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Annalisa Ferrando, Sara Lamboglia, Judit Rariga, Maurice Schmidt

Adoption and investment in AI across the euro area

Insights from harmonised firm-level data

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Contents

Abstract

This paper explores the adoption of artificial intelligence (AI) technologies among euro area firms, using harmonised firm-level data from two dedicated modules of the Survey on the Access to Finance of Enterprises (SAFE) conducted in June and December 2025. Based on responses from around 6,000 firms across 12 euro area countries, the study examines AI adoption rates, drivers, barriers and economic implications. The findings suggest that AI diffusion among euro area firms is progressing rapidly but unevenly, with significant variation across countries and firm characteristics. Approximately 70% of firms report some level of AI use, but only 7% classify their adoption as significant. Adoption is highest in the Netherlands, Finland and Austria, and lowest in Italy and Ireland. Larger and younger firms, particularly in technology-intensive sectors, are leading adopters. Firms identify expected improvements in business processes as the main driver of adoption, while key barriers include skill shortages, data privacy concerns and system incompatibilities. Current AI use and investment are primarily financed through internal funds, complemented by grants and subsidised bank loans. AI adoption is positively associated with firm productivity, turnover growth, fixed investment and own selling price expectations, particularly among intensive users. Survey data show no evidence yet of aggregate labour shedding; instead, AI adoption is positively associated with employment growth. However, firms' inflation expectations appear largely unaffected by current AI use.

JEL codes: C93, D22, E31, L25, O33

Keywords: artificial intelligence, firm-level survey data, productivity, inflation expectations

Non-technical summary

Artificial intelligence (AI) is increasingly viewed as a transformative technology with the potential to reshape production processes, business models and economic structures. Whether AI will raise productivity, lower costs, affect prices and ultimately alter the macroeconomy depends critically on how broadly and deeply firms adopt it. For monetary policymakers, understanding the pace and distribution of AI adoption is essential to assess implications for inflation, investment and potential output.[1]

This paper provides the first comprehensive cross-country picture of AI adoption among euro area firms, drawing on two dedicated modules of the European Central Bank (ECB) and European Council Survey on the Access to Finance of Enterprises (SAFE), a harmonised firm-level survey covering over 6,000 firms across 12 euro area countries. The June 2025 module focused on past AI investment and its share of total investment, while the December 2025 module examined the depth of AI use across technologies, motives and barriers, financing patterns, business expectations (such as turnover and selling prices) and planned investment.

Around 70% of euro area firms report some AI use, but only 7% describe their use as significant – a share that is similar across size classes, pointing to a common ceiling on intensive adoption. About 30% remain non-users, indicating that AI has not yet diffused uniformly. Adoption rates differ markedly across countries: the Netherlands, Finland and Austria report AI use above 80%, while Italy and Ireland fall below 65%. These gaps reflect both the proportion of non-adopters and the depth of use among adopters, implying that policy priorities differ between countries focused on triggering initial adoption and those focused on scaling up intensive use.

Firm characteristics systematically shape adoption. Large firms are more likely to use AI, but the share of significant users is similar across sizes. Firms founded around or after the emergence of advanced large language models in late 2022 show substantially higher rates of intensive AI use, suggesting that they embedded AI into operations from inception. Sectoral differences are pronounced: firms in technological sectors have the highest share of significant adopters, while for construction, accommodation and transport it is low. Listed and venture capital-backed firms are among the most advanced users; family-owned and single-owned firms are concentrated among non-users or infrequent adopters.

The primary motivation for adopting AI is the improvement of core and non-core business processes, a pattern that holds across countries, sizes and sectors. Personnel cost reduction and support for research and development and innovation play secondary roles. Among non-adopters and limited users, the most frequently cited barrier is a lack of AI skills, followed by data, privacy and ethical concerns, and incompatibility with existing systems. The perception that AI is not useful is more common among micro and small firms.

AI adoption and investment are predominantly financed through internal funds, grants and subsidised bank loans provided by public entities, with conventional bank

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[1] See also Lagarde (2025a) and Lagarde (2025b).

loans also providing some support. For small and medium-sized enterprises (SMEs), all three sources are significantly associated with both current AI use and planned AI investment, while for large firms, internal funds and subsidised bank loans dominate and bank lending plays no significant role in expected AI investment. This pattern is consistent with euro area SMEs being more reliant on bank loans than large firms.

Firms making significant use of AI report substantially higher expectations for turnover growth and fixed asset investment, consistent with a self-reinforcing dynamic in which AI-intensive firms perceive their competitive positions as strengthening. Only significant users – not infrequent or moderate users – expect higher own selling prices, by around 0.85 percentage points relative to non-users, suggesting a greater cost pass-through or quality improvements for these firms. Wage and input cost expectations do not differ significantly across adoption categories, indicating that broader labour market and cost effects remain limited at the current stage.

In terms of productivity, there is no statistically significant difference between AI users and non-users. However, firms in technological sectors that adopt AI are significantly more likely to report higher current and expected productivity. Even low-intensity use is associated with productivity increases in this sector, suggesting that the initial adoption step matters most. However, future productivity is expected to increase only among firms that make significant use of AI.

On employment, our findings do not show any evidence of workforce reduction. On the contrary, the positive connection to employment expectations suggests that AI adoption may be associated with an increase in workforce demand rather than job cutbacks.

We find no relationship between current AI adoption and inflation expectations. The main exception is moderate AI users, who report consistently lower expected euro area inflation across all horizons.

The paper reports findings from a randomised controlled trial conducted as part of the December 2025 survey and introduced in Baumann et al. (2025). The trial provided firms with information about domestic competitors' historical investments in AI. Approximately 10% of firms anticipate investing in AI in the near future, though there is considerable variation across firms. Notably, firms tend to significantly underestimate the prevalence of AI adoption among their competitors. Around 80% of firms underestimate the proportion of AI adopters within their sector, country and size category, with the average underestimation amounting to approximately 18 percentage points. Larger firms appear to underestimate AI adoption rates more than SMEs, potentially due to their perception of being market leaders. Misperceptions are least pronounced in digitally intensive sectors, where firms likely have better competitive intelligence about cutting-edge technologies.

When provided with information about competitors' previous AI investments, Baumann et al. (2026) find that firms adjust their expectations about future competitor adoption upward by roughly 4 percentage points and increase their own planned AI investment rates by nearly 2 percentage points. These findings highlight the role of informational frictions in slowing the diffusion of emerging technologies. They suggest that disseminating knowledge about aggregate adoption patterns – through statistical publications or surveys – could help accelerate the spread of new technologies like AI.

1 Introduction

Artificial intelligence (AI) is increasingly recognised as a transformative general-purpose technology with the potential to revolutionise production processes, business models and economic structures across industries. Like previous general-purpose technologies, however, its macroeconomic effects will depend not only on the pace of technological progress, but also on how widely, deeply and effectively firms adopt it. Understanding which firms use AI, what motivates or prevents adoption, how firms finance AI-related investment and how AI use affects firms' expectations for productivity, prices and broader economic outcomes is therefore key for both economic research and policymaking.[2]

Between 2014 and 2024 digital investment in the euro area grew at a remarkable pace, outstripping overall GDP growth by more than three times and exceeding the growth rate of total business investment by 1.5 times (Lane, 2026). Intangible investments – such as software, databases, and research and development spending in the information and communication sector – comprised the majority of digital investment during this period. By 2025 digital investment accounted for approximately 13% of total investment in the euro area, significantly lower than the 27% share observed in the United States (Andersson et al., 2026).

Against this backdrop of rapid, and potentially uneven, digital transformation, this paper aims to deepen our understanding of AI adoption and investment by utilising unique, harmonised firm-level data from the Survey on the Access to Finance of Enterprises (SAFE), conducted jointly by the European Central Bank (ECB) and the European Commission. For the first time, the 2025 survey rounds included dedicated ad hoc modules focused specifically on AI adoption and investment.

The June 2025 round asked firms whether they had invested or were currently investing in AI, defined as technologies that streamline processes and production, including data analysis, customer service tools and process automation. Firms were also asked to report the share of their total investment allocated to AI. The December 2025 round broadened the focus to the use of specific AI technologies, including predictive tools (e.g. machine learning and voice/image recognition), generative tools (e.g. chatbots and content creation) and robotic process automation. It also collected information on barriers to adoption and on firms' expectations about competitors' AI investment.

The evidence reveals a rapidly evolving and yet markedly uneven diffusion of AI across euro area firms. According to the December 2025 SAFE round, around 70% of euro area firms report some degree of AI usage – ranging from experimental engagement to significant integration. Yet intensive use remains limited: only 7% of firms report significant AI adoption. This share is broadly similar across firm size classes, suggesting that deep AI integration is not exclusively a feature of large firms. At the same time, overall adoption rates differ substantially across countries.

[2] See also Lagarde (2025a), Lagarde (2025b) and Lane (2026).

AI use is highest in the Netherlands, Finland and Austria, where more than 80% of firms report some form of adoption, and lowest in Italy and Ireland, where the share falls below 65%. These cross-country differences reflect not only variation in the share of non-adopters but also differences in the depth of use among adopters. For instance, in the Netherlands and Belgium, nearly one in five firms report significant AI use, well above the euro area average, whereas in many southern and eastern euro area countries, adoption remains concentrated at the experimental or moderate stage.

Firm characteristics are also strongly associated with AI adoption. Large firms are much more likely to use AI than small and medium-sized enterprises (SMEs): 87% of firms with at least 250 employees report some AI use, compared with 60% of micro firms. However, the share of significant AI users is broadly consistent across size classes, at around 7-8%, suggesting that intensive AI integration is not confined to large firms. Sectoral differences are particularly pronounced as well. Firms in information and communications technology (ICT) and research and development (R&D) exhibit the highest levels of significant AI use, while those in construction show the lowest. Firm age matters as well: younger firms – particularly those founded around or after the emergence of advanced large language models (LLMs) in late 2022 – demonstrate higher rates of intensive AI use than mid-aged firms. This pattern is consistent with the possibility that these younger firms integrated AI into their business models from inception. Ownership structure is another relevant dimension: listed and venture capital-backed firms are among the most advanced users, whereas family-owned and single-owned firms are more concentrated among non-users or infrequent adopters.

Our findings align with other firm-level studies conducted across countries. Yotzov et al. (2026) report that approximately 70% of firms in the United States, United Kingdom, Germany and Australia use some form of AI – a figure consistent with euro area evidence from the SAFE data – and that adoption is more prevalent among larger, more productive and higher-paying firms, corroborating patterns identified in our analysis. Similarly, Calvino, Costa and Haerle (2026), using harmonised microdata from 15 Organisation for Economic Co-operation and Development (OECD) countries, find that larger firms are on average 20 percentage points more likely to adopt AI than small firms, with AI and big data analysis concentrated in ICT and professional services sectors. They also highlight the critical role of human and technological capital, including ICT skills, training and digital infrastructure, as key complements to adoption.

SAFE evidence also indicates that the reasons for adopting AI tend to be broadly consistent across firms, while the barriers they encounter are more varied. The dominant motivation for adopting AI is the improvement of core and non-core business processes. Other relevant motives include reducing personnel cost and supporting innovation-related activities. By contrast, barriers to adoption – such as shortages of AI-related skills, ethical and data privacy concerns, and incompatibility with existing systems – vary more systematically by firm size and country. This suggests that the constraints slowing AI diffusion are heterogeneous and may require tailored policy responses.

The survey also points to an informational barrier: many firms substantially underestimate the extent to which their competitors are investing in AI. On average, firms underestimate the share of AI investors among comparable competitors by around 18 percentage points. Such misperceptions may weaken competitive pressure as a driver of adoption and thereby slow the diffusion of AI technologies.

The SAFE data make it possible to examine how firms finance AI adoption. While the survey focuses mainly on traditional forms of financing, such as bank-based funding or internal resources, clear patterns emerge. AI adoption is predominantly funded through internal resources, while grants, subsidised bank loans (public support provided in the form of guarantees or reduced interest rate loans) and bank loans play a secondary but still relevant role. This pattern holds across firm sizes, but with important nuances. For SMEs, internal funds, subsidised bank loans and bank loans are all significantly associated with current AI use and expected AI investment. For large firms, by contrast, internal funds and subsidised bank loans dominate, while bank loans do not play a significant role in planned AI investment. Sectoral heterogeneity is also important. In industry all three financing sources matter, while in services and trade, internal funds are the key channel. Subsidised bank loans provide meaningful complementary support particularly in ICT and R&D. Among ownership types, reliance on self-financing is particularly evident among family-owned and single-owned firms. These patterns are consistent with broader evidence that the euro area's bank-centred financial system may be less well suited to the intangible, long-horizon investments often required for AI adoption, especially compared with economies where (public and private) equity have a larger scale and venture capital and private credit markets are deeper.

A key aim of this paper is to examine how the intensity of AI adoption shapes firms' forward-looking expectations across a range of economic outcomes. Controlling for firm size, sector and country, firms making significant use of AI report substantially higher expectations for turnover growth and fixed asset investment than non-users. This suggests a potentially self-reinforcing dynamic: firms that have already integrated AI more extensively tend to be more optimistic about their future growth and investment prospects.

With respect to prices, firms making significant use of AI anticipate higher selling prices over the next 12 months, by around 0.85 percentage points relative to non-users. No comparable effect is observed among infrequent and moderate users, suggesting that upward price effects may arise once AI adoption becomes sufficiently deep. This may reflect the pass-through of AI-related investment costs, quality improvements or changes in firms' market positioning. Conversely, there seems to be no indication that AI adoption might lead to lower selling prices, notwithstanding potential efficiency gains. Additionally, there are no statistically significant differences in wage or input cost expectations across adoption categories, suggesting that firms do not yet anticipate notable labour cost savings or reductions in intermediate input costs from AI. At the same time, the evidence does not indicate a strong or consistent relationship between AI adoption and firms' aggregate inflation perceptions.

The paper also investigates the relationship between AI adoption and productivity. Using a novel productivity proxy constructed from SAFE survey responses on changes in turnover and employment – and validated against more traditional measures of labour productivity based on firms' financial statements – we find that the association between AI adoption and firm-level productivity is positive but heterogeneous across sectors. On average, there is no statistically significant difference in productivity between AI users and non-users. However, firms in the ICT and R&D sector that use AI are significantly more likely than non-users to report both higher current productivity and higher expected productivity. For current productivity, even low-intensity AI use is associated with a higher likelihood of productivity gains, suggesting that the initial adoption step may be particularly important. For expected productivity, the effect is statistically significant only among firms making significant use of AI, pointing to a non-linear relationship between adoption depth and forward-looking performance gains.

On employment patterns, our findings currently show no evidence of labour shedding, with AI seemingly complementing rather than replacing workers at this stage. However, as these results are based on a snapshot, they cannot provide insights into potential longer-term shifts or displacement risks.

On inflation expectations, the evidence shows no clear overall relationship between current AI adoption and projected aggregate inflation. The main exception is firms with moderate AI adoption, which consistently report lower expected euro area inflation across all time horizons, with the gap widening at longer time horizons: approximately 0.4 percentage points lower at the one-year horizon and 0.8 percentage points lower at the five-year horizon. The absence of a strong link between AI adoption at the firm level and aggregate inflation expectations is consistent with the theoretical ambiguity surrounding the macroeconomic effects of AI, as recently highlighted by Lane (2026). AI has the potential to exert disinflationary pressures by improving productivity and lowering some costs. However, it may also boost aggregate demand, require costly complementary investments or increase prices through quality enhancements and market power effects. At its current stage of adoption, these competing forces do not yet appear to result in a clear or consistent impact on firms' aggregate inflation expectations.

Firms' planned AI investment further illustrates the uneven and potentially self-reinforcing nature of its diffusion. On average, firms expect to allocate 9% of their total investment to AI over the next year, but planned investment varies significantly based on current adoption intensity. Firms already using AI, especially significant users, plan to invest substantially more than non-users. This suggests a reinforcing cycle where early adopters continue to deepen their use of AI, while non-users and infrequent users risk falling further behind. Service firms lead AI investment, particularly in ICT and R&D, due to their proximity to the technological frontier and the scope for AI in data-intensive and intangible activities. Some SMEs also plan to invest in AI, and their expected AI investment rates are close to those of large firms. However, AI-investing SMEs remain a relatively small group and account for only a limited share of total euro area employment. Most SME AI investors are infrequent or moderate users, and they are concentrated mainly in industry and services.

To better understand the influence of competitive pressure on AI investment decisions, Baumann et al. (2025) designed a randomised controlled trial in the December 2025 SAFE round. The experiment was designed to test whether firms' perceptions of competitors' AI investment affect their own planned AI investment. Initially, firms were asked to estimate the share of comparable domestic competitors investing in AI. A randomly selected treatment group was then provided with information on the actual share of comparable firms investing in AI, based on data from the June 2025 SAFE round, while the control group received no such information. As shown by the authors, the results revealed that firms systematically underestimate the extent of competitors' AI investment. When informed about competitors' actual AI investment, treated firms revised their estimates upward and reported higher expected own AI investment rates compared with their non-treated peers. This suggests that informational frictions can influence the diffusion of AI and that reporting on competitors' behaviour can strengthen firms' incentives to invest. This finding may also point to "fear of missing out" behaviour driving AI use and investment, over and above the specific business case and prospects of efficiency gains.

The results presented in this paper contribute to three main strands of the rapidly growing literature on AI and firm behaviour. The first strand focuses on the diffusion of AI technologies and the factors shaping their adoption. Existing studies highlight the clustering of AI adoption among large and high-performing firms (Acemoglu and Restrepo, 2022; Acemoglu, 2024; Babina et al., 2024), emphasising the role of knowledge intensity, labour costs and managerial capacity as key predictors of adoption (Bencivelli et al., 2025; Ropele and Tagliabracci, 2026). Our euro area evidence supports and builds upon these findings by showing that firm characteristics affect not only whether firms adopt AI, but also the extent to which they integrate AI into their operations.

