from the input it receives, how to generate outputs such as predictions, content, recommendations, or decisions that can influence physical or virtual environments. Different AI systems vary in their levels of autonomy and adaptiveness after deployment." (OECD, 2023). In essence, AI technologies enable the analysis of vast, often unstructured data (including language, images, and sounds) and train models to perform tasks autonomously, adapting over time through learning. This capability supports both the automation of existing workflows and the creation of novel products and business models.

AI adoption in firms reflects a combination of *internal enablers* and *external pressures*. Internally, key prerequisites include in-house knowledge (notably AI-specific skills and data science capabilities) and complementary technologies, particularly those related to data infrastructure and software systems. Externally, firms respond to a mix of demand-side pull (e.g., need for new solutions or efficiency gains), competitive pressure, and the broader regulatory and policy environment. In sum, the adoption of AI follows patterns familiar from other general-purpose technologies: diffusion depends not just on technological capability but on the alignment of organizational, technical, and institutional conditions. The current landscape shows that where these drivers are in place, typically in advanced industries, larger firms, and digitally advanced regions, AI adoption is accelerating, delivering tangible benefits.

3. Diffusion of AI technologies

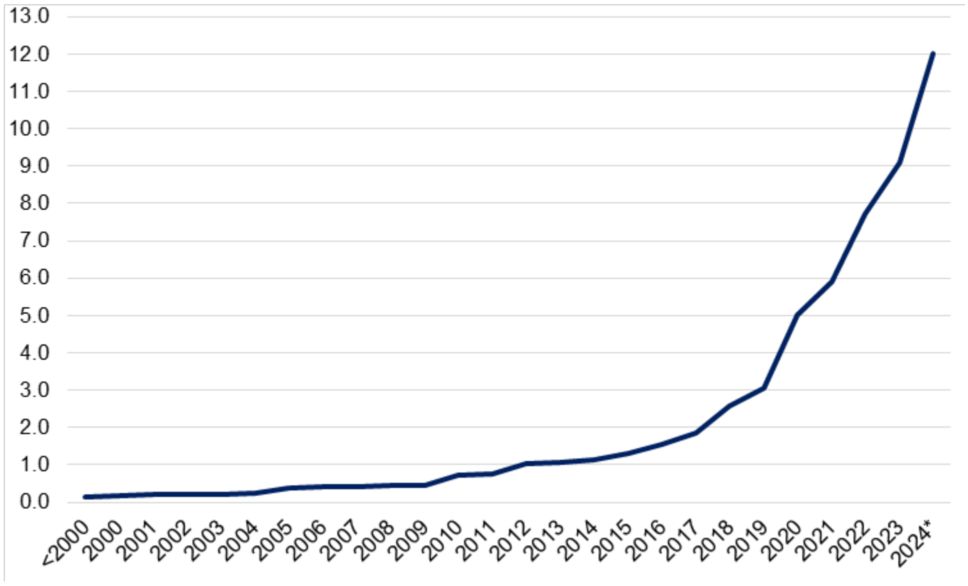
AI adoption has been rapidly increasing worldwide, with firms using AI technologies rising in major economies such as the U.S., Germany, France, South Korea, and across the EU. This surge has driven strong demand for AI-related jobs and skills, reflected in growing AI job vacancies, extensive large language models (LLMs) task complementarities, and widespread corporate reskilling plans, while AI patent filings continue to accelerate. Adoption patterns show that companies most often deploy AI in organizational decision-making, marketing, cybersecurity, and R&D, with usage concentrated in ICT and professional services and varying by firm size and sector according to where the highest returns on AI investments are expected.

In the United States, the share of firms adopting AI-related technologies rose from 3.2% during 2016–2018 to 6.6% by 2024 (Zolas et al., 2020; Acemoglu et al., 2022; Bonney et al., 2024; McElheran et al., 2024). In Germany, 7% of firms had implemented at least one AI-based method before 2018, increasing to 12% by 2023 (Rammer et al., 2022; Czarnitzki et al., 2023; Rammer, 2025). In France, 6.2% of firms adopted at least one AI technology between 2021 and 2023, a rate comparable to that observed in Belgium, Israel, and Japan (Calvino & Fontanelli, 2023; Calvino & Fontanelli, 2025). In South Korea, the share of AI users among firms climbed from 1.4% in 2017 to 4.3% in 2022 (Cho et al., 2023; Chang et al., 2025). Across the European Union, the proportion of businesses using AI technologies increased from 7.7% in 2021 to 13.5% in 2024 (Eurostat, 2025).[1]

Most recent data from Germany show that the diffusion rate of AI among firms is still at its steeply rising section (Figure 1).