The second strand examines the economic effects of AI adoption. This body of research demonstrates that AI can enhance labour productivity and profitability while facilitating the reallocation of employment toward higher-skilled occupations (Czarnitzki et al., 2023; Ropele and Tagliabracci, 2026). However, studies have also highlighted potential risks such as job displacement, growing inequality and increasing productivity dispersion (Acemoglu and Restrepo, 2019; Acemoglu, 2021). Recent evidence also points to substantial heterogeneity in the effects of AI. Bergeaud (2024) finds that AI's impact on European productivity varies by labour shares, task exposure and adoption feasibility. Aldasoro et al. (2026) show AI improves productivity via capital deepening, with benefits concentrated in medium to large firms. Complementing this perspective, Yotzov et al. (2026) provide forward-looking evidence showing that firms expect AI to boost productivity while reducing employment, although realised effects on workforce dynamics have so far remained modest. In the French context, Calvino and Fontanelli (2026) find that the positive AI-productivity relationship holds primarily for firms that develop AI in-house, whereas firms relying on external AI solutions exhibit no significant productivity premium.

Within the same strand of literature, other studies highlight the importance of complementary investments like workforce training and software infrastructure, emphasising the role of intangible capital and human-AI complementarities in productivity gains. Calvino, Costa and Haerle (2026) find that AI adopters' productivity premiums diminish once human and technological capital are considered, with pre-existing digital capabilities driving advantages more than AI itself. These findings align with theories of technology diffusion that point to uneven adoption across firm sizes and countries (Comin and Mestieri, 2018) and macroeconomic analyses identifying barriers like skill gaps and organisational inertia (Acemoglu, 2024; Aghion and Bunel, 2024; Filippucci, Gal, and Schief, 2024).

Interestingly, Babina (2026) suggests that the mixed findings might arise from variations in measurement approaches, such as patent-based data versus survey-reported usage. Building on this evidence, our analysis highlights sectoral heterogeneity and demonstrates that productivity gains from AI adoption are presently concentrated in knowledge-intensive sectors, such as ICT and R&D.

The third strand of literature investigates how technological innovation influences firms' expectations. Previous research reveals that firms adjust their beliefs in response to aggregate economic shocks and information treatments (Coibion and Gorodnichenko, 2015; Weber et al., 2022; Cullen et al., 2025). More recently, Ropele and Tagliabracci (2026) find that Italian firms adopting AI anticipate lower medium-term to long-term inflation, reflecting a gradual incorporation of expected efficiency gains into their pricing strategies. This paper adds to this literature by analysing the relationship between adoption intensity – ranging from experimental to significant use – and euro area firms' expectations for turnover, investment, prices and inflation in a harmonised cross-country context. In addition, we report the recent results of Baumann et al. (2026) showing that information about competitors' AI investments influences firms' intended AI investment behaviour.

In summary, this paper contributes to a deeper understanding of AI adoption and investment and its implications for firm-level outcomes. It highlights the uneven adoption of AI across firm sizes, countries and sectors, suggesting that significant integration is concentrated among firms with advanced digital capabilities, better access to financing and proximity to the technological frontier. While AI adoption has the potential to support firm-level productivity and growth, its broader macroeconomic effects are likely to depend on the speed and extent to which adoption spreads beyond early adopters and knowledge-intensive industries. The findings also underscore the importance of complementary investments, favourable financing conditions, workforce skills development, organisational adaptability and better information flows in driving the next phase of AI diffusion.

The remainder of this paper is structured as follows. Section 2 describes the SAFE survey and its AI-related modules conducted in June and December 2025. Section 3 examines heterogeneity in AI adoption across countries, firm sizes, sectors, ages and ownership structures. Section 4 explores the drivers and barriers to AI adoption. Section 5 analyses the financing of AI investments. Section 6 presents regression evidence on the relationship between AI adoption and firms' expectations for indicators of business activity, their selling price expectations and aggregate inflation. It also includes a box on the relationship between AI adoption and productivity. Section 7 investigates firms' expected future AI investments by adoption intensity and firm characteristics. Section 8 briefly reports the results of Baumann et al. (2026) on firms' perceptions of competitors' AI investments and the role of competitive pressure in shaping firms' own future AI investment. Finally, Section 9 concludes.

2 AI adoption and investment in the SAFE

The Survey on the Access to Finance of Enterprises (SAFE) is a European firm-level survey launched in 2009. Initially conducted biannually, its frequency increased to a quarterly basis starting in January 2024. Each round includes a sample of approximately 6,000 firms from 12 euro area countries: Austria, Belgium, Germany, Spain, Finland, France, Greece, Ireland, Italy, Netherlands, Portugal and Slovakia. Once a year the sample is increased to 11,000 firms from all euro area countries. The fieldwork typically lasts three to five weeks, with interviews primarily conducted via computer-assisted telephone interviewing (CATI). Some firms complete the questionnaire online using computer-aided web interviewing (CAWI). Responses are provided by senior executives, such as general managers, financial directors or chief accountants, who are knowledgeable about the firm's key business activities and decisions.

The survey gathers information on firm-level structural characteristics, recent economic developments and financing conditions, including firms' financing needs and access to finance. The sample consists of non-financial firms from the manufacturing, construction, trade and services sectors, stratified by country, enterprise size and sector to ensure broad representation. Published statistics are weighted to reflect the economic significance (e.g. number of employees) of each size class, sector and country.

In June 2025 and December 2025 the survey included ad hoc questions on the adoption of and investment in AI technologies, as detailed in the next subsection.[3]

2.1 June 2025 survey round

In June 2025 the survey asked firms whether they had ever invested in or were currently investing in AI technologies. Firms were provided with the following definition:

"*Firms of all sizes can use artificial intelligence to streamline internal processes and production. Common applications include data analysis, customer service enhancement and process automation. For example, artificial intelligence helps anticipate customer demand, optimise inventory as well as provides chatbots and content creation tools.*" It then asked firms to indicate the percentage of their total investment devoted to AI over the past 12 months.

[3] See Survey on the Access to Finance of Enterprises – second quarter 2025 questionnaire , ECB, July 2025 and Survey on the Access to Finance of Enterprises – fourth quarter 2025 questionnaire, ECB, February 2026.

2.2 December 2025 survey round

In December 2025 the survey focused on AI adoption and the reasons for (or barriers to) its use. Firms were asked to assess their use of specific AI technologies, including predictive tools (e.g. text mining, voice and image recognition, machine learning), generative tools (e.g. chatbots, text or image generation) and robotic process automation. The question was phrased as follows:

QA1 : "How would you assess the use of AI technologies in your firm? 1. Not currently in use; 2. Very infrequent use or use in pilot projects/experimentally; 3. Moderate use; 4. Significant use; 5. Don't know"

Of the 5,067 firms surveyed, 3,268 reported using AI technologies to varying degrees. These firms were then asked to identify the two main reasons for adopting AI:

QA2: "Please indicate the two main reasons your firm is using AI technologies: 1. Reduce personnel costs; 2 Improve non-core area processes (i.e. quality or efficiency in administrative and other supporting tasks); 3. Improve core area processes (i.e. quality or efficiency in core activities of the firm; 4. Expand the range of products or services; 5. Support R&D and/or innovation; 5. Don't know."

For firms that reported limited use of AI (4,614), the survey explored the reasons for either not using AI or not using it more intensively[4]:

"*QA3: Please indicate the two main reasons for either not using AI or not using AI more intensively in your firm: 1. AI is not useful for my firm; 2. AI costs exceed expected benefits; 3. Lack of AI skills; 4. Data/privacy/ethical concerns; 5. Distrust of AI-based results; 6. Incompatibility with existing systems; either software or hardware; 7. Don't know"*

In the same survey wave, a randomised control trial was proposed by Baumann et al. (2025) aiming to assess firms' awareness of AI investment among competitors.[5] Firms were first asked about the perceived diffusion of AI investment in their country and in three major euro area countries (Germany, France and Italy) up to June 2025:

"QB1: Thinking about other firms like yours, in the same sector and of a similar size, what percentage of these do you think had invested in AI technologies up to June 2025? 1. In your country; 2. In Germany, France and Italy"

Firms were also asked to estimate the expected share of similar firms making AI investments in the next 12 months. For this question, half of the sample received information on competitor behaviour, as reported in the June 2025 survey (Table 1), while the other half received no information:

"QB2: Thinking about the next 12 months, what percentage of firms similar to yours do you expect to make investments in AI technologies? 1. In your country; 2. In

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4 Both questions were posed to a subsample of 2,914 firms that were using AI but not to a significant degree.

5 The randomised control trial is registered at the AER RCT Registry.

Germany, France and Italy [READ IF NECESSARY: Please provide your best estimate of the average percentage across these three countries."[6]

Finally, all firms were asked about their own investment plans in AI over the next 12 months.

"QA4: Over the next 12 months, what percentage of your firm's total investment do you expect to allocate to AI technologies?"

6 For further details, see Baumann et al. (2026).

3 AI adoption: a tale of heterogeneity

The adoption of AI among firms in the euro area is advancing along a dynamic but uneven path, with significant variation across countries and firm characteristics. These differences highlight the diverse challenges and opportunities firms face as they transition from experimentation to the integration of AI technologies into their operations.

3.1 Across countries

Across the euro area, firms are experimenting with and gradually integrating AI technologies. Around 70% report varying levels of AI adoption: 33% use it experimentally, 31% apply it moderately, and 7% report significant implementation.

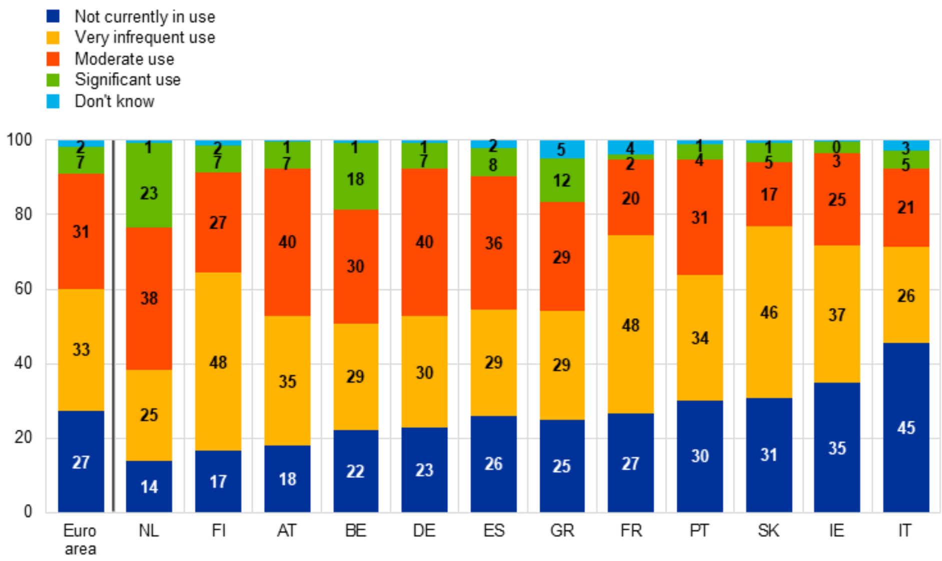
The survey evidence points to sizeable cross-country differences in the diffusion of AI use (**Chart 1**). The share of firms using AI is highest in the Netherlands, Finland and Austria (at 85%, 82% and 81% respectively), followed by Belgium and Germany (both at 77%). Spain, France, Greece, Portugal and Slovakia are broadly aligned with the euro area average, while Ireland and Italy exhibit the lowest adoption rates (at 65% and 52% respectively).

The intensity of adoption also varies considerably across euro area countries. The Netherlands and Belgium stand out as leaders in intensive AI adoption: 23% of firms in the Netherlands report significant AI use, followed by 18% in Belgium, well above the euro area average of 7%. By contrast, Finland, France, Ireland, Italy, Slovakia and Portugal report the lowest proportions of firms with moderate or significant AI adoption, ranging from 22% in Slovakia and France to around 35% in Portugal and Finland, all below the euro area average of 38%. A third group of countries, consisting of Austria, Germany, Spain and Greece, exceeds the euro area average but remain below the frontrunners, with the share of firms reporting moderate or significant use ranging from 41% in Greece to 47% in Germany and Austria.

Chart 1

Use of AI across euro area countries

(percentages of respondents)



Source: Survey on the Access to Finance of Enterprises (SAFE).
Notes: The chart shows the weighted share of firms by the intensity of AI use, for all euro area firms and by country. Countries are sorted by share of firms that do not currently use AI.

Taken together, this cross-country evidence suggests that AI adoption in the euro area cannot be reduced to a simple distinction between “leaders” and “laggards”. Rather, countries differ both in the size of their non-adopting firm segment and in the depth of AI use among adopters. The euro area average adoption rate of around 70% is also strikingly consistent with the findings of Yotzov et al. (2026), who report a similar share across four major economies (United States, United Kingdom, Germany and Australia) surveyed over the same period, suggesting a broadly convergent pattern of AI diffusion across advanced economies. Cross-country heterogeneity in AI adoption is also documented in Calvino, Costa and Haerle (2026), who use harmonised firm-level microdata across 15 OECD countries to show that, while AI adoption has been rising, significant variation persists across sectors and countries. A similar pattern of heterogeneity in AI adoption is also reported by the European Investment Bank (EIB) (2026), indicating that policy challenges vary across countries: in some the priority is to move a large share of firms from non-use to initial experimentation, while in others the key challenge is to support a broad base of experimental users in scaling up towards more intensive AI deployment.

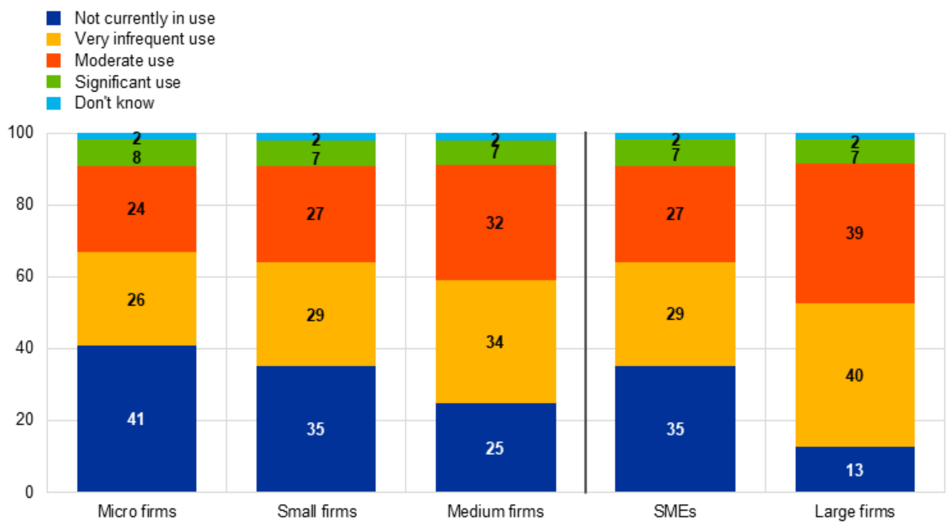
3.2 Across firm demographics (size, sector, age, ownership)

When analysed by firm size, non-use of AI is substantially more common among SMEs than among large firms (**Chart 2**). Around 35% of SMEs report not using AI at all, compared with 13% of large firms. Within the SME segment, non-use is highest among micro firms, at 41%, declining to 35% among small firms and 25% among medium-sized firms. At the same time, the share of firms at an intermediate stage of adoption – defined as using AI at least very infrequently or moderately – increases steadily with size: from 50% of micro firms to 56% of small firms, 66% of medium-sized firms and 79% of large firms. Conversely, the share of firms at an advanced stage of AI adoption (namely significant users) remains modest but relatively similar across all size classes, at around 7-8%. Overall, the evidence indicates that, while firm size is strongly associated with whether firms adopt AI at all, intensive use remains limited to a core group of firms and is relatively evenly distributed across firm size classes.

Chart 2

Use of AI, by firm size

(percentages of respondents)



Source: Survey on the Access to Finance of Enterprises (SAFE).
Notes: The chart shows the weighted share of firms by the intensity of AI use and firm size. Size classes are micro firms (less than 10 employees), small firms (between 10 and 50), medium firms (between 50 and 250) and large firms (more than 250 employees). "SMEs" stands for small, micro and medium firms (below 250 employees).

Looking across sectors reveals notable disparities in AI adoption (**Chart 3**). Panel a) presents results for the four main sectors – construction, trade, industry and services – based on the sectoral composition in the survey. Panel b) offers a more granular breakdown of the services sector into three subsectors: ICT and R&D; accommodation and transport; and other services.[7]

In the construction sector, the share of firms not currently using AI is the highest, at 34%, while the share of advanced users is the lowest, at 4%. This points to the low pace of technological integration in the sector compared with others. By contrast, moderate or infrequent AI use is relatively evenly distributed across the other sectors, indicating that firms are widely exploring AI applications, though often at an early stage. Services show the highest share of advanced users, at 10%, compared with 4-5% in the other sectors. A more granular sectoral breakdown reveals substantial heterogeneity within the services sector. Firms in ICT and R&D exhibit the lowest share of non-users, at 9%, and the highest share of advanced users, at

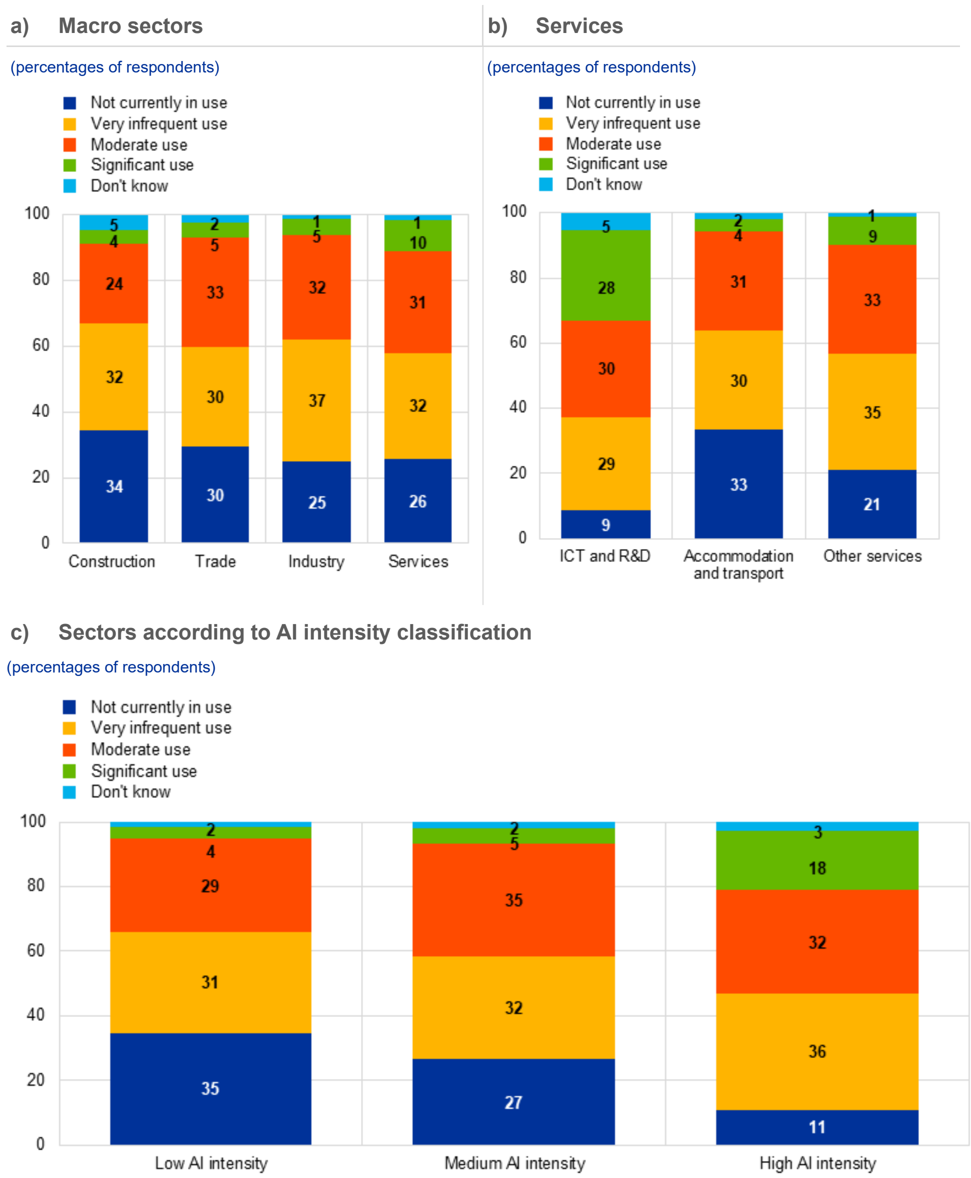
[7] The survey reports four macro sectors based on the one-digit NACE classification. A sectoral refinement is based on the two-digit classification. We use this further granular information to focus more on the service sectors.