Figure 1: Diffusion rate of AI among firms in Germany

[1] As with other general-purpose technologies, AI requires substantial complementary investments in organizational capital, workforce upskilling, and business-process redesign, factors that have historically slowed diffusion (Brynjolfsson & Hitt, 2003; Brynjolfsson et al., 2021). Indeed, by 2023, firm-level AI adoption in the U.S. remained modest compared to earlier general-purpose technologies such as electric power and personal computers (Filippucci et al., 2024). Likewise, the geographic dispersion of digital-technology jobs, especially those involving machine learning, across U.S. regions is projected to unfold over several decades (Kalyani et al., 2025). Yet from an employee's perspective, the diffusion of generative AI tools among U.S. workers to date appears at least as rapid as the earlier spread of computers and the internet (Bick et al., 2024).



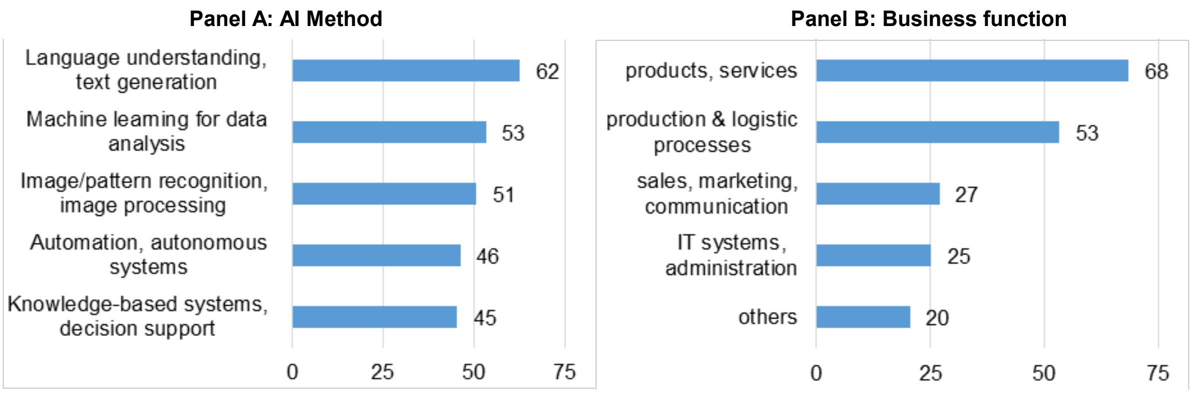
* estimated value

Source: German CIS, own calculation.

Empirical evidence also indicates a growing demand for AI-related jobs and skills. In the U.S., AI-related job vacancies surged beginning in 2010 and accelerated through the 2010s, reflecting deeper integration of AI into firms' development processes (Alekseeva et al., 2021; Acemoglu et al., 2022; Kalyani et al., 2025). Between 2018 and 2023, the share of AI roles among all U.S. job postings rose by 21% (Bone et al., 2024). Recent estimates suggest that 48% of U.S. occupations could have at least half of their tasks complemented by LLMs (Eloundou et al., 2024) and that AI is used intensively in roughly 36% of U.S. occupations (Handa et al., 2025). European labor markets likewise recorded employment gains linked to AI-enabled automation between 2011 and 2019 (Albanesi et al., 2025). A 2025 global survey of C-level executives and senior managers found that 72% expect to reskill more than 10% of their workforce within the next three years due to AI adoption (McKinsey & Company, 2025). Mirroring these labor-market trends, AI patent applications by firms have accelerated markedly over the past decades, indicating continued technological diffusion (Damioli et al., 2021; Dibiaggio et al., 2022).

Usage rates of specific AI technologies vary markedly across firms. Conditional on AI adoption, U.S. companies in 2024 most frequently deployed virtual agents or chatbots, natural language processing, and voice/speech recognition systems (Bonney et al., 2024). Over the same period, text-mining and natural-language-generation tools registered the highest uptake among EU enterprises (Eurostat, 2025). In the case of Germany, as shown in Panel A of Figure 2, language understanding and text generation (62%) were the main AI methods employed by firms in 2023. The prominence of natural language processing reflects the rapid emergence of generative-AI platforms, such as ChatGPT, GitHub Copilot, and DALL-E, over the past few years (Brynjolfsson et al., 2025). For example, just twelve months after ChatGPT's public release, 50% of Danish workers in AI-exposed occupations reported using the tool; adoption ranged from 79% of software developers to 34% of financial advisors (Humlum & Vestergaard, 2024).

Figure 2: Type of AI use in firms in Germany 2023

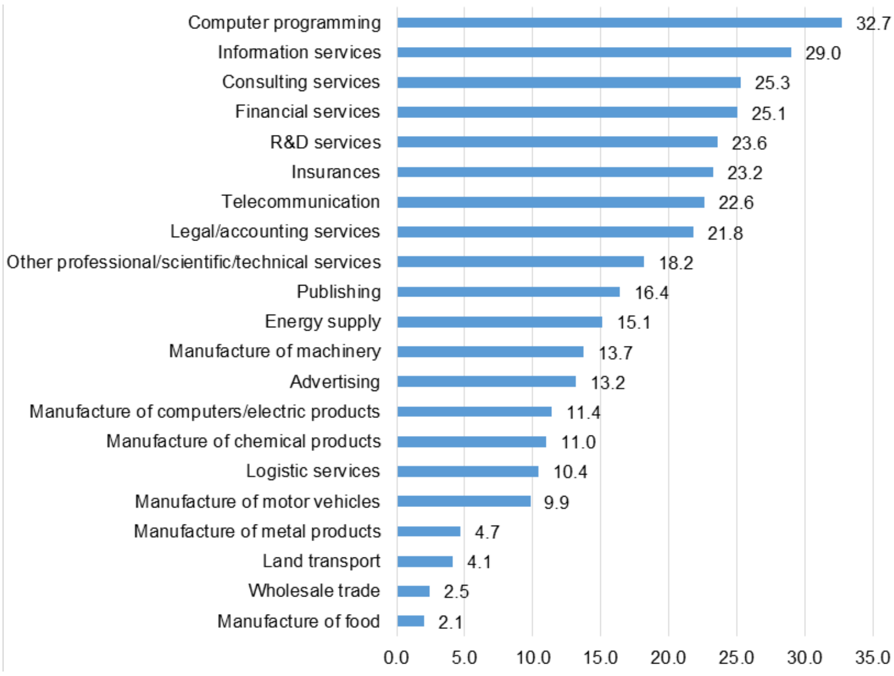


Source: German CIS, own calculation.

When broken down by business function, AI adoption is highest in organizational processes, such as planning and investment decisions, and commercial and marketing activities, including marketing automation, even before the surge in generative AI in early 2023. For example, between 2021 and 2023, French firms most often deployed AI to support decision-making, analyze employee performance, conduct risk assessments, and power virtual assistants alongside other core organizational tasks (Calvino & Fontanelli, 2025). German firms in 2023, as shown in Panel B of Figure 2, mainly adopted AI for products and services (68%), as well as for production and logistics processes (53%). Usage patterns in business functions also vary by firm size: in 2024, small enterprises in the EU primarily applied AI software to marketing and sales activities (35%), whereas large enterprises focused on cybersecurity applications (47%) (Eurostat, 2025). Although functional uses of AI remain in their nascent stages, many firms are already planning organizational adjustments. Among U.S. companies surveyed in 2024 that expect to implement AI within the next six months, the most commonly anticipated measures are training existing staff and redesigning workflows to integrate AI tools effectively (Bonney et al., 2024).

Sectoral patterns of AI adoption have remained remarkably consistent across nations. In OECD countries, including Belgium, Denmark, France, Italy, Japan, and Korea, firms in the information and communication technology (ICT) and professional and scientific services sectors recorded the highest AI-usage rates during 2019–2020, whereas transport and storage, wholesale and retail, construction, and accommodation and food sectors showed the lowest uptake (Calvino & Fontanelli, 2023). A similar distribution appears in the U.S.: in 2024, the information sector (NAICS 51) and the professional, scientific, and technical services sector (NAICS 54) led in AI use, while construction (NAICS 23) and agriculture, forestry, fishing, and hunting (NAICS 11) lagged behind (Acemoglu et al., 2022; Bonney et al., 2024). Aggregated EU figures for 2024 reinforce this pattern: over 30% of firms in ICT and professional, scientific, and technical activities employ AI, whereas fewer than 10% of companies in construction, accommodation, and transportation and storage do so (Eurostat, 2025). As reported in Figure 3, in 2023, German firms in computer programming (32%) and information services (29%) reported the highest adoption rates, whereas firms in food manufacturing (2%) and wholesale trade (2%) reported the lowest.