28%. This reflects their higher propensity to leverage AI technologies, likely supported by their inherently digital and knowledge-intensive activities. By contrast, accommodation and transport display much lower levels of AI adoption.

The AI intensity taxonomy, based on the OECD methodology, provides a complementary sectoral perspective (**Chart 3**, panel c). In sectors classified as high-intensity (such as IT services, media, telecommunications and scientific R&D), only 11% of firms report not using AI, compared with 27% in medium-intensity sectors and 35% in low-intensity sectors. At the same time, firms across all three groups are mainly concentrated in the intermediate adoption categories. As expected, significant use is most prevalent in high-intensity sectors (18%), whereas it remains limited in low-intensity and medium-intensity sectors (4-5%).

Chart 3

Use of AI, by sector classification



Source: Survey on the Access to Finance of Enterprises (SAFE).
Notes: The charts shows the weighted share of firms by the intensity of AI use and different sectoral classifications. Panel b): "ICT and R&D" refers to information and communications technology and research and development. "Other services" includes real estate and professional/technical activities, education and health/social services as well as sports and recreation. Panel c): AI intensity is based on an OECD classification which categorises sectors as high, medium or low AI intensity on the basis of a composite measure that combines four indicators: AI human capital, AI innovation, AI exposure and AI use. The sectors included in the classifications are, among others: food products, basic materials, construction and accommodation ("low AI intensity"); chemicals, electrical equipment and machinery, wholesale and retail trade, and transportation ("medium AI intensity"); and IT services, telecommunications, financial services and scientific R&D ("high AI intensity"). See OECD (2024), "A sectoral taxonomy of AI intensity", OECD Artificial Intelligence Papers, No 30, December.

Overall, the patterns in **Chart 2** and **Chart 3** are consistent with earlier EIB evidence pointing to a strong size gradient in AI adoption and relatively higher AI use in technology-intensive sectors compared with traditional and resource-constrained industries. Yotzov et al. (2026) and Calvino, Costa and Haerle (2026) corroborate these patterns in an international context. At the same time, the patterns we identified also show how AI diffusion remains incomplete, even in sectors classified as AI-intensive.[8] This heterogeneity in AI adoption underscores the need for targeted policies that address sector-specific barriers and support broader uptake of AI technologies.

Chart 4 and **Chart 5** complement the previous evidence by examining AI use across firms of different ages and ownership structures. Firms are grouped into three age categories: young firms, defined as those no more than five years old; mid-aged firms, between five and ten years old; and mature firms, ten years or older.[9]

Chart 4 illustrates AI adoption across firms of different ages. The share of firms reporting no AI use is relatively consistent across age groups: around one-quarter of young firms do not use AI, compared with 27-35% among firms aged five years or older. More pronounced differences emerge when looking at the intensity of AI use. Around 41% of young firms report moderate use of AI, compared with 24-31% in the older age groups, while 15% of young firms report significant use – more than double the share among mid-aged and mature firms (7-9%). The data point to an interesting age-related AI adoption pattern. Firms aged between five and ten years display lower levels of AI adoption with respect to both young and mature firms.[10] One possible explanation is that the youngest firms were founded after or very close to the release and emergence of advanced LLMs like ChatGPT in November 2022, a pivotal moment in the accessibility and widespread adoption of generative AI technologies. These firms may therefore have been better positioned to embed AI into their business models from the outset, capitalising on their agility and familiarity with these transformative tools to foster innovation and enhance operational efficiency.

8 European Investment Bank (2025).

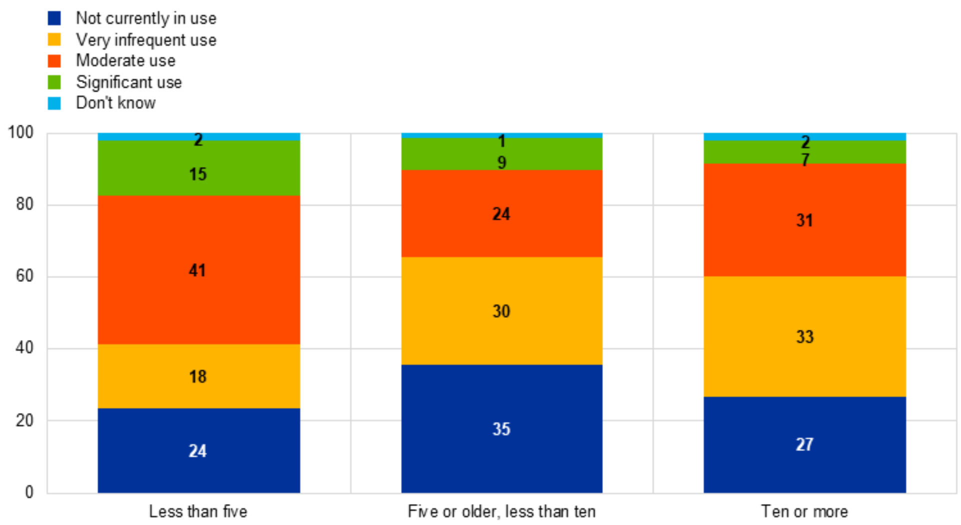
9 The sample is dominated by mature firms, which accounts for 92% of observations, compared with 5% for mid-aged firms and 3% for young firms.

10 This specific age-related AI adoption pattern has not been directly documented in the existing literature. Some studies, such as Calvino et al. (2022), highlight the coexistence of both young-small and old-large AI adopters. By contrast, McElheran et al. (2024) find that AI adoption in the United States declines monotonically as firms age. Meanwhile, Li and Liu (2026) observe an inverted U-shaped relationship between AI adoption and firm age in Canada, with adoption peaking among firms approximately eight years old.

Chart 4

Use of AI, by firm age

(percentages of respondents)



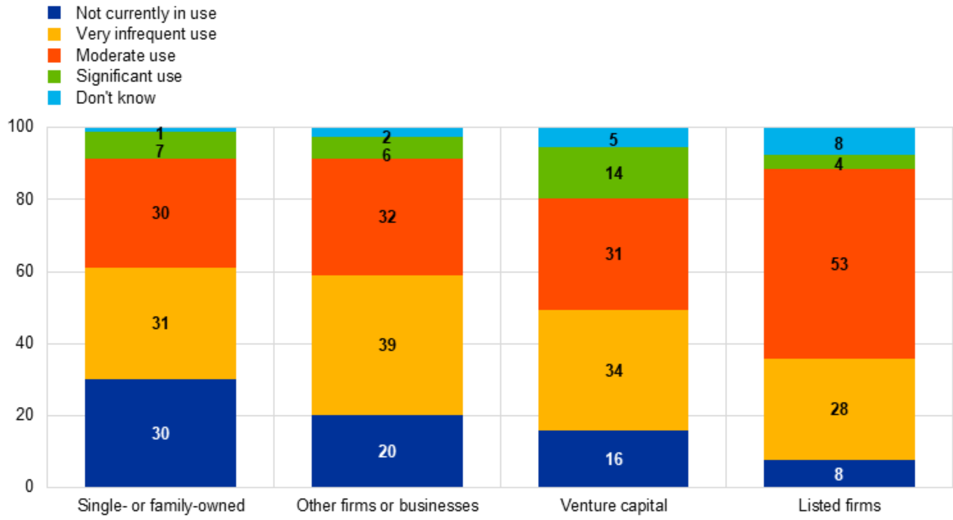
Source: Survey on the Access to Finance of Enterprises (SAFE).
Note: The chart shows the weighted share of firms by the intensity of AI use and years of firm age.

Ownership structures are also associated with differences in AI adoption (**Chart 5**). Listed firms and venture capital-backed firms emerge as the most advanced adopters, exhibiting the highest shares of moderate and significant users and the lowest shares of non-users. This may reflect stronger incentives and greater capabilities to invest in digital technologies, supported by better access to finance, managerial expertise and scale. By contrast, family-owned or single-owned firms are more likely to report either no use or only very infrequent use of AI, pointing to potential gaps in skills, information or resources that may hinder the diffusion of AI beyond frontier firms.

Chart 5

Use of AI, by type of ownership

(percentages of respondents)



Source: Survey on the Access to Finance of Enterprises (SAFE).
Notes: The chart shows the weighted share of firms by the intensity of AI use and type of ownership in the firm. “Single- or family-owned” indicates firms whose majority ownership stake is through single owners, family members or entrepreneurs. “Other firms or businesses” includes firms owned by other enterprises or business associates.

3.3 AI adoption and structural characteristics

Chart 6 provides an overview of the relationship between the economic conditions of firms in the last quarter of 2025 and their level of adoption of AI. Survey data show that firms with significant use of AI report increasing turnover and profits more frequently than less advanced AI users, even though costs are broadly comparable across groups. Specifically, a net 13% of significant users reported an increase in turnover over the past three months, compared with a net 7-8% of moderate and infrequent users and 2% of non-users. The disparity is even more pronounced for profits, with significant users reporting net profit increases, while less advanced users and non-users indicate net decreases.

Overall, labour costs and other costs are increasing across firms regardless of their use of AI, though the net percentage is slightly higher for significant users (59%, compared with 49% for non-users). This is in line with significant users more frequently reporting an increase in their workforce (net 25% in contrast with a net 2%, 5% and 0% of moderate, infrequent and non-users respectively).

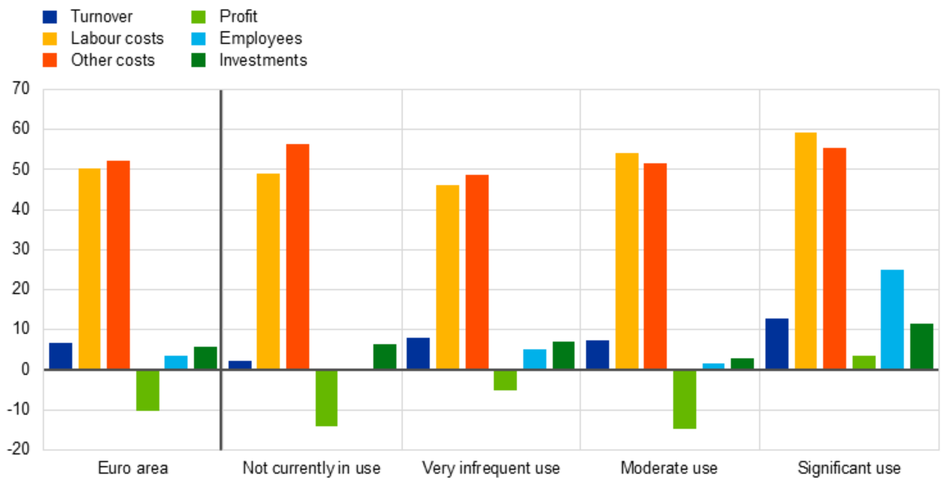
In terms of fixed investments over the past three months, a net 11% of significant users report increases, whereas this percentage does not exceed 7% for less advanced or non-users.

After controlling for size, sector and location, the differences between significant AI users and less advanced or non-users remain for cost of labour, employment and fixed investment, while narrowing slightly for profits. Over the past three months, firms making significant use of AI were 10 percentage points more likely to experience higher cost of labour and 21 percentage points more likely to report increased employment compared with firms that do not use AI. Similarly, these firms were 10 percentage points more likely to have increased fixed investments.

Chart 6

Economic performance of firms, by AI use

(net percentages of respondents)



Source: Survey on the Access to Finance of Enterprises (SAFE).
Note: Net percentages of firms reporting an increase relative to a decrease in economic outcome variables, by intensity of AI use.

4 Factors shaping firms’ use of AI

The use of AI among firms reflects a range of motivations, both for adopting these technologies and for limiting their use. The following analysis first examines the factors driving AI adoption among firms that report some degree of AI use. It then turns to firms that have not yet used AI or have used it to a limited extent and discusses the reasons they provide for their limited or non-existent use.

4.1 Drivers of AI adoption among AI using firms

4.1.1 Across countries

Across all countries, AI adoption appears to be driven primarily by the objective of improving core and non-core business processes, while cost reduction and innovation-related motives play a comparatively smaller role (**Chart 7**). At the euro area level, 33% of firms report using AI to enhance core business processes and 28% to improve non-core processes. By contrast, 15% cite reducing personnel costs as a motive, 13% use AI primarily to support R&D and innovation, and 10% to expand their product or service range.

Grouping the 12 euro area countries into advanced, intermediate and lower adopters, according to the cumulative shares of firms using AI to some extent, reveals some heterogeneity in the factors driving adoption.

In the advanced adopters group (Netherlands, Austria and Finland), one-third of firms use AI to improve core business processes, and just over a quarter use it to enhance non-core processes. Relative to the euro area average, these firms place slightly more emphasis on cost reduction and innovation, with 16% citing the reduction of personnel costs and 16% citing support for R&D and innovation. Only 9% report using AI mainly to expand their product or service offering.

Among the intermediate adopters (Belgium, Germany, Spain, Greece and France), the shares of firms using AI to enhance core (34%) and non-core (30%) business processes are broadly in line with the euro area average. In this group, 15% of firms report using AI to reduce personnel costs, while fewer (11%) cite support for R&D and innovation as a primary motive, and 10% use AI to expand their product and service offering.

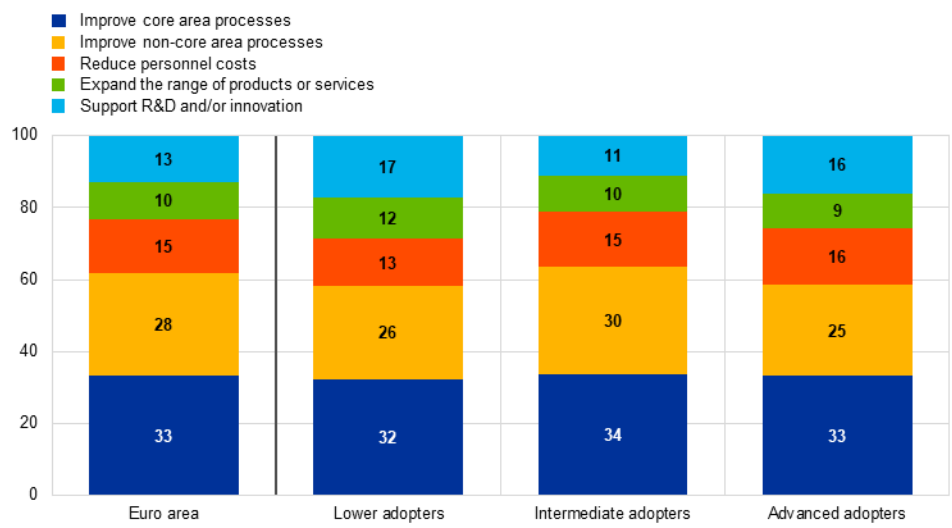
Among lower adopters (Ireland, Italy, Slovakia and Portugal), firms also deploy AI primarily to improve business processes. As among advanced adopters, core process improvements are cited more often than non-core process improvements, at 32% and 26% respectively. Firms in this group are less likely to cite personnel cost reduction (13%) as a main reason for adoption, but more likely than the euro area average to report using AI to support R&D and innovation (17%, compared with 13%

for the euro area) and to expand their product or service range (12%, compared with 10%).

The relatively small differences across country groups suggest that, at this stage, AI adoption in the euro area is primarily driven by common technological and organisational considerations rather than by country-specific factors. Widely available off-the-shelf AI solutions – such as customer relationship management tools, predictive maintenance software and data analytics packages – tend to be implemented first in areas where efficiency gains are most immediate and easiest to realise, notably in core and support business processes. Common EU-level regulatory, data protection and labour market frameworks may also contribute to the broadly similar pattern of motives across countries, by shaping firms' scope for automation and data use in comparable ways.

Chart 7

Reasons for using AI, by group of countries



Source: Survey on the Access to Finance of Enterprises (SAFE).
Notes: Firms which use AI very infrequently, moderately or significantly. The chart shows the weighted share of firms by reasons for using AI and by country groups. "Lower adopters" (IE, IT, SK and PT), "intermediate adopters" (BE, DE, ES, GR and FR) and "advanced adopters" (NL, AT and FI) are categorised by the countries' share of moderate and significant AI users, where advanced adopters have the highest shares.