Figure 3: AI adoption by firms in Germany 2023, by selected industries



Source: German CIS, own calculation.

While marketing and sales remain the most common AI applications across industries, firms tailor their use of AI to the functions promising the highest returns. In the U.S., the primary barrier to future AI adoption is its perceived inapplicability to core business activities (Bonney et al., 2024). Private surveys reveal that global companies focused on service operations predominantly deploy AI in media and telecommunications, technology firms concentrate on software development and engineering, and professional-services organizations apply AI to knowledge management (McKinsey & Company, 2025). In Europe, 26.2% of manufacturing firms use AI to optimize production processes; utilities companies (covering electricity, gas, steam, air conditioning, and water supply) most often employ AI for ICT cybersecurity (34.8%); and in the ICT sector the leading AI application is research, development, and innovation activities (43.5%) (Eurostat, 2025).

Recent literature has begun to unpack the sector- and function-specific implications of AI adoption, including supply-chain management (Culot et al., 2024), marketing activities (Labib, 2024), strategic decision-making (Csaszar et al., 2024), business-model innovation (Kanbach et al., 2024), production and manufacturing (Heimberger et al., 2024), circular-economy innovations (Czarnitzki et al., 2025), engineering design (Alam et al., 2024), innovation management (Gama & Magistretti, 2025), and financial institutions (Bahoo et al., 2024).

4. Characteristics of AI adopting firms

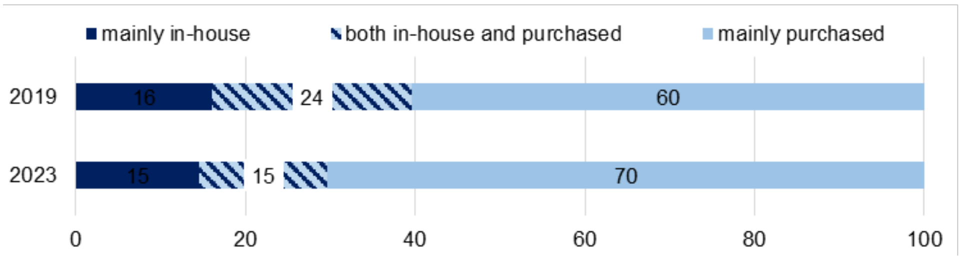
Empirical evidence consistently demonstrates a positive association between firm size and AI adoption. Across multiple countries, including the United States (McElheran et al., 2024), Germany (Rammer et al., 2022), the United Kingdom (Calvino et al., 2022), France (Calvino & Fontanelli, 2025), South Korea (Chang et al., 2025), and numerous OECD and other European economies (Calvino & Fontanelli, 2022; Eurostat, 2025), larger firms exhibit higher rates of AI uptake. Two mechanisms help explain this relationship. First, larger firms typically possess greater financial and organizational resources, enabling them to self-select into AI adoption: they are more likely to invest heavily in R&D, post specialized AI skills in job openings, and absorb the integration and training costs associated with advanced technologies (Alekseeva et al., 2021; Brynjolfsson et al., 2021; Acemoglu et al., 2022). Second, the adoption of AI itself may drive firm growth by lowering the costs of product and process innovation, thereby generating higher value-added and reinforcing further investment in AI capabilities (Damioli et al., 2023; Babina et al., 2024).

Empirical studies also reveal a negative relationship between firm age and AI adoption: younger firms are more likely to deploy AI than their older counterparts. This pattern holds across multiple OECD economies (Calvino & Fontanelli, 2022), in France (Calvino & Fontanelli, 2025), South Korea (Chang et al., 2025), and the United States (Acemoglu et al., 2022). Such a trend aligns with the notion that younger firms face fewer legacy-system constraints and lower reorganization costs when reallocating staff and automating tasks. Supporting this trend, recent U.S. evidence shows that firms most often undertake four key organizational adjustments when integrating AI: reskilling existing employees, developing new workflows, acquiring cloud and data-storage services, and overhauling data-management practices (Bonney et al., 2024). OECD reports show that startups are disproportionately likely to experiment with AI (Calvino & Fontanelli, 2023). In the context of AI startup firms, Bessen et al. (2022) find that the use of proprietary data in the development of algorithms is a key component for their business and for capturing venture capital funds.