4.1.2 Across firm demographics (size, sector, age, ownership)

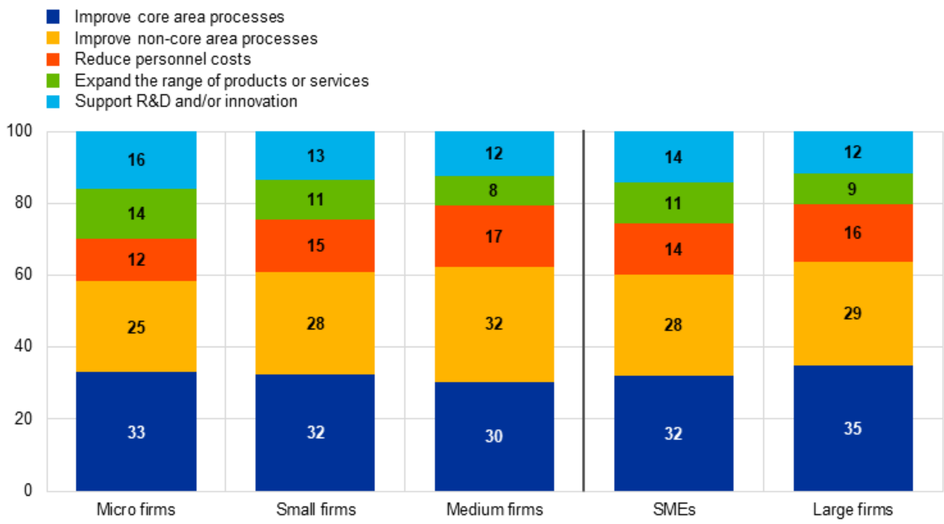
When considering firm size, further nuances emerge, as shown in **Chart 8**. Large firms, on one hand, and SMEs, particularly micro firms, on the other hand, show distinct priorities in their motives for adopting AI, reflecting differences in resources and strategic focus. Overall, large firms are more likely to focus on improving processes and reducing costs, consistent with their greater scale and capacity to integrate AI solutions into existing operations. SMEs, meanwhile, appear somewhat more likely to use AI more strategically to expand product offerings and foster innovation, reflecting their need to differentiate themselves in competitive markets.

Within the SME category, however, there is also heterogeneity: small and medium-sized firms show more similarities to large firms than to micro firms.

The motive of reducing personnel costs varies notably across firm sizes. Large and medium-sized firms attach greater importance to this motive compared with small and especially micro firms. By contrast, micro firms are more likely to report using AI to expand their range of products or services: 14% cite this motive, compared with 9% of large firms and 11% of SMEs overall. In the same way, the use of AI to support R&D and innovation is slightly more prevalent among micro firms (16%) than among large firms (12% of large firms). This evidence suggests that smaller firms may use AI more selectively to strengthen their competitive position, develop new offerings or serve in niche markets, while larger firms tend to focus more on operational efficiencies.

Chart 8

Reasons for using AI, by firm size



Source: Survey on the Access to Finance of Enterprises (SAFE).
Notes: Firms which use AI very infrequently, moderately or significantly. The chart shows the weighted share of firms by reasons for using AI and by firm size. Size classes are micro firms (less than ten employees), small firms (between ten and 50), medium firms (between 50 and 250) and large firms (more than 250 employees). "SMEs" stands for small, micro and medium firms (below 250 employees).

Chart 9 provides a sectoral perspective on the motives for adopting AI. The results point to distinct priorities across sectors, reflecting differences in operational and strategic needs. While labour-intensive industries focus on cost reduction and process optimisation, knowledge-intensive sectors place greater emphasis on R&D, innovation and product diversification.

Reduction in personnel costs is a key driver of AI adoption across sectors, particularly in labour-intensive industries such as trade (21%), construction (18%) and accommodation and transport (18%). Firms in these sectors rely on AI to enhance workforce management efficiency and automate routine and repetitive tasks, thereby reducing reliance on manual labour and optimising operational costs. By contrast, firms in ICT and R&D place significantly less emphasis on this motive, with only 9% of firms prioritising cost reduction.

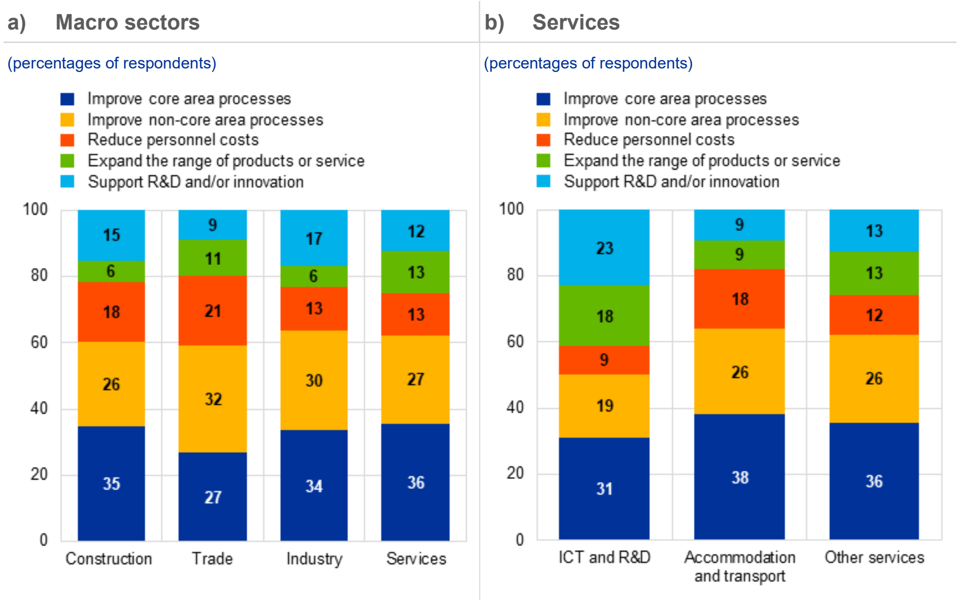
Improving non-core processes emerges as another significant driver of AI adoption. Trade (32%) and industry (30%) prioritise this motive, reflecting the importance of AI in optimising logistics, enhancing customer service and streamlining support functions. On the other hand, ICT and R&D report the lowest emphasis on improving non-core processes at 19%.

Expanding the range of products or services is most prominent in ICT and R&D, where 18% of firms cite it as a key motive for adopting AI. This reflects the sector's stronger focus on diversification and the development of new offerings. By contrast, this motive is the least frequently reported in industry and construction (at 6% in both sectors), where AI adoption appears to be driven more by operational efficiency.

Supporting R&D and innovation is particularly important for firms in ICT and R&D sectors, where 23% identify it as a primary driver of AI adoption. This underscores the sector's reliance on AI to advance technological capabilities and foster innovation. Industry (15%) and construction (14%) also place significant emphasis on R&D, leveraging AI to improve manufacturing processes and product design. By contrast, accommodation and transport (9%) and trade (9%) attach less importance to this motive, reflecting a stronger focus on customer-facing or logistical purposes rather than research-driven use of AI.

Chart 9

Reasons for using AI, by sector classification



Source: Survey on the Access to Finance of Enterprises (SAFE).
Notes: Firms which use AI very infrequently, moderately or significantly. The chart shows the weighted share of firms by reasons for using AI and by different sectoral classifications. Panel b): "ICT and R&D" refers to information and communications technology and research and development. "Other services" includes real estate and professional/technical activities, education and health/social services as well as sports and recreation.

The reasons for adopting AI technologies vary significantly with firm age (**Chart 10**). Mature firms tend to focus on maintaining efficiency and optimising existing processes, mid-aged firms appear to strike a balance between operational improvements and growth, while younger firms place greater emphasis on scalability and market expansion. More specifically, among firms that have been operating for ten years or more, AI adoption is primarily aimed at improving core business processes, with 34% identifying this as their main motive. In addition, 29% of these firms use AI to improve non-core business processes, such as administrative tasks or logistics, indicating a focus on refining support functions to complement their core operations. However, their AI adoption to expand the range of products or services or to support R&D and innovation remains relatively limited. This suggests that long-established firms are primarily focused on improving efficiency within their existing structures rather than pursuing diversification or innovation as primary goals.

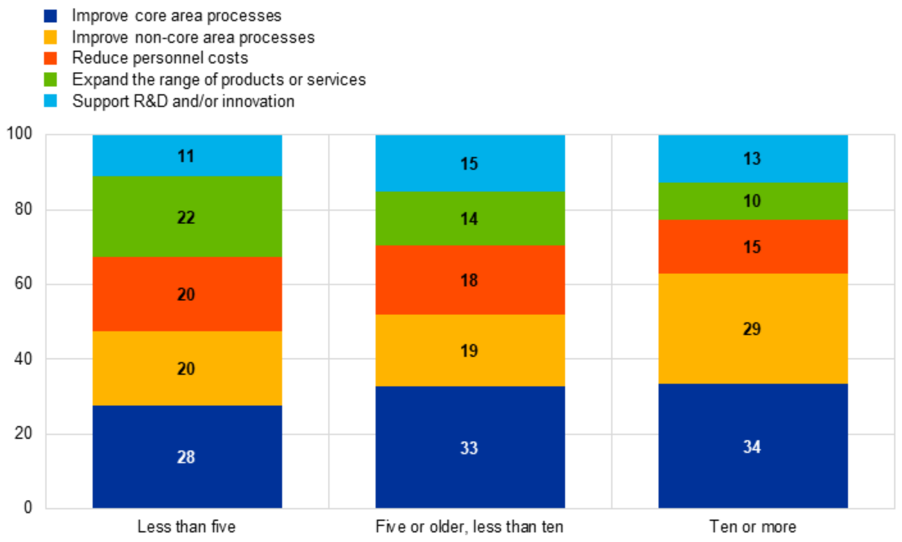
Firms that have been operating for more than five years but less than ten years demonstrate a more balanced distribution of motives for AI adoption. As with older firms, improving core business processes is the main driver, cited by 33% of firms. However, mid-aged firms place relatively greater emphasis on expanding their range of products or services (14%) and supporting R&D and innovation (15%) compared with older firms. This pattern reflects a dual focus on efficiency and growth, as these firms seek to consolidate their market position while exploring new opportunities for expansion and differentiation. Interestingly, their use of AI to improve non-core processes (19%) is lower than among both older and younger firms, possibly indicating a more targeted approach to AI investment in areas most directly linked to their strategic objectives.

Younger firms, established no more than five years ago, display distinct priorities in their reasons for adopting AI. Being founded around or after the emergence of widely accessible AI tools, such as ChatGPT and other LLMs, these firms are likely to be more familiar with the transformative potential of AI technologies in the everyday operations of a business. Their awareness of AI's capabilities enables them to integrate these tools strategically from an early stage. For these firms, expanding the range of products or services is a particularly important motive, cited by 22% of young firms. In addition, 20% of younger firms prioritise improving non-core processes, such as customer service and logistics, to create efficient and scalable operations that support their rapid growth. Improving core business processes remains the most frequently cited motive among young firms, at 28%, but it is less prominent than among older firms. This may reflect the fact that younger firms are still in the process of fully defining and optimising their core operations and therefore use AI across a broader range of business functions rather than concentrating it mainly on established processes. Finally, support for R&D and innovation is cited by only 11% compared with mid-aged firms. This may reflect resource constraints or a stronger focus on more immediate goals such as operational growth and product development.

Chart 10

Reasons for using AI, by firm age

(percentages of respondents)



Source: Survey on the Access to Finance of Enterprises (SAFE).
Notes: Firms which use AI very infrequently, moderately or significantly. The chart shows the weighted share of firms by reasons for using AI and by years of firm age.

The motives for adopting AI also vary by ownership structure, pointing to important differences in how firms deploy AI and the benefits they expect to derive from it (**Chart 11**).

Listed firms report that they adopt AI primarily to improve core business processes and support research, development and innovation. The relatively high share citing R&D and innovation (26%) suggests that publicly traded firms tend to view AI as a strategic technology to enhance competitiveness and long-term productivity, rather than mainly as a tool for short-term cost reduction. Process optimisation in non-core areas is also an important factor, while expanding the range of products or services (13%) and reducing personnel costs are mentioned less frequently.

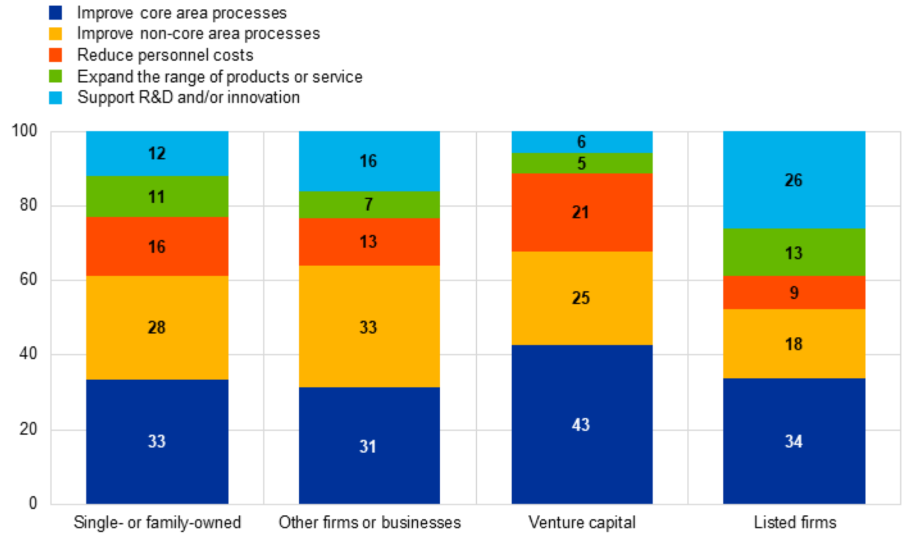
Family-owned and single-owned firms focus most strongly on using AI to improve both core (33%) and non-core business processes (28%). Compared with listed firms, they place somewhat greater emphasis on reducing personnel costs, indicating a somewhat stronger focus on efficiency gains and cost containment alongside process optimisation. By contrast, they are less likely to use AI as a tool to support R&D and innovation or to expand their product or service portfolio.

Venture capital-backed firms also identify improvements in core business processes as the dominant factor behind AI adoption, with the highest share among all ownership categories. They also use AI to enhance non-core processes and, to a notable extent, to reduce personnel costs (21%). However, support for R&D and innovation or the expansion of product and service offerings are rarely cited by venture capital-backed firms as primary motives for AI adoption. This suggests that, in the sample considered, AI is perceived mainly as a scaling technology – enabling rapid optimisation and efficiency in business operations – rather than as a main driver of experimental R&D activities or diversification.

Finally, firms owned by other enterprises or business associates display a more balanced pattern of AI adoption motives. A relatively high share of these firms uses AI to improve both non-core and core processes, while AI also plays a comparatively stronger role in supporting R&D and innovation than it does among family-owned or venture capital-backed firms. As in other ownership groups, reducing personnel costs and extending the range of products or services remain secondary motives.

Chart 11
Reasons for using AI, by type of ownership

(percentages of respondents)



Source: Survey on the Access to Finance of Enterprises (SAFE).
Notes: Firms which use AI very infrequently, moderately or significantly. The chart shows the weighted share of firms by reasons for using AI and by type of ownership in the firm. “Single- or family-owned” indicates firms whose majority ownership stake is through single owners, family members or entrepreneurs. “Other firms or businesses” includes firms owned by other enterprises or business associates.

4.2 Barriers to adoption and greater AI utilisation

4.2.1 Across countries

Chart 12 shows the reasons firms give for not adopting AI, or for not using it more intensively, broken down by country group. In contrast to the previous section, these country groups are defined according to the extent of AI non-adoption. The first group (“lagging adopters”) comprises countries with the highest shares of firms not currently using AI (Italy and Ireland); the second group (“partial adopters”) includes countries with intermediate shares of non-adopters (Portugal, Slovakia, Spain, Greece and France); and the third group ("widespread adopters") consists of countries with the lowest shares of non-adopters (Austria, Belgium, Germany, Finland and the Netherlands).

Across country groups, firms report broadly similar reasons for not adopting AI or for not using it more intensively, but the relative importance of specific barriers differs with the stage of AI diffusion. A lack of AI-related skills is the most frequently cited impediment in all three groups, reported by 25% of firms in the euro area. The shares are very similar across country groups – 27% for lagging and 24% among both partial and widespread adopters – indicating that shortages of relevant human capital constitute a pervasive structural barrier to AI diffusion, irrespective of current adoption levels.

Concerns related to data, privacy and ethics are the second most frequently reported barrier overall, reported by 19% of firms in the euro area. They are particularly salient among partial adopters, where 21% of firms mention them, compared with 16% among lagging adopters and 18% of widespread adopters. This pattern suggests that, as AI diffusion progresses beyond initial experimentation, firms may be particularly sensitive to regulatory, reputational and ethical dimensions associated with AI deployment at greater scale.

Distrust in AI-based results is mentioned less frequently overall but shows a clearer variation across country clusters. In the euro area, 13% of firms identify distrust in AI output as a main barrier. This share is highest among partial adopters (16%), suggesting that firms in these countries may have enough exposure to AI technologies to recognise their potential, while still being cautious about the reliability and quality of AI-generated output. By contrast, among lagging adopters, attitudinal barriers such as distrust in AI appear less relevant, consistent with a situation where other, more basic constraints may be more binding.

Cost-related considerations play a more limited role across all three country groups. At the euro area level, only 9% of firms report that AI costs exceed the expected benefits, with broadly similar shares across clusters. Likewise, 16% of firms view AI as not useful for their activities, with no major differences across country groups. These results indicate that neither perceived lack of usefulness nor an unfavourable cost-benefit assessment are the primary drivers of cross-country differences in AI adoption. Rather, most firms, including those in lagging adopter countries, recognise at least some potential relevance of AI for their activities.

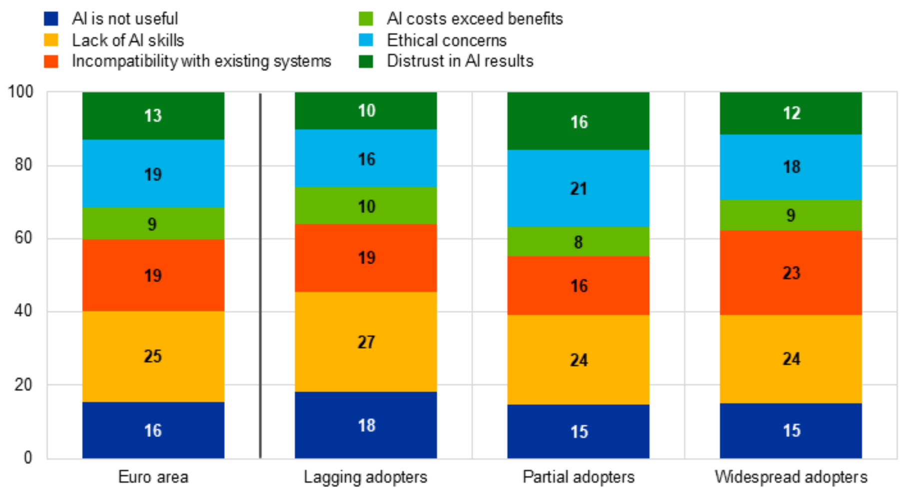
By contrast, incompatibility with existing systems – whether software or hardware – is mentioned by 19% of euro area firms and reaches 23% among widespread adopters. This suggests that, as AI diffusion progresses, firms increasingly encounter practical implementation challenges related to integrating AI tools into their existing technological infrastructure.

Overall, the distribution of responses indicates that non-adoption of AI is driven less by perceptions that AI is irrelevant or uneconomic and more by structural and implementation-related constraints.

Skill shortages remain the most pervasive barrier, while concerns around data, privacy and ethics also play an important role. The relative importance of barriers varies with the stage of diffusion: lagging adopters are held back mainly by skills gaps and ethical concerns; partial adopters report relatively stronger concerns about data, privacy, ethics and the reliability of AI output; and widespread adopters face more frequent compatibility issues, reflecting the operational challenges of scaling AI use.

Chart 12
Reasons for not using AI, by group of countries

(percentages of respondents)



Source: Survey on the Access to Finance of Enterprises (SAFE).
Notes: Firms which do not use AI or use AI very infrequently or moderately. The chart shows the weighted share of firms by reasons for not using AI and by country groups. Lagging (IT, IE), partial (PT, SK, ES, GR, FR) and widespread adopters (AT, BE, DE, FI, NL) are categorised by the countries' share of firms not using AI, where lagging adopters have the highest shares of non-adoption.

4.2.2 Across firm demographics (size, sector, age, ownership)

Across all firm sizes, structural constraints dominate as the primary impediments to AI adoption, but the relative importance of specific barriers differs significantly between SMEs and large firms, as well as within the SME segment itself (**Chart 13**).

Large firms tend to report more advanced and systemic challenges related to AI adoption. In particular, 23% of large firms cite incompatibility with existing systems – either software or hardware – as a significant barrier, compared with 17% of SMEs overall. This reflects the technical integration challenges faced by larger organisations operating with complex legacy infrastructures, which may be difficult to adapt to new AI technologies. Ethical concerns are also more pronounced for large firms, with 23% identifying them as a barrier, compared with 16% of SMEs. This might reflect larger firms' greater exposure to regulatory compliance requirements, data governance risks and reputational scrutiny, given their scale and visibility. At the same time, large firms are much less likely to perceive AI as irrelevant to their activities, with only 8% citing this aspect compared with 20% of SMEs overall. Skill shortages remain the most frequently cited barrier across all firm sizes, affecting 26% of large firms and 24% of SMEs, indicating that human capital constraints are a pervasive structural obstacle to AI diffusion irrespective of firm size.

Within SMEs, important differences emerge between micro, small and medium-sized firms. Micro and small firms (up to 50 employees) tend to face more fundamental barriers related to awareness and perceived relevance of AI. Around 23% of micro firms and 21% of small firms report that AI is not useful for their operations, significantly higher than the 12% reported by medium firms and the 8% cited by large firms. This suggests that smaller firms may find it harder to identify concrete AI applications for their business activities, or may operate in sectors where AI use cases are less evident. Distrust in AI-generated results is slightly more common among micro firms (15%) compared with small (13%) and medium-sized firms (13%). This may reflect greater scepticism about the reliability and quality of AI-generated output, possibly reinforced by more limited exposure to advanced digital technologies.

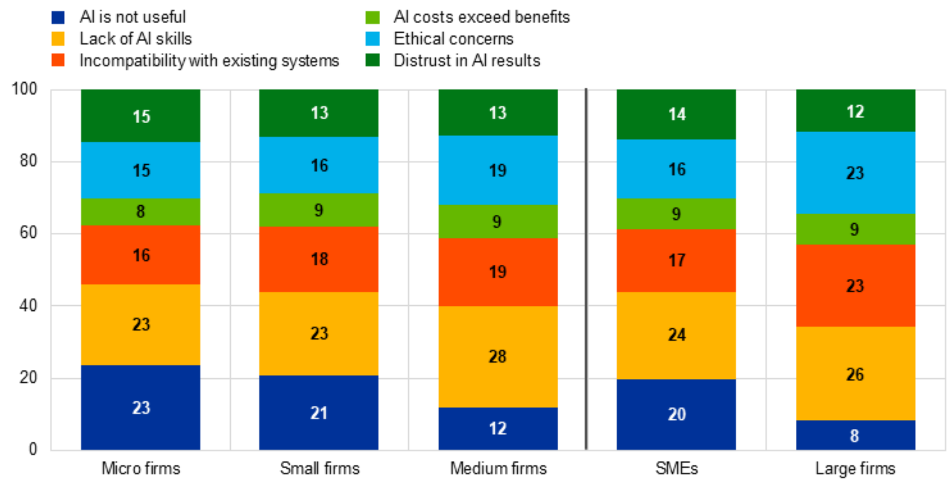
Medium-sized firms (50 to 250 employees) occupy an intermediate position between smaller SMEs and large firms and display a distinct pattern of barriers. They are more likely to cite structural barriers such as skill shortages (28%) and ethical concerns (19%), reflecting their greater operational complexity and more advanced digital needs compared with micro and small firms. Incompatibility with existing systems is also reported more frequently by medium-sized firms (19%) than by micro (16%) and small firms (18%), indicating that as firms grow, their organisational and technological infrastructures become more difficult to adapt to AI technologies. Unlike micro and small firms, medium-sized firms are less likely to perceive AI as irrelevant, with only 12% citing this barrier. This suggests that they are generally more aware of AI’s potential benefits but still face practical challenges in scaling and integrating AI effectively.

In summary, the comparison between SMEs and large firms reveals distinct challenges in AI adoption. While shortages of AI-related skills are a common barrier across all firm sizes, smaller firms are more likely to face attitudinal and awareness-related obstacles, such as perceiving AI as irrelevant or distrusting its output. Large firms, by contrast, are more focused on technical integration, ethical considerations and compliance-related issues. Within the SME segment, micro and small firms appear particularly constrained by limited awareness, resources and exposure to AI technologies, while medium-sized firms face more advanced challenges linked to scaling, organisational complexity and operational integration.

Chart 13

Reasons for not using AI, by firm size

(percentages of respondents)



Source: Survey on the Access to Finance of Enterprises (SAFE).
Notes: Firms which do not use AI or use AI very infrequently or moderately. The chart shows the weighted share of firms by reasons for not using AI and by firm size. Size classes are micro firms (less than ten employees), small firms (between ten and 50), medium firms (between 50 and 250) and large firms (more than 250 employees). “SMEs” stands for small, micro and medium firms (below 250 employees).

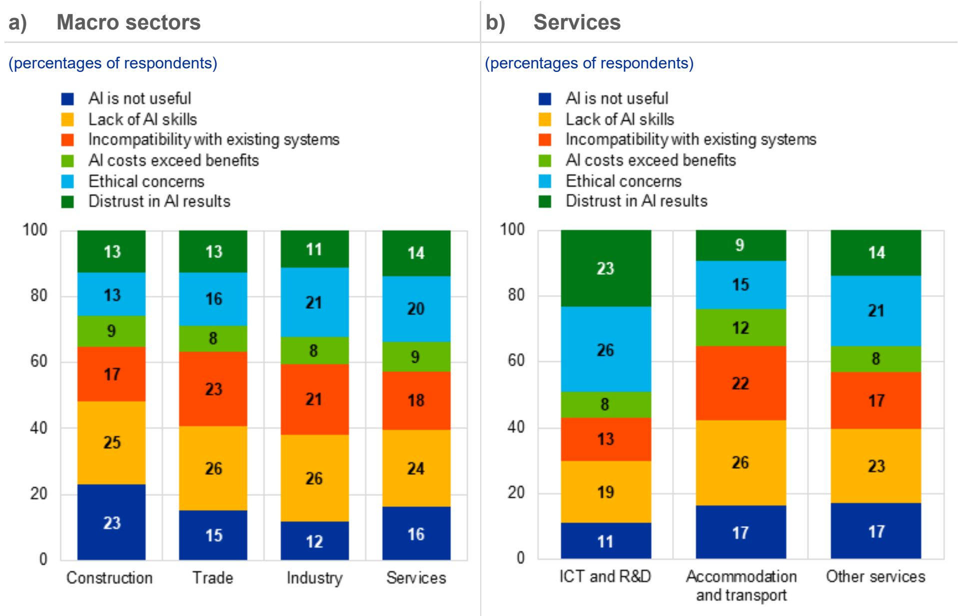
Chart 14 shows that barriers to AI adoption vary markedly across sectors. In construction – the sector with the highest share of non-adopters – the perception that AI is not useful is the most frequently cited barrier (23%), consistent with limited awareness of AI’s potential applicability to predominantly manual and site-specific activities. Skill shortages (25%) and incompatibility with existing systems (17%) are also widely reported. In industry, by contrast, the barrier profile is more structural. Skill shortages are the leading constraint (26%), followed closely by system incompatibility and ethical concerns, reflecting the challenges of integrating AI into complex production processes and established IT infrastructures. Trade displays a similar pattern, with skill shortages and system incompatibility among the dominant barriers, although the perception that AI is not useful is more prevalent than in industry.

Within services, the more detailed breakdown in panel b) reveals considerable heterogeneity. ICT and R&D firms stand out clearly: the perception that AI is not useful is the lowest among all subsectors (11%), while ethical concerns (26%) and distrust in AI-based results (23%) are the highest across all groups. This distinctive pattern likely reflects the more advanced engagement of these firms with AI technologies, which brings heightened awareness of governance, reliability and data sensitivity issues rather than basic concerns about AI’s relevance. Skill shortages and system incompatibility are comparatively less prominent, suggesting that human capital and infrastructure constraints are less binding for these digitally intensive firms. Accommodation and transport presents a contrasting picture: skill shortages (26%) and system incompatibility (22%) are the leading barriers, while distrust in AI results is the lowest among service subsectors (9%). This points to firms that may be broadly open to AI adoption but constrained by implementation capacity. Other services occupy an intermediate position, with skill shortages and ethical concerns emerging as the main obstacles.

Overall, the sectoral evidence suggests that barriers to AI adoption differ according to the nature and maturity of AI use. In lower-intensity sectors such as construction, non-adoption is more closely linked to attitudinal constraints, primarily perceived lack of relevance and limited implementation capacity. In more advanced and knowledge-intensive sectors, structural bottlenecks associated with skills, data governance and system compatibility dominate.

Chart 14

Reasons for not using AI, by sector classification



Source: Survey on the Access to Finance of Enterprises (SAFE).
Notes: Firms which do not use AI or use AI very infrequently or moderately. The chart shows the weighted share of firms by reasons for not using AI and by different sectoral classifications. Panel b): “ICT and R&D” refers to information and communications technology and research and development. “Other services” includes real estate and professional/technical activities, education and health/social services as well as sports and recreation.

Chart 15 shows that barriers to AI adoption differ noticeably across firm age groups. Mature firms (ten years or more) display the most structurally driven barrier profile. Skill shortages are the leading constraint (25%), followed by ethical and privacy concerns (19%) and incompatibility with existing systems (19%). This combination suggests that mature firms often recognise AI’s potential but face difficulties in integrating it into established organisational structures, legacy IT systems and existing workforce capabilities. Notably, only 15% of mature firms perceive AI as not useful, indicating a relatively high awareness of its relevance.

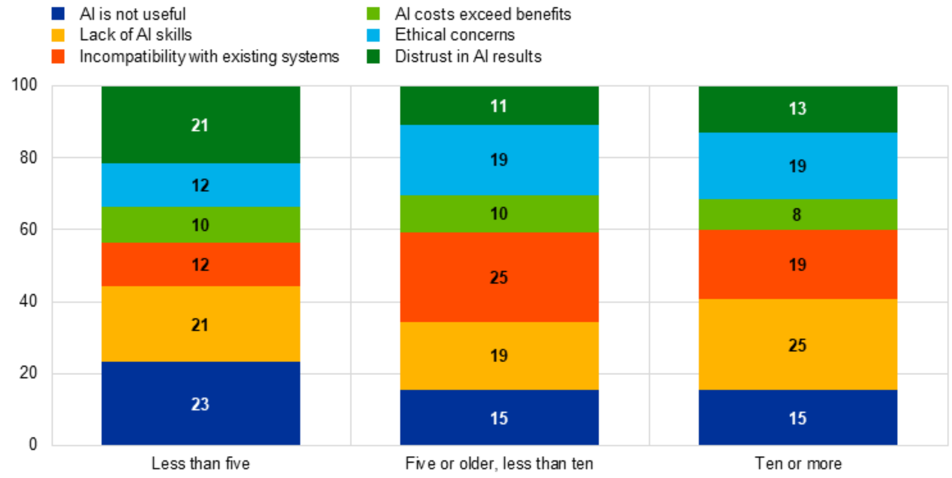
Mid-aged firms (five to ten years) stand out for the importance of system incompatibility, which is cited by 25% of firms – the highest across all age groups. This may reflect a critical transition phase in which firms have already accumulated some digital and operational infrastructure but lack the resources or scale to modernise it rapidly. Skill shortages are less frequently reported by this group (19%), suggesting that human capital constraints may be somewhat less binding than technical integration challenges.

Younger firms (less than five years) display a markedly different barrier profile. The perception that AI is not useful (23%) and distrust in AI-based results (21%) are both the highest across all age groups, while ethical concerns (12%) and system incompatibility (12%) are the lowest. This pattern suggests that younger firms are constrained less by legacy systems, compliance requirements and integration challenges, and more by doubts about the usefulness and reliability of AI tools.

Chart 15

Reasons for not using AI, by firm age

(percentages of respondents)



Source: Survey on the Access to Finance of Enterprises (SAFE).
Notes: Firms which do not use AI or use AI very infrequently or moderately. The chart shows the weighted share of firms by reasons for not using AI across different firm ages.

Finally, the reasons why firms either do not adopt AI or use it only to a limited extent also vary across ownership structures (**Chart 16**). Among listed firms, survey responses reveal a relatively balanced profile of barriers, with skill shortages (23%) and system incompatibility (23%) emerging as the most prominent constraints. These are followed by ethical concerns (19%) and distrust in AI output (19%). The relatively high level of distrust – the highest among all ownership types – may reflect the greater scrutiny faced by publicly listed firms, where errors, biased output or poorly governed AI applications can entail significant reputational and regulatory risks. Notably, only 12% of listed firms view AI as not useful for their activities, indicating a strong awareness of its strategic relevance.

Family-owned and single-owned firms are primarily constrained by skill shortages (24%), while system incompatibility (18%) and ethical concerns (18%) also feature prominently. At the same time, 18% of these firms perceive AI as not useful – the highest share among all ownership groups – suggesting that smaller, owner-managed businesses may face greater difficulties in identifying concrete AI applications relevant to their activities or may have less exposure to AI use cases that demonstrate its potential value.

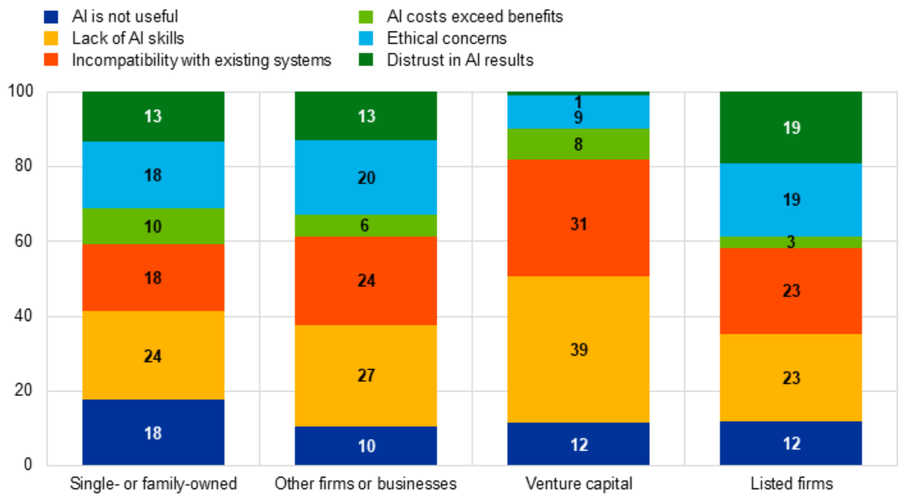
Venture capital-backed firms stand out sharply. Skill shortages (39%) and system incompatibility (31%) are by far the highest shares across all ownership types. This points to fast-growing firms that are scaling rapidly but face acute human capital and infrastructure bottlenecks. Conversely, distrust in AI results (1%) and ethical concerns (9%) are strikingly low, suggesting these firms are held back primarily by execution constraints rather than scepticism about AI or concerns about its governance.

Firms owned by other enterprises or business associates display a broadly average barrier profile, with skill shortages (27%) and system incompatibility (24%) as the main barriers, while other barriers are reported at more moderate levels.

Chart 16

Reasons for not using AI, by type of ownership

(percentages of respondents)



Source: Survey on the Access to Finance of Enterprises (SAFE).
Notes: Firms which do not use AI or use AI very infrequently or moderately. The chart shows the weighted share of firms by reasons for not using AI and by type of ownership in the firm. “Single- or family-owned” indicates firms whose majority ownership stake is through single owners, family members or entrepreneurs. “Other firms or businesses” includes firms owned by other enterprises or business associates.