AI adoption by firms also depends critically on a firm's digital infrastructure and complementary technological assets and ICT skills. Firms rarely adopt AI in isolation; instead, AI is layered on top of existing digital capabilities. Empirical studies find that AI use is strongly linked to the presence of complementary digital technologies and processes within the firm (Calvino & Fontanelli, 2025). European companies that innovated in AI between 1995 and 2016 benefited from complementarities with specialized knowledge in network and communication technologies, as well as in high-speed computing and data analysis (Igna & Venturini, 2023). In practice, companies adopting AI almost invariably use tools like cloud computing, big data analytics, enterprise software, and automation hardware. For example, U.S. data shows that AI use primarily appeared in firms that already had a high reliance on digital information systems and cloud computing (McElheran et al., 2024). Consistently, cross-country analyses show that firms with greater intangible capital, like software tools, databases, and digital know-how, have a higher probability of using AI (Calvino & Fontanelli, 2023).

The literature also distinguishes between firms that purchase AI systems and those that develop AI technologies in-house. AI developers are typically venture-backed start-ups or R&D-intensive incumbents (Bessen et al., 2022; Damioli et al., 2021). In contrast, AI buyers, ranging from large enterprises to SMEs with existing digital infrastructures, focus on integrating off-the-shelf or API-based AI solutions into their workflows (McKinsey & Company, 2025). Recent evidence indicates that growth volatility among French firms is concentrated among AI buyers, a tendency that may be reduced by increasing the share of ICT engineers and technicians in their workforces (Fontanelli et al., 2025). Over the last years, as presented in Figure 4, the share of German AI buyers increased from 60% in 2019 to 70% in 2023, while the share of German AI developers remained around 15%.

Figure 4: AI using firms in Germany by who developed the AI technology used



Source: German CIS, own calculation.

Other factors also appear to influence a firm’s decision to adopt AI. For example, German data show that firms facing unfilled high-skill vacancies are not only more likely to adopt AI but also to deploy it extensively across their operations (Carioli et al., 2024). Companies on the technological frontier, those that invest heavily in research or develop new products, are likewise more prone to implement AI solutions (Rammer et al., 2025). In the U.S., young firms that recently introduced product or process innovations have proven far more likely to use AI than those without recent innovations (McElheran et al., 2024).

4.1 Recent estimates on the determinants of AI adoption in German firms

Consistent with the evidence surveyed above, Table 1 presents the probability of various AI outcomes as a function of firm characteristics (measured in the previous period) using recent information from the German CIS from 2019 to 2025.[2] Larger firms are significantly more likely to adopt AI (with a marginal effect of 0.031). Similarly, R&D intensity, whether continuous or occasional, emerges as one of the strongest predictors of AI adoption (with effects of 0.152 and 0.110, respectively). Younger firms are also more likely to adopt AI (negative coefficient on age), consistent with the notion that these firms may face fewer organizational rigidities and legacy constraints. Moreover, firms located in peripheral regions are less likely to adopt AI. The only significant strategy determinant for adopting AI is related to the offering of new products by firms. In terms of competition factors, short product life cycle, rapid technological change, and threats from market entry all significantly correlate with the decision of firms to adopt AI. Industry effects further reinforce known sectoral patterns: adoption is highest in IT services, financial services, and consulting services.

In Table 2, we examine the differences between the adoption of general AI technologies and generative AI (GenAI). While the determinants of both types of adoption overlap in several respects, the regression results reveal distinctive patterns associated with GenAI. In particular, GenAI adoption is significantly more likely among younger, larger, and highly skilled firms, with especially strong associations with the share of graduates, R&D intensity, and innovation activity. Exporting firms also show a higher likelihood of adopting GenAI. Although broad sectoral patterns are similar, firms that adopt *only* GenAI appear to operate in competitive environments that are less shaped by rapid technological change but more frequently affected by market uncertainty.

[2] See Appendix A for a detailed description of the sample and variables used in the analysis.