5 Financing AI adoption and investment

The availability and structure of financing are crucial in determining the pace and scale of AI adoption. Implementing AI technologies often requires significant upfront investment in software, hardware, data infrastructure, specialised skills and staff training. Understanding how firms finance these investments helps identify potential barriers to adoption and informs policies aimed at promoting broader access to AI technologies. This section examines the relationship between firms' financing sources and both AI adoption and expected AI investments. The analysis is based on regression evidence and focuses on three traditional sources of financing reported by firms in the December 2025 survey: bank loans, subsidised bank loans and internal funds. The results are presented across firm size, sector and ownership structure.[11]

Across the euro area, all three financing sources are positively and significantly associated with the likelihood of using AI (**Chart 17**, panel a). The association is strongest for internal funds (8.7 percentage points), followed by subsidised bank loans (7.2 percentage points) and bank loans (5.4 percentage points). These results indicate that firms with access to financing – particularly their own resources and targeted public or subsidised credit – are more likely to adopt AI. This pattern holds for both SMEs and large firms, though the magnitude and significance vary. For SMEs, all three sources are statistically significant, with subsidised bank loans and internal funds equally important (both around 8 percentage points) and bank loans somewhat less so (4.6 percentage points). This suggests that SMEs' AI adoption may depend particularly on retained earnings and targeted financing instruments, with standard bank lending playing a more limited but still relevant role. By contrast, for large firms, only internal funds yield a statistically significant coefficient (9.4 percentage points). This likely reflects the relatively lower financing constraints faced by large firms, which are better positioned to fund AI adoption through their own resources or internal capital allocation mechanisms.

Turning to expected AI investment (**Chart 17**, panel b), internal funds remain the dominant financing channel at the euro area level (9.9 percentage points), with subsidised bank loans (7.2 percentage points) and bank loans (4.3 percentage points) also significant. For SMEs, all three financing sources are again significantly associated with expected AI investment. In this case, bank loans appear to play a somewhat larger role relative to the aggregate results, highlighting the relevance of external credit access for smaller firms aiming to expand their AI adoption. For large firms, only subsidised bank loans (8.7 percentage points) and internal funds (8.0 percentage points) are statistically significant; bank loans are negative and insignificant. This implies that large firms are more likely to depend on internal

[11] In the survey round addressing AI adoption and investment, firms were asked about traditional sources of financing, including credit lines, bank loans, subsidised bank loans (involving, for example, support from public sources in the form of guarantees or reduced interest rate loans), trade credit and the use of internal funds.

resources or targeted financing instruments rather than traditional bank lending when planning future AI investments.

Chart 17

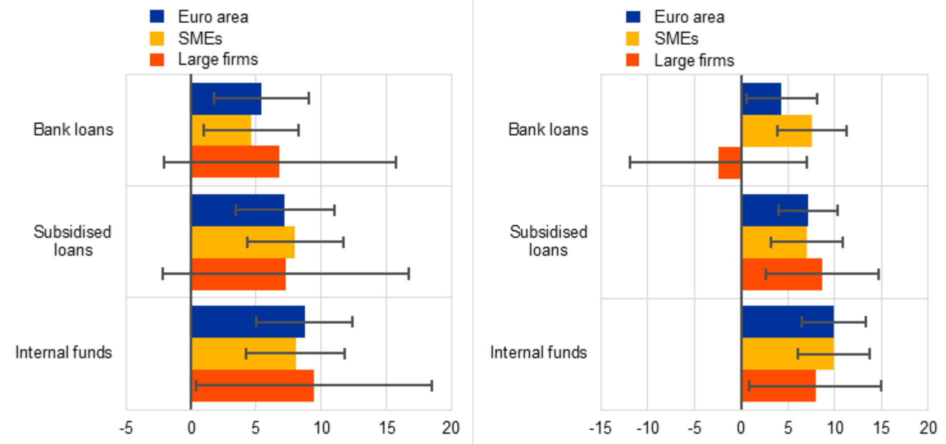
Use of AI and expected AI investment, by source of financing and firm size

a) Use of AI

(percentage points)

b) Expected AI investment

(percentage points)



Source: Survey on the Access to Finance of Enterprises (SAFE).
Notes: Panel a): Coefficients of firm-level regressions of AI use (the dummy takes the value 1 if the firm is using AI to some extent) on types of financing, for the euro area and by firm size. Panel b): Coefficients of firm-level regressions of expected AI investment (the dummy takes the value 1 if the firm is expecting to invest in AI) on types of financing, for the euro area and by firm size. “SMEs” stands for small, micro and medium firms (below 250 employees). Survey-weighted regressions with industry, country and firm size fixed effects. Whiskers represent 90% confidence intervals.

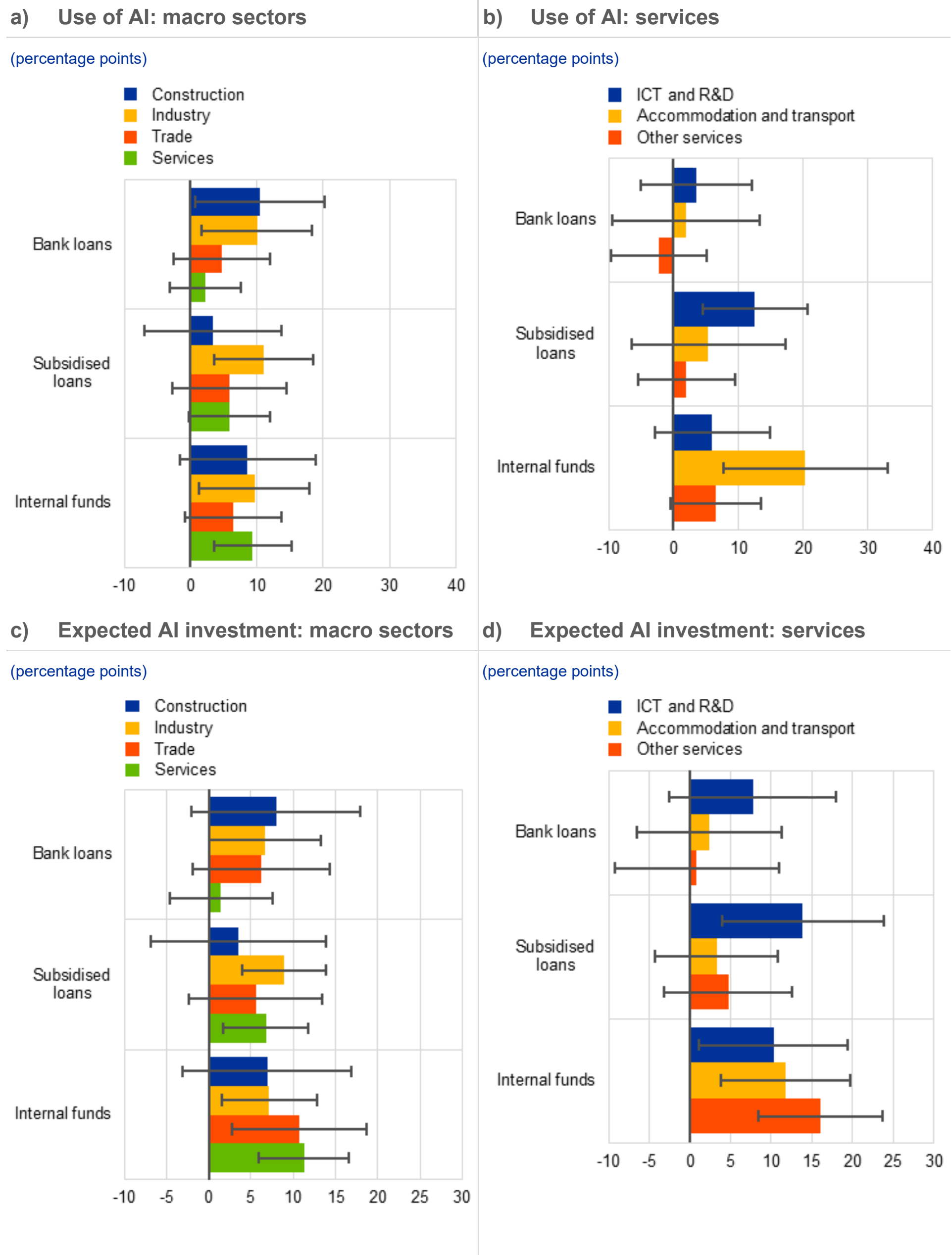
The importance and significance of financing sources vary considerably across sectors (**Chart 18**, panel a). In industry, all three sources carry broadly similar weights and are statistically significantly associated with AI use, with broadly similar magnitudes: bank loans (10.0 percentage points), subsidised bank loans (11.1 percentage points) and internal funds (9.6 percentage points). In construction, by contrast, only bank loans are statistically significant (10.4 percentage points), while subsidised bank loans and internal funds are positive but imprecisely estimated, possibly reflecting the sector’s lower overall rate of AI adoption and its stronger reliance on bank-based financing. In trade and services, the picture is more differentiated: internal funds are the dominant channel in both sectors (6.4 percentage points in trade, marginally significant; 9.4 percentage points in services), while subsidised bank loans also matter in services but not in trade. By contrast, bank loans are not significantly associated with AI use in either sector.

Within services, a notable heterogeneity emerges across subsectors (**Chart 18**, panel b). In accommodation and transport, only internal funds are statistically significant (20.4 percentage points), pointing to a strong role for self-financing. In ICT and R&D, only subsidised bank loans are significant (12.6 percentage points), consistent with firms in this sector benefiting more from public support schemes or targeted innovation-related financing. In other services, internal funds are marginally significant (6.5 percentage points).

The sectoral patterns for planned AI investment partly mirror those observed for current use (**Chart 18**, panel c). In industry, all three financing sources remain statistically significant: bank loans (6.7 percentage points), subsidised loans (8.9 percentage points) and internal funds (7.2 percentage points). In construction, none of the three sources reaches conventional significance thresholds, suggesting that financing structures are not yet systematically linked to future AI investment plans in this sector. In trade, only internal funds are significant (10.8 percentage points), while in services, internal funds (11.3 percentage points) and subsidised bank loans (6.8 percentage points) are both significant. Within services, these results are driven mainly by other service activities, where internal funds are particularly important (16.1 percentage points), and by information, communications and R&D, where subsidised bank loans stand out (13.8 percentage points) (**Chart 18**, panel d).

Chart 18

Use of AI and expected AI investment, by source of financing and sector classification



Source: Survey on the Access to Finance of Enterprises (SAFE).
Notes: Panels a) and b): Coefficients of firm-level regressions of AI use (the dummy takes the value 1 if the firm is using AI to some extent) on types of financing, for different sectoral classifications. Panels c) and d): Coefficients of firm-level regressions of expected AI investment (the dummy takes the value 1 if the firm is expecting to invest in AI) on types of financing, for different sectoral classifications. Survey-weighted regressions with industry, country and firm size fixed effects. Whiskers represent 90% confidence intervals. Panels b) and d): "ICT and R&D" refers to information and communications technology and research and development. "Other services" includes real estate and professional/technical activities, education and health/social services as well as sports and recreation.

For single-owned or family-owned firms, all three financing sources are statistically significantly associated with AI use (**Chart 19**, panel a), with internal funds (8.0 percentage points) and subsidised bank loans (7.3 percentage points) slightly ahead of bank loans (3.8 percentage points, marginally significant). For firms with other ownership structures (i.e. owned by other enterprises or business associates), bank loans (10.2 percentage points) and internal funds (11.8 percentage points) are both significantly significant, while subsidised bank loans are only marginally so. For listed firms and venture capital-backed firms, none of the three sources is statistically significant. This likely reflects the small sample sizes for these groups, as well as their already high unconditional rates of AI adoption, which leave limited variation to explain.

Turning to expected AI investment (**Chart 19**, panel b), all three sources remain significant for single-owned or family-owned firms, with internal funds (12.7 percentage points) and subsidised bank loans (8.9 percentage points) leading, consistent with AI use results. For firms with other ownership structures, none of the three sources is statistically significant, in contrast to the results for current AI use. This may reflect greater uncertainty about future investment plans within this heterogeneous category. For listed firms, the point estimates are economically large – internal funds (22.6 percentage points), subsidised bank loans (15.8 percentage points) and bank loans (12.6 percentage points) – but are estimated with very wide confidence intervals owing to the small sample size of around 50 firms. As a result, they are statistically indistinguishable from zero.

Across all three dimensions of heterogeneity, the predominance of internal funds emerges as the most robust finding. This indicates that AI adoption among euro area firms has so far relied primarily on retained earnings. Although this analysis does not capture the role of market-based sources of finance, existing studies, as in Arnold, Claveres and Frie (2024), suggest that the euro area's bank-centred financial system may be less well suited to supporting the intangible, long-term investments required for AI adoption. More recently, Babina (2026) underscores this point, noting that internal capability-building and in-house AI development – which require substantial upfront investment – yield different economic outcomes than the purchase of off-the-shelf solutions, a distinction that is particularly relevant in financing environments where long-term risk capital is scarce. At the same time, alternative financing channels remain relatively underdeveloped, which may constrain firms' ability to invest in transformative AI technologies. Venture capital activity in the euro area has grown, but the pool of risk capital remains shallow compared with the United States, limiting firms' ability to scale up. Private credit has emerged as a useful complementary source – directed disproportionately towards high-AI-intensity sectors such as IT and healthcare – but its overall volume in the euro area remains well below US levels.[12] As a result, firms' capacity to adopt AI appears to depend heavily on their balance sheet strength. Better-capitalised firms are more able to finance adoption internally or access external credit on favourable terms, while financially weaker firms may be unable to undertake AI-related investments that would otherwise be profitable. This points to a potential financing gap in AI diffusion, especially for firms with limited internal resources and restricted access to external risk capital.

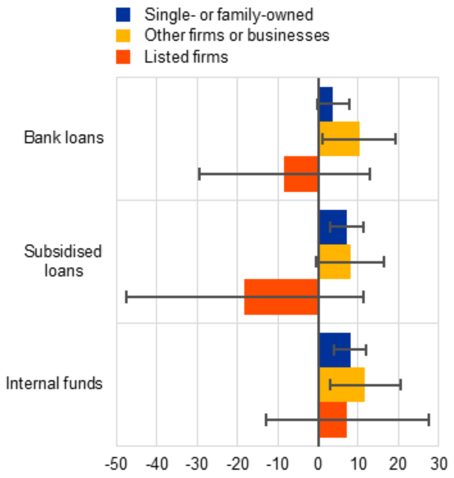
[12] See also Aldasoro, Doerr and Rees (2026).

Chart 19

Use of AI and expected AI investment, by source of financing and ownership

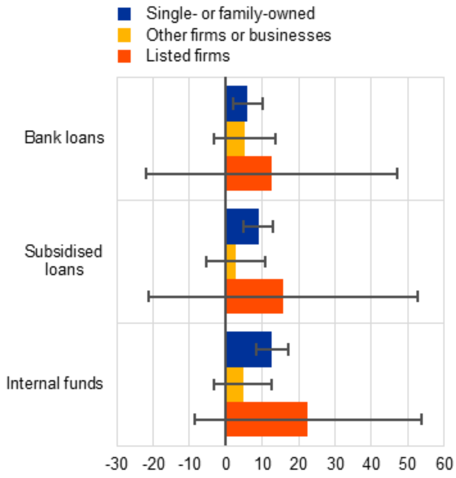
a) Use of AI

(percentage points)



b) Expected AI investment

(percentage points)



Source: Survey on the Access to Finance of Enterprises (SAFE).
Notes: Panel a): Coefficients of firm-level regressions of AI use (the dummy takes the value 1 if the firm is using AI to some extent) on types of financing, by type of ownership in the firm. Panel b): Coefficients of firm-level regressions of expected AI investment (the dummy takes the value 1 if the firm is expecting to invest in AI) on types of financing, by type of ownership in the firm. “Single- or family-owned” indicates firms whose majority ownership stake is through single owners, family members or entrepreneurs. “Other firms or businesses” includes firms owned by other enterprises or business associates. Survey-weighted regressions with industry, country and firm size fixed effects. Whiskers represent 90% confidence intervals.

6 AI adoption and firms’ business outlook

Understanding firms’ expectations about key economic outcomes, such as turnover, investment, wages, employment and inflation is crucial for assessing future business activity and broader macroeconomic trends. Expectations capture the forward-looking dimension of firm behaviour and can serve as leading indicators of investment cycles, hiring decisions and aggregate demand.

The SAFE elicits firms’ expectations using two distinct approaches. For turnover and fixed asset investment, firms provide qualitative assessments, indicating whether they expect these variables to increase, decrease or remain unchanged over the next three to six months. For selling prices, wages and employment, firms are instead asked to provide quantitative estimates expressed as percentage changes over a 12-month horizon. Inflation expectations are also collected quantitatively over three horizons: one year, two years and five years ahead.

Against this backdrop, this section examines whether firms’ expectations differ according to their degree of AI adoption. The underlying rationale is that AI technologies may affect firms perceived growth prospects, operational efficiency, investment needs and labour demand; and these effects may be reflected in their forward-looking assessments.

As a natural extension, the discussion also examines the impact of AI adoption on firms’ productivity. For this purpose, we introduce a novel productivity proxy derived from SAFE responses, based on firms’ reported changes in turnover and employment (Box 1).

6.1 Impact on investment, productivity and employment

We begin by analysing the relationship between the intensity of AI adoption and firms’ expectations for real outcomes (**Chart 20**, panel a). Regression analysis reveals that, after controlling for firm size, sector and country, firms making significant use of AI are more likely to expect higher turnover and increased fixed asset investment over the next three months by 17 and 9 percentage points respectively, compared with firms that do not use AI at all. These results are consistent with a self-reinforcing dynamic in which AI-intensive firms may perceive their competitive position as improving, which in turn feeds into more optimistic short-term growth expectations, leading to more positive expectations for sales and investment.

The association with employment expectations is also positive. Firms making significant use of AI expect headcount to grow by approximately 1.1 percentage points more over the next 12 months than comparable non-AI-using firms, though this estimate is imprecisely measured (**Chart 20**, panel b). This may reflect firms’ anticipated need to hire workers with the technical skills required to operate and maintain AI systems, or to scale up operations following productivity gains enabled by AI integration. Thus far, our findings align with Aldasoro et al. (2026) and Santos and Molica (2026) in showing no current evidence of labour shedding. However, this does not preclude the emergence of structural trends that could indicate displacement risks over the longer term, as documented by the European Economic and Social Committee (2026). Such risks are particularly pronounced in roles involving routine cognitive tasks (e.g. clerical, administrative, bookkeeping), female-dominated occupations and sectors with high exposure to non-routine cognitive tasks, as AI capabilities continue to advance. Additionally, Yotzov et al. (2026) highlight that while most firms report minimal measurable employment impacts to date, executives anticipate significantly larger effects within the next three years, including productivity gains accompanied by slower employment growth.

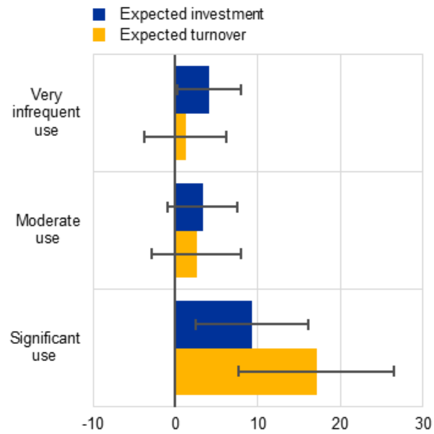
By contrast, firms reporting very infrequent or moderate use of AI display smaller differences relative to non-users for both turnover and investment expectations, and these differences are less statistically distinguishable. This suggests that the relationship between AI adoption and forward-looking optimism is non-linear, becoming more evident only among firms that have integrated AI more intensively into their operations.

Chart 20

AI use and firms' expectations about real outcomes

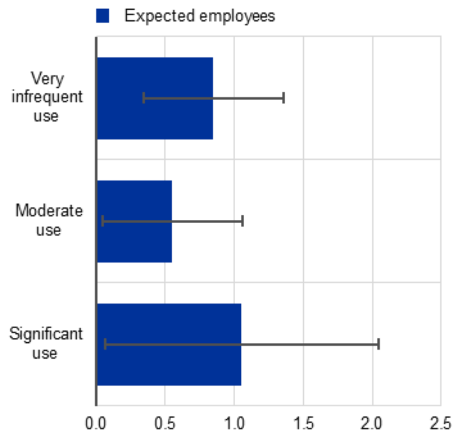
a) Expected investment and turnover

(percentage points)



b) Expected employees

(percentage points)



Source: Survey on the Access to Finance of Enterprises (SAFE).
Notes: Panel a): Coefficients of firm-level regressions of expected turnover and investment (which are dummy variables that take the value 1 if the firm expects an increase in the next three months) on AI usage, with the category "no use" omitted. Panel b): Coefficients of firm-level regressions for the continuous variable expected increases over the next 12 months of number of employees on AI usage. Survey-weighted regressions with industry, country and firm size fixed effects and controls for firms' characteristics (turnover and fixed investment in the past three months). Whiskers represent 90% confidence intervals.

Box 1

AI adoption and labour productivity: evidence from a novel survey-based measure

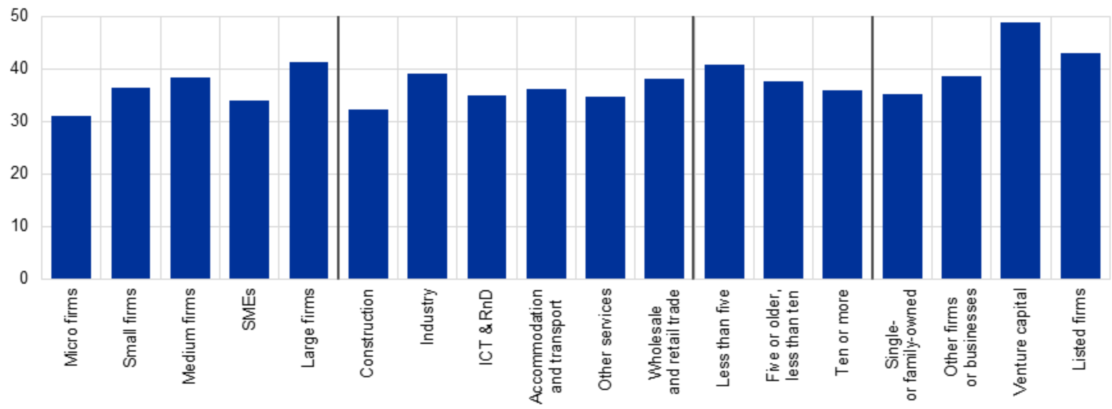
This box introduces a novel survey-based indicator designed to proxy firms' labour productivity and examines its relationship with artificial intelligence (AI) adoption. The indicator is derived from responses to the Survey on the Access to Finance of Enterprises (SAFE) on changes in turnover and employment numbers. Specifically, it is defined as a binary variable that classifies firms as either productive or not productive according to whether their reported change in turnover exceeds their reported change in employment, thereby capturing cases in which turnover per employee is likely to have increased. Firms are classified as productive if, over the surveyed period[13], they report (i) an increase in turnover together with a decrease or no change in the number of employees, or (ii) unchanged turnover together with a reduction in the number of employees. Conversely, firms are classified as not productive if they report (i) decreased or unchanged turnover with increased employee numbers, or (ii) decreased turnover with either unchanged or increased employment.[14]

Descriptive evidence points to meaningful heterogeneity across firm characteristics. Large and medium-sized firms exhibit the highest shares of firms with increasing labour productivity (41% and 38%), while micro and small firms slightly lag behind (31% and 36% respectively, Chart A). Firm age is also associated with productivity performance: younger firms show a slightly higher share of productivity increases (41%) compared with mature ones (around 36%). Across sectors, the services sector records the highest share of firms with increasing labour productivity, whereas construction lags behind. Regarding ownership structure, listed companies and firms backed by venture capital show the highest share of firms classified as experiencing productivity gains.

Chart A

Productive firms in the SAFE, by firm characteristics

(percentages)



Source: Survey on the Access to Finance of Enterprises (SAFE).
Notes: The chart shows the percentages of productive firms according to the productivity proxy, by firm characteristics. Size classes are micro firms (less than ten employees), small firms (between ten and 50), medium firms (between 50 and 250) and large firms (more than 250 employees). "SMEs" stands for small, micro and medium firms (below 250 employees). "ICT and R&D" refers to information and communications technology and research and development. "Other services" includes real estate and professional/technical activities, education and health/social services as well as sports and recreation. "Single- or family-owned" indicates firms whose majority ownership stake is through single owners, family members or entrepreneurs. "Other firms or businesses" includes firms owned by other enterprises or business associates.

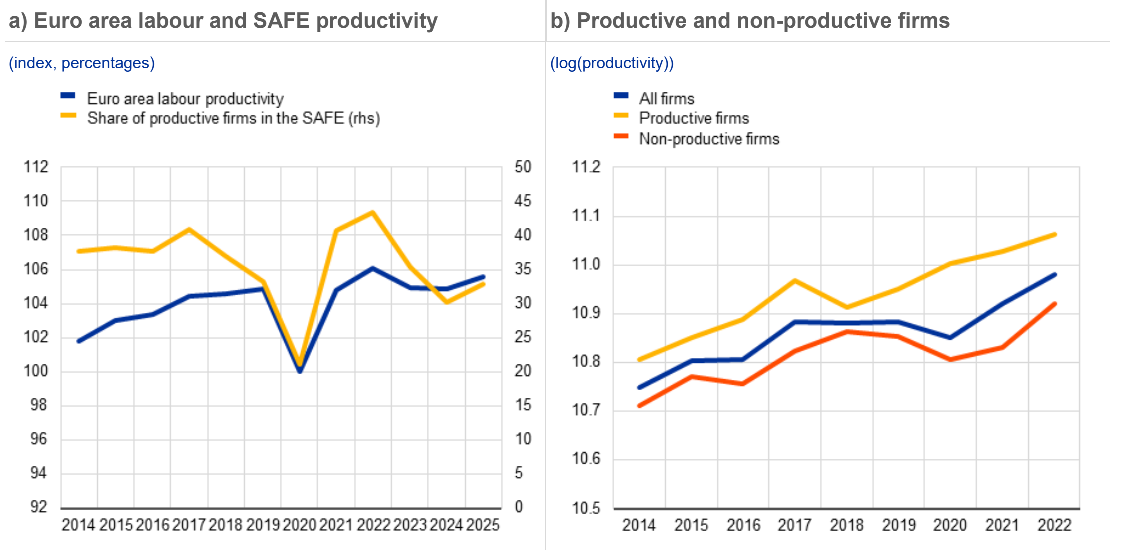
13 The surveyed period is three months or six months depending on whether the firm replies to the half-yearly or quarterly survey.

14 Firms reporting other combinations of changes in turnover and employment are excluded from the analysis since their productivity cannot be assessed from their answers.

To validate the productivity indicator, two complementary assessments are performed. First, the share of productive firms identified as having increasing labour productivity is compared with aggregate labour productivity developments in the euro area over time (**Chart B**, panel a). The proxy exhibits a clear co-movement with the aggregate measure. For instance, the share of productive firms hits a trough at 21% in 2020 – a year coinciding with the lowest euro area labour productivity since 2014, amid the economic disruptions caused by the COVID-19 pandemic. By contrast, in 2022, when aggregate labour productivity recovered strongly, the share of firms classified as productive peaked at 43%, highlighting the proxy's responsiveness to the macroeconomic conditions. Second, SAFE firms are matched with balance sheet data to calculate labour productivity, defined as value added per employee. Over the period 2014-22, firms classified as productive according to the proxy systematically display higher average labour productivity than those classified as not productive (**Chart B**, panel b). This provides further support for the validity of the proxy as a measure of firm-level productivity dynamics.[15]

Chart B

Labour productivity of firms in the SAFE



Sources: ECB, Survey on the Access to Finance of Enterprises (SAFE) and ORBIS.
Notes: Panel a): Share of productive firms in the SAFE, according to the productivity proxy, and euro area labour productivity index, as measured by GDP divided by persons in employment. Panel b): Productivity (logarithm of value added per employee) measured in the SAFE-ORBIS dataset; for those firms in the SAFE the productivity proxy is defined for "all firms" and for firms considered productive (non-productive) by the proxy.

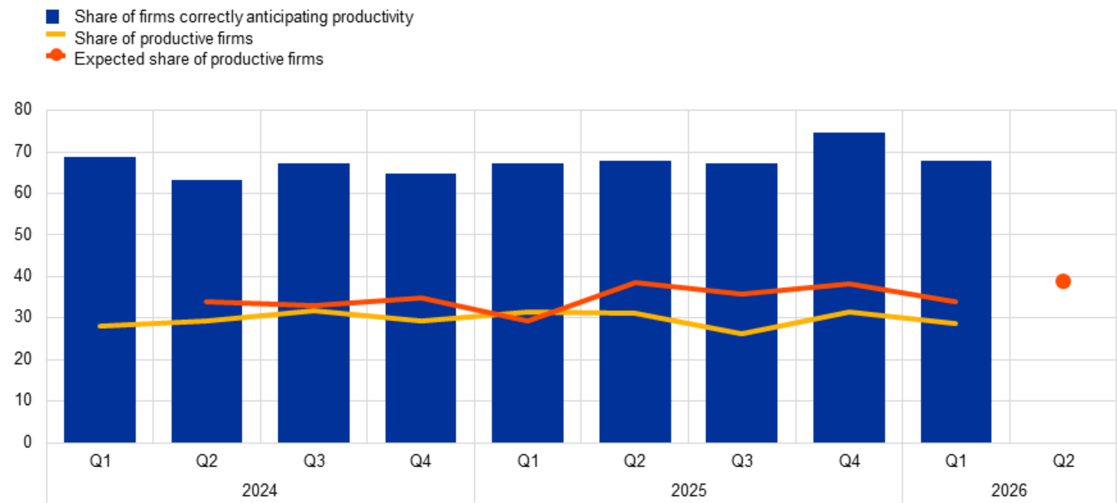
Survey data also allow the construction of an indicator for expected productivity using a similar methodology. Since 2024 the survey has incorporated questions on future turnover and employment expectations. Interestingly, while the share of firms expected to be productive consistently exceeds the actual share of productive firms, data from firms responding to consecutive SAFE waves show that their productivity expectations align with actual outcomes in 68% of cases on average. This finding suggests a reasonably strong predictive accuracy for the expected productivity proxy (**Chart C**).

[15] The restriction of the period to 2022 is due to data incompleteness of the ORBIS dataset starting in 2023.

Chart C

Productivity and expected productivity in the SAFE

(percentages)



Source: Survey on the Access to Finance of Enterprises (SAFE).
Note: The chart shows the weighted share (expected share) of productive firms according to the productivity proxy and the share of firms correctly anticipating whether they will be productive according to the proxy.

Building on these indicators of current and expected productivity, the analysis then examines whether AI adoption is associated with stronger productivity performance (**Chart D**). The regression results indicate that the relationship between AI use and labour productivity is positive but concentrated in specific sectors.

On average, AI users do not differ significantly from AI users in terms of productivity performance. However, in more knowledge-intensive activities, particularly in the information and communications technology and research and development sectors, AI adoption is associated with a higher likelihood of reporting productivity gains. Specifically, after controlling for firm size and location, firms using AI in this sector are more likely to report higher productivity over the past three months, as well as higher expected productivity for the next three months, compared with non-users. More specifically, for current productivity, all three levels of AI use – whether very infrequent/pilot, moderate or significant – are positively and significantly associated with a higher likelihood of reporting increased productivity but these effects are not statistically different from one another, suggesting that even low-intensity AI use contributes similarly to recent productivity gains as more intensive AI adoption. For expected productivity, AI use remains positively associated with the probability of anticipating higher productivity, though this effect is statistically significant only for firms with significant AI use.

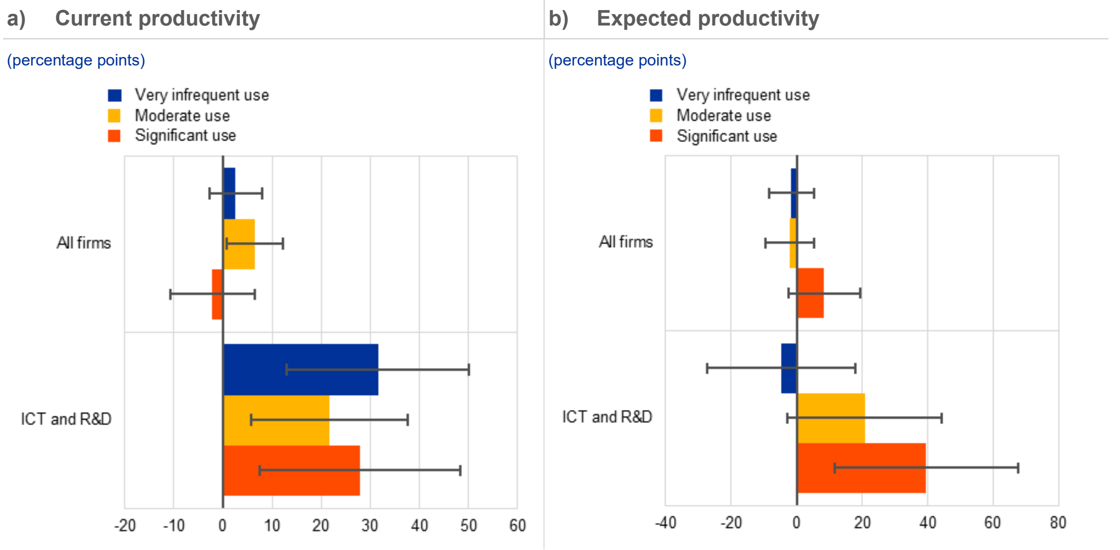
These results are in line with existing research, which suggest that the productivity benefits of AI are currently concentrated in innovators and knowledge-intensive sectors. Firms in these sectors likely possess the complementary skills, data infrastructure and organisational practices needed to translate AI adoption into measurable performance gains.[16] At the current stage of diffusion, AI

[16] See Bonney et al. (2024) on sectoral heterogeneity and Pellegrino and Piva (2020), Gal et al. (2019) and Babina et al. (2024) for further evidence on the positive impact of digital and AI technologies on productivity being concentrated in knowledge-intensive, ICT-intensive or R&D-active firms. Calvino and Fontanelli (2026) further show, for France, that only firms developing AI in-house exhibit a significant productivity premium, highlighting the role of integration depth.

therefore appears to act less as a uniform productivity enhancer across all firms and more as an enabling technology whose effects are strongest where the necessary complementarities are already in place.

Chart D

AI use and firms' expectations about real outcomes



Source: Survey on the Access to Finance of Enterprises (SAFE).
Notes: Coefficients of firm-level regressions of current (panel a) and expected productivity (panel b) on AI usage, with the category "no use" omitted. "All firms" indicates the regression on the total sample of firms for which the productivity proxies are defined. "ICT and R&D" refers to the regression on the subsample in the information and communications technology and research and development sectors. Survey-weighted regressions with industry (only for "all firms"), country and firm size fixed effects. Regressions in panel b) include controls for current productivity. Whiskers represent 90% confidence intervals.

6.2 Impact on pricing behaviour

The relationship between AI adoption and pricing behaviour mirrors, to some extent, the pattern observed for real outcomes, with meaningful differences emerging only among the most intensive AI users (**Chart 21**). After controlling for firm size, sector and country, firms making significant use of AI expect their selling prices to increase by around 0.85 percentage points more over the next 12 months than firms not using AI at all. By contrast, firms reporting very infrequent or moderate use of AI do not show statistically distinguishable differences in selling price expectations relative to non-users.

This non-linearity is consistent with the broader pattern documented above for turnover and investment: the forward-looking effects of AI adoption appear concentrated among deep adopters, while more limited engagement with the technology leaves expectations largely unchanged. Higher selling price expectations among significant AI users may reflect anticipated improvements in product quality, service differentiation or productivity-enhancing investments that strengthen pricing power.