Table 1: Determinants of AI adoption in firms in Germany (2019-2025): results of probit regressions (marginal effects)

Determinants (all measured in t-1)	AI adoption	AI mainly developed in-house	AI mainly developed by others	AI developed both in-house and by others	Early AI adopters (before 2015)	Middle AI adopters (2015-2019)	Late AI adopters (2020 or later)
Age (years, log)	-0.008***	-0.001	-0.004	-0.000	0.002*	-0.003**	-0.001
Size (FTE, log)	0.031***	0.002***	0.012***	0.005***	0.003***	0.007***	0.005***
R&D, continuous	0.152***	0.019***	0.056***	0.032***	0.022***	0.040***	0.030***
R&D, occasional	0.110***	0.019***	0.063***	0.013***	0.010**	0.031***	0.030***
Innovative, no R&D	0.061***	0.002	0.051***	0.006**	0.004*	0.018***	0.017***
Credit rating	-0.005	-0.001*	-0.002	-0.002	0.001	-0.001	-0.004***
Share of graduates	0.079***	0.008***	0.013*	0.014***	0.008***	0.012***	0.013***
Part of group	0.009**	0.002*	0.007	-0.001	-0.001	0.002	0.002
Export activity	0.015***	0.001	0.010***	0.002	0.002	0.001	0.003**
Product diversity	0.029***	-0.001	0.029***	-0.002	0.000	0.003	0.008***
Location: periphery	-0.014***	-0.002**	-0.008**	-0.004***	-0.002	-0.003*	-0.003**
Strategy							
New product offerings	0.027***	0.002**	0.011***	0.005***	-0.001	0.006***	0.005***
Price leadership	-0.009	0.001	-0.004	-0.001	0.005	-0.007***	-0.002
Quality leadership	-0.001	0.000	-0.004	0.000	0.000	-0.002	-0.002
Niche products	0.001	-0.000	0.004	0.001	-0.000	0.001	0.002
Standardised products	0.013	0.003	0.005	-0.001	0.001	-0.002	0.005
Customer-spec. solut.	0.003	-0.002*	0.003	-0.001	-0.003**	0.002	0.001
Competitive situation							
Short product life cycles	0.022**	0.001	0.008	0.001	0.001	0.004	0.001
Rapid technol. change	0.017**	0.004	-0.002	0.003	0.004	0.001	0.002
Easy substitution	-0.004	-0.000	0.013**	-0.002	-0.003*	0.002	0.004**
Threat by market entries	0.027***	0.001	0.010	0.005	0.005	0.004	0.003
High market uncertainty	-0.003	0.000	0.007	0.001	-0.000	0.002	0.003
Threat by foreign comp.	0.004	0.002	-0.009*	0.001	0.004	0.001	-0.003
High price elast. dem.	-0.001	-0.001	0.000	-0.000	-0.001	-0.003	-0.000
Industry (ref.: metals)							
Consumer products	0.009	0.001	0.008	0.001	-0.002	-0.006	0.010*
Non-metal materials	-0.008	-0.003**	0.008	-0.002	-0.005**	0.007	-0.001
Chemistry/pharmaceut.	-0.006	-0.001	-0.006	0.002	-0.001	0.002	-0.001
Electronics, electr. eq.	0.047***	0.011*	0.004	0.008	0.004	0.013*	0.010
Machinery, vehicles	0.018*	-0.000	0.003	0.008	-0.004	0.004	0.007
Utilities, waste manag.	0.027**	-0.001	0.004	0.010	-0.003	0.011	0.004
Construction, trade	0.037***	0.000	0.003	-0.000	-0.005*	0.004	0.008
Transport	0.013	0.004	0.007	-0.003	0.000	0.004	0.003
Media services	0.120***	0.002	0.072***	0.014	0.014*	0.010	0.037***
IT services	0.186***	0.024**	0.039**	0.041***	0.013	0.053***	0.043***
Financial/consult. serv.	0.233***	0.009	0.166***	0.018**	0.019**	0.068***	0.066***
Technical/R&D services	0.060***	0.005	0.032**	0.008	0.004	0.013*	0.013**
Other industries	0.025**	-0.003	0.010	0.009	0.001	0.001	0.007
# observations	32,238	14,647	14,663	14,647	14,574	14,590	14,574

***, **, *: statistically significant at p<0.01, p<0.05, p<0.1

Source: German CIS, own calculations

Table 2: Determinants of AI adoption and the use of generative AI in firms in Germany 2025: results of probit regressions (marginal effects)

Determinants	AI adoption	Use of generative AI	only AI adoption	only generative AI	AI adoption & generative AI
Age (years, log)	-0.010	-0.033***	0.009**	-0.009	-0.020**
Size (FTE, log)	0.057***	0.072***	0.003	0.010***	0.049***
R&D, continuous	0.343***	0.345***	0.036***	0.054***	0.313***
R&D, occasional	0.319***	0.308***	0.053***	0.067***	0.280***
Innovative, no R&D	0.218***	0.225***	0.040***	0.060***	0.183***
Credit rating	-0.027*	-0.039**	-0.002	-0.008	-0.024*
Share of graduates	0.190***	0.281***	-0.021*	0.036**	0.194***
Part of group	0.052***	0.068***	-0.000	0.011	0.049***
Export activity	0.016	0.058***	0.001	0.034***	0.017
Product diversity	0.069**	0.094***	-0.004	0.012	0.070***
Location: periphery	-0.044***	-0.051***	-0.009	-0.016*	-0.031**
Strategy					
New product offerings	0.045***	0.040**	0.005	-0.001	0.037***
Price leadership	-0.018	0.004	-0.014*	0.004	0.000
Quality leadership	-0.001	-0.001	-0.002	-0.004	0.002
Niche products	0.012	0.028	-0.008	0.004	0.019
Standardised products	0.014	0.012	0.016	0.011	-0.007
Customer-spec. solut.	0.010	0.016	-0.005	-0.002	0.015
Competitive situation					
Short product life cycles	0.012	0.016	0.005	0.002	0.004
Rapid technol. change	0.019	-0.053	0.023	-0.033**	-0.009
Easy substitution	0.021	0.037*	-0.002	0.010	0.025
Threat by market entries	0.020	0.036	-0.002	0.009	0.020
High market uncertainty	0.026	0.038*	0.012	0.021*	0.009
Threat by foreign comp.	-0.004	0.002	-0.014*	-0.013	0.012
High price elast. dem.	0.002	-0.013	0.006	-0.004	-0.004
Industry (ref.: metals)					
Consumer products	0.101**	0.089**	0.017	0.012	0.076*
Non-metal materials	0.041	0.023	-0.004	-0.012	0.044
Chemistry/pharmaceut.	-0.004	-0.018	-0.002	-0.006	0.001
Electronics, electr. equ.	0.103**	0.082*	0.019	0.002	0.084**
Machinery, vehicles	0.049	0.035	0.004	-0.002	0.045
Utilities, waste manag.	-0.000	-0.048	0.020	-0.017	-0.042
Construction, trade	0.143***	0.108**	0.013	-0.008	0.122***
Transport	0.039	0.027	-0.000	-0.011	0.034
Media services	0.342***	0.214***	0.044	-0.045**	0.295***
IT services	0.392***	0.382***	0.022	0.007	0.361***
Financial/consult. serv.	0.431***	0.376***	0.035	-0.005	0.397***
Technical/R&D services	0.112**	0.076*	0.014	-0.006	0.098**
Other industries	0.132***	0.112**	0.001	-0.008	0.131***
# observations	4,972	4,972	4,972	4,972	4,972
# AI users	1,439	1,726	229	516	1,210

***, **, *: statistically significant at p<0.01, p<0.05, p<0.1

Source: German CIS, own calculations

5. Productivity effects of adopting AI

Empirical evidence from a variety of countries, firms, and productivity metrics suggests that AI adoption is positively associated with firm-level productivity gains. Before the recent surge in generative AI applications, studies have exploited establishment-level surveys, job-vacancy and resume data, and AI-patent filings to estimate the productivity impact of AI-related investments. A key caveat, however, is that adopters often differ systematically from non-adopters, complicating causal inference. With the advent and public release of generative AI tools, such as ChatGPT, Claude, and GitHub Copilot, new empirical work has shifted to measuring the effects of AI use on individual worker productivity. These studies leverage experimental or quasi-experimental variation in task execution to identify causal effects, yielding precise estimates for specific activities but limiting generalizability beyond those narrow contexts or tasks.

Babina et al. (2024) exploit U.S. vacancy data from 2007 to 2018 to show that firms' AI investments are positively linked to subsequent growth and valuation: a one-standard-deviation increase in the share of AI-skilled employees corresponds to 18–22% higher sales, employment, and market value. The authors attribute these gains to both product and process innovations, which in turn lower operating costs and drive firm expansion. Using an establishment-level AI-exposure index derived from occupational data, Acemoglu et al. (2022) find that AI systems deployed between 2007 and 2010–2018 functioned primarily as task replacers, yielding more modest productivity improvements. Complementing these findings, several studies report an AI-skill wage premium: workers with AI competencies earn higher wages, consistent with the productivity gains associated with these skills (Alekseeva et al., 2021; Bone et al., 2024).

Firm-level analyses of AI patenting further corroborate the positive productivity effects of AI adoption. Damioli et al. (2021) examine a global sample of companies that filed AI-related patents between 2000 and 2016 and find that each additional AI patent application is associated with higher revenue per employee. In the United States, Alderucci et al. (2020) report that firms with AI patents exhibit greater output per worker than non-patentees. Using European patent data from 2009 to 2014, Benassi et al. (2022) show that a larger stock of "Fourth Industrial Revolution" patents (including AI) correlates with higher firm-level productivity. More recently, da Silva Marioni et al. (2024) exploit variation in AI patenting success across France, Germany, Italy, and the U.K. between 2011 and 2019 to estimate productivity gains attributable to AI. Depending on the model specification, they report productivity effects ranging from 2.1 to 17%.

The final group of analyses draws on firm-level survey data to assess AI's productivity impacts without experimental variation. For instance, Calvino & Fontanelli (2022) examine OECD firms from 2016 to 2021 and find that AI-using companies exhibit 4–15 percent higher labor productivity, measured as turnover per employee, although this association attenuates once other ICT investments are controlled for. Similarly, Czarnitzki et al. (2023) employ an instrumental-variable approach on 2018 German survey data to demonstrate that AI adoption boosts both sales and value-added, a finding corroborated by Licht & Wohlrabe (2024) in their subsequent German study. Calvino & Fontanelli (2025) analyze 2019 French establishments and report that productivity gains occur primarily among firms developing new AI technologies in-house. In contrast, Acemoglu et al. (2022) use the 2019 U.S. Annual Business Survey, which captures multiple advanced technologies, and find no significant link between AI adoption and labor productivity, noting that this null result may reflect either a lag in realizing AI's benefits or measurement confounding from concurrent technology uptake (e.g., cloud computing). Across these non-experimental studies, the evidence consistently points to larger firms capturing greater productivity gains from AI, in line with the resource-buffer hypothesis outlined earlier.[3]

Following the recent surge in generative AI, several studies have used experimental or quasi-experimental designs to quantify its impact on employee task performance. In a controlled trial, Peng et al. (2023) find that software developers granted access to GitHub Copilot completed tasks 56% faster than a control group. Cui et al. (2025) show similar findings in field experiments with professional programmers. In an online experiment, Noy and Zhang (2023) randomly assigned participants to use ChatGPT for mid-level professional writing tasks and observed significant improvements in both completion time and output quality. Brynjolfsson et al. (2025) exploit variation in tasks performed by customer-support agents and report a 15% productivity boost, along with enhanced worker learning and job satisfaction, when AI assistance is available. Dell'Acqua et al. (2025) show that consultants

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[3] Empirical evidence from studies of advanced digital technologies related to AI, such as the Internet of Things, advanced robotics, and cloud computing, suggests similar productivity effects on firm performance across countries (Behrens & Trunschke, 2020; DeStefano et al., 2023; Nucci et al., 2023).

randomly given access to GPT-4 produce higher-quality deliverables and work more efficiently. Notably, these studies consistently find that lower-skill workers account for a large share of productivity gains from generative AI. However, because the evidence is task-specific, translating these results into firm-level productivity estimates remains challenging.[4]

6. Conclusion

The evidence reviewed in this chapter highlights the rapid diffusion of artificial intelligence (AI) across firms, with adoption patterns shaped by a combination of technological capabilities, organizational characteristics, and sector-specific dynamics. While core enablers such as firm size, R&D intensity, and workforce skills consistently increase the likelihood of AI adoption, important heterogeneity emerges across different adoption strategies and technologies. Firms developing AI in-house, adopting early, or implementing generative AI tend to be larger, younger, and more innovation-intensive than their peers. At the same time, the broader availability of off-the-shelf AI tools has expanded access to a wider range of firms, supporting the continued diffusion of AI technologies. Productivity estimates from both firm-level and task-based experimental studies point to meaningful gains from AI use, particularly among firms with strong absorptive capacity or among lower-skill workers assisted by generative AI. Taken together, this outlook highlights that AI adoption is not only accelerating but also becoming more diverse in its drivers, uses, and potential impacts across firms and sectors.

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[4] Related studies examine generative AI's impact on worker productivity in legal analysis (Choi & Schwarcz, 2023), job-post writing assistance (Wiles & Norton, 2024), and advisory support for small entrepreneurs (Otis et al., 2024).

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APPENDIX A

Add sample selection criteria and variable definitions used in Tables 1 and 2.