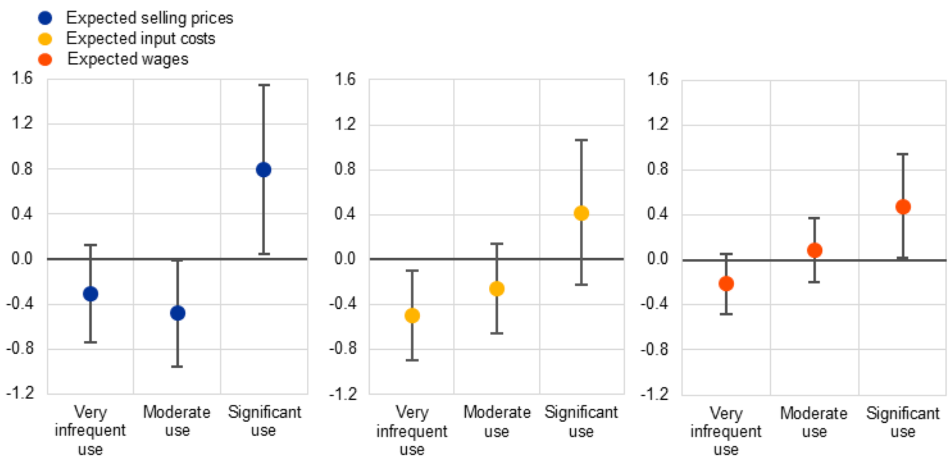
On the cost side, the picture is more nuanced. Firms with moderate or significant AI use report expectations for input cost increases broadly in line with those of non-users, suggesting that AI adoption at these intensities does not yet translate into perceived cost savings on intermediate inputs. The main exception is firms experimenting with AI, which expect input costs to rise approximately 0.5 percentage points less than non-users. This result should be interpreted with caution, however, as it may reflect compositional differences within this group rather than a causal effect of AI use on cost dynamics.

Wage expectations do not differ significantly across AI adoption categories. This is consistent with the imprecise employment estimates discussed above and suggests that, at least over the survey horizon, firms do not yet anticipate AI adoption to exert a measurable differential impact on labour costs.

Chart 21

AI use and firms' expectations about selling prices, input costs and wages

(percentage points)



Source: Survey on the Access to Finance of Enterprises (SAFE).
Notes: Coefficients of firm-level regressions of continuous variable expected increases over the next 12 months of selling prices, input costs and wages on AI usage. Survey-weighted regressions with industry, country and firm size fixed effects and controls for firms' characteristics. Whiskers represent 90% confidence intervals.

6.3 Impact on inflation expectations

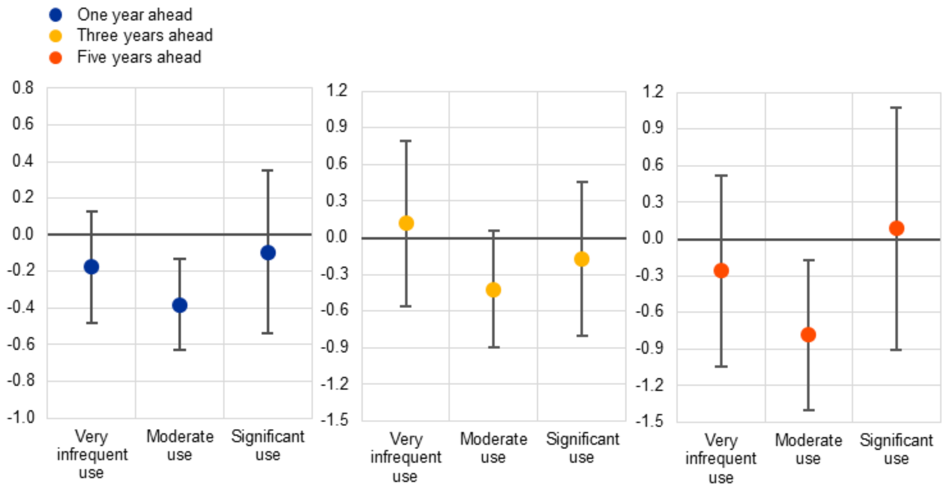
Regarding inflation expectations, we find no relationship between current AI adoption and inflation expectations, with one notable exception (**Chart 22**). Conditional on firm size, sector and country, firms making very infrequent or significant use of AI show no statistically distinguishable differences in inflation expectations at any of the three horizons – one year, three years and five years ahead – relative to non-users. Firms with moderate use of AI, however, report consistently lower inflation expectations across all horizons, with the gap widening at longer time horizons: approximately 0.4 percentage points lower at the one-year horizon and 0.8 percentage points lower at the five-year horizon.

The absence of a link between AI adoption and inflation expectations is consistent with theoretical ambiguity about AI's net inflationary impact, given competing demand-side, supply-side and distributional channels. Lane (2026) argues that permanent productivity gains from AI are unlikely to trigger immediate increases in spending or prices, as individuals tend to adjust their habits gradually. On the supply side, while AI adoption has the potential to lower costs over time, its high energy requirements during the adoption phase could temporarily drive up energy prices, partially offsetting the cost-saving benefits. These opposing dynamics likely account for the lack of a consistent inflationary signal in the firm-level survey data thus far. The divergence in inflation expectations between moderate AI users and significant AI users may reflect firm-level differences in how they anticipate the balance of these competing forces.

Chart 22

AI use and firms' expectations about euro area inflation

(percentage points)



Source: Survey on the Access to Finance of Enterprises (SAFE).
Notes: Coefficients of firm-level regressions of firms' expectations about euro area inflation over the next one, three or five years on AI usage. Survey-weighted regressions with industry, country and firm size fixed effects. Whiskers represent 90% confidence intervals.

7 Firms’ expected investment in AI

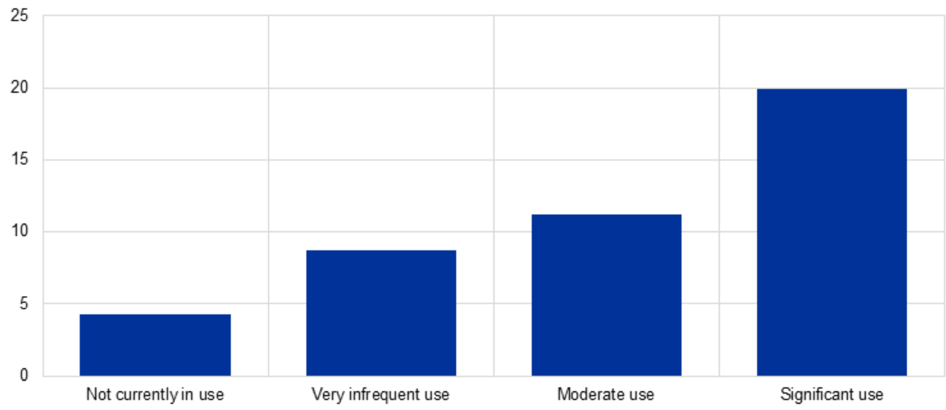
This section analyses firms’ forward-looking plans for AI investment over the next 12 months, drawing on the December 2025 SAFE round. It explores the expected share of total investment allocated to AI across varying levels of current AI adoption and examines how these investment plans differ by country, firm size, sector and ownership structure. The findings highlight a self-reinforcing dynamic: firms already using AI intensively plan to increase their investments, while non-users and occasional adopters anticipate significantly lower investment levels. A dedicated subsection focuses on SMEs planning to invest in AI, providing a detailed characterisation of this group based on current adoption intensity, sector and ownership type.

Firms currently using AI expect to invest more in AI over the next 12 months compared with non-users, pointing to a self-reinforcing cycle of adoption and innovation (**Chart 23**). On average, firms expect to allocate 9% of their total investment to AI, although this share varies considerably by firm characteristics and by current level of AI adoption. Firms that do not currently use AI anticipate allocating only a small share of their investment to AI (4% on average), with large firms expecting a slightly higher share (6%) compared with SMEs (4%). By contrast, firms at a more advanced stage of AI adoption report substantially higher planned investment rates. Firms making moderate use of AI expect to allocate 11% of their investment to AI, while significant AI users report the highest expected allocation, at 20%. Within this latter group, SMEs plan to devote a larger share of investment to AI than large firms, with expected allocation of 21% and 17% respectively. Overall, these patterns suggest that AI adoption may reinforce itself over time: firms already using AI are more likely to invest further in developing, expanding and integrating these technologies, while non-users plan comparatively limited AI-related investment.

Chart 23

Expected investment in AI over the next 12 months, by current AI usage intensity

(percentages of overall investment)



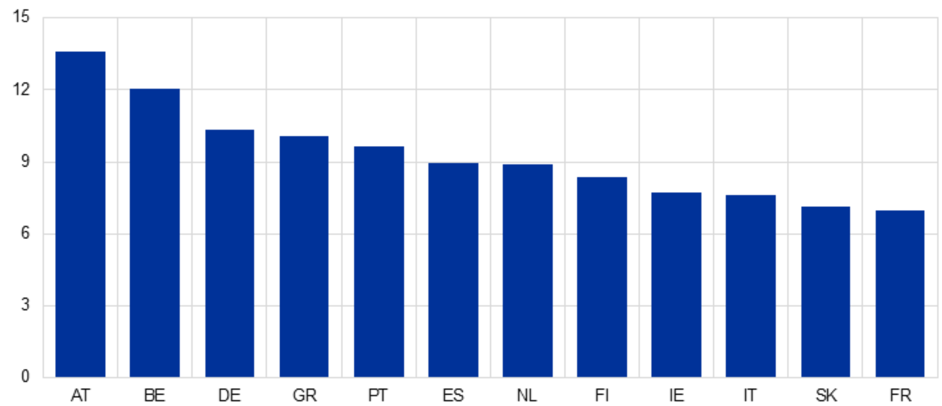
Source: Survey on the Access to Finance of Enterprises (SAFE).
Note: The chart shows the weighted expected AI investment relative to total investment over the next 12 months by current AI usage intensity.

Across the 12 euro area countries covered in the December round of the SAFE, firms in Austria report the highest expected AI investment over the coming 12 months, followed by Belgium and Germany (14%, 12% and 10% respectively, **Chart 24**). Among the four largest euro area economies, Germany leads in expected share of AI investment, followed by Spain (9%), Italy and France (8% and 7% respectively).

Chart 24

Expected investment in AI over the next 12 months, by country

(percentages of overall investment)



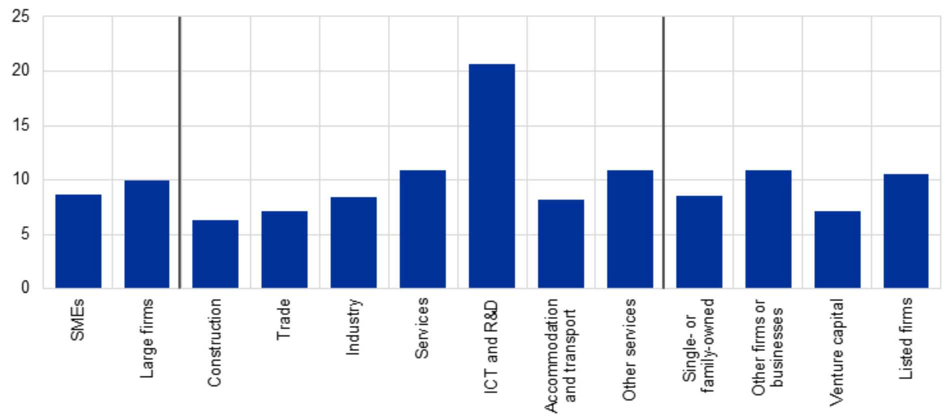
Source: Survey on the Access to Finance of Enterprises (SAFE).
Note: The chart shows the weighted expected AI investment relative to total investment over the next 12 months by country.

Across size classes, SMEs and large firms plan to allocate similar shares of total investment in AI – both close to 10%. This suggests that some smaller firms are also operating near the technological frontier rather than systematically lagging behind larger incumbents (**Chart 25**). By sector, firms in services anticipate dedicating the highest share of their investment to AI (11%), followed by industry (8%), trade (7%) and construction (6%). These patterns likely reflect the greater potential for AI applications in intangible, data-driven and customer-focused activities. Within the services sector, firms operating in ICT and R&D-related industries expect to allocate the largest share of their total investment to AI, surpassing many other service activities. This trend aligns with their superior digital capabilities and closer proximity to the technological frontier. Ownership structure also plays a significant role in shaping expected AI investment. Firms owned by other enterprises, business associates or publicly listed entities report the highest planned shares of AI investment. This may be attributed to their stronger governance frameworks, easier access to financial resources and greater pressure from shareholders or stakeholders to modernise and remain competitive. In contrast, single-owned or family-owned firms and venture capital-backed enterprises report lower expected AI investment rates. This disparity may reflect more conservative investment approaches, constraints in accessing financing or a strategic focus on narrower innovation goals.

Chart 25

Expected investment in AI over the next 12 months, by firm characteristics

(percentages of overall investment)



Source: Survey on the Access to Finance of Enterprises (SAFE).
Notes: The chart shows the weighted expected AI investment relative to total investment over the next 12 months by firm characteristics. “SMEs” stands for small, micro and medium firms (below 250 employees). “ICT and R&D” refers to information and communications technology and research and development. “Other services” includes real estate and professional/technical activities, education and health/social services as well as sports and recreation. “Single- or family-owned” indicates firms whose majority ownership stake is through single owners, family members or entrepreneurs. “Other firms or businesses” includes firms owned by other enterprises or business associates.

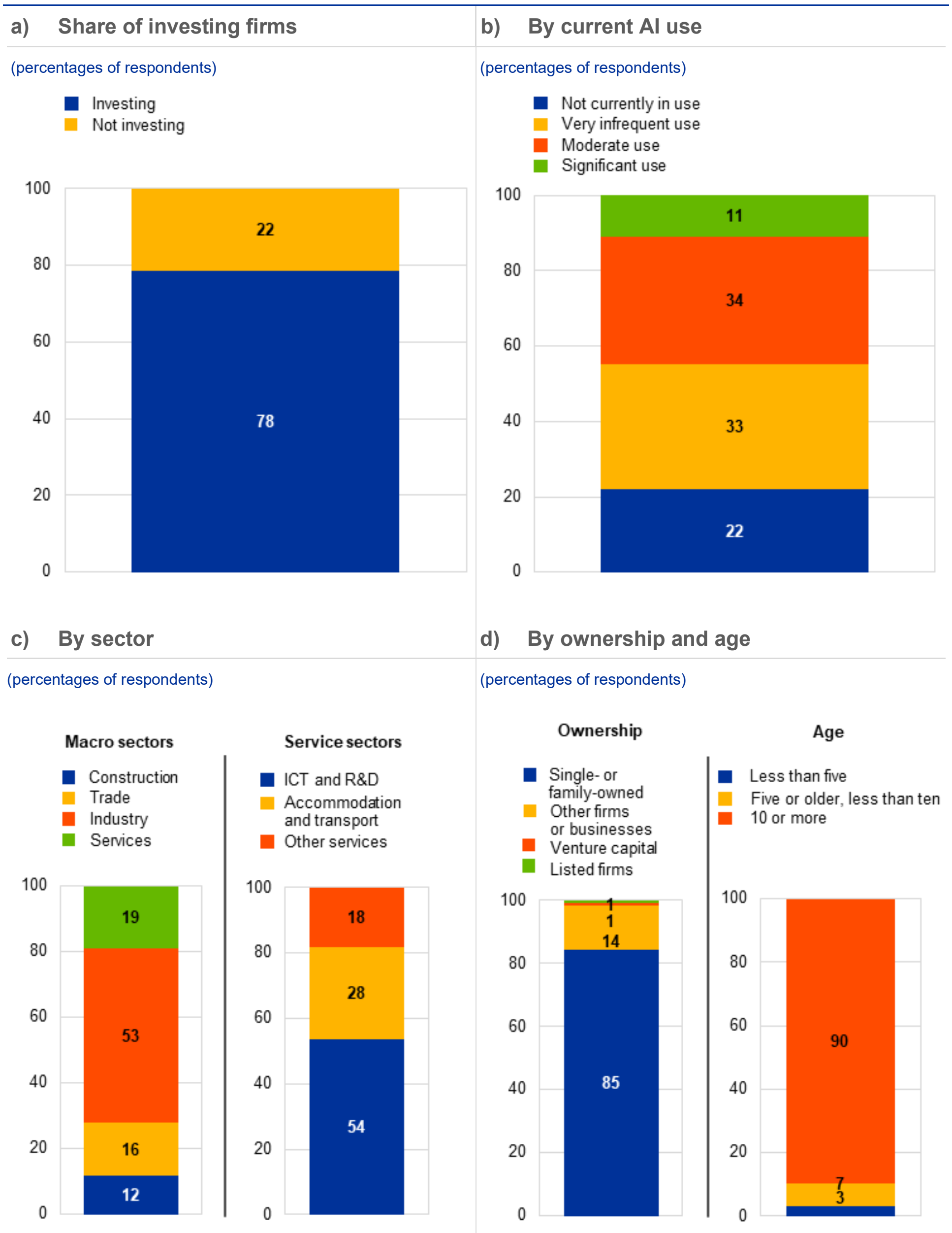
7.1 Which SMEs are planning to invest in AI?

While the aggregate picture presented above covers all firm sizes, SMEs deserve particular attention given their predominance in the euro area economy and their distinct financing and structural characteristics. This subsection profiles the group of SMEs that plan to invest in AI over the coming year. Identifying which SMEs are driving planned AI investment – and assessing how limited their aggregate weight remains – is relevant for assessing the likely macroeconomic impact of AI diffusion and the scope for targeted policy support.

According to the December 2025 survey wave, 22% of SMEs plan to invest in AI in the coming year. Among these SMEs, most are currently infrequent or moderate AI users, accounting for 33% and 34% respectively. A further 11% are significant users, while 22% do not use AI at all. This suggests that planned investments are driven both by firms seeking to deepen existing use and by new adopters (**Chart 26**). SMEs planning to invest in AI are predominantly in industry, followed by services, trade and construction (53%, 19%, 16% and 12% respectively). This distribution reflects the growing role of AI in automating production processes. Within services, AI-investing SMEs are mainly concentrated in ICT and R&D, as well as accommodation and transport. This is consistent with the high potential for AI in digital-intensive activities, logistics and capacity management. In terms of ownership, these firms are mostly single-owned or family-owned or owned by other enterprises or businesses associates, which may indicate that both traditional and group-affiliated SMEs see strategic value in AI, despite differences in governance structures and access to resources. Although their expected AI investment shares are close to those of large firms, their aggregate economic impact is likely to remain more limited, as they account for only around 5% of total employment in the euro area. Thus, while a subset of SMEs appears to be actively engaging with AI and operating close to the technological frontier, the macroeconomic effects of SME-led AI investment may depend on whether adoption broadens beyond this relatively small group.

Chart 26

SMEs expecting to invest in AI



Source: Survey on the Access to Finance of Enterprises (SAFE).
Notes: Panel a): Share of SMEs that are investing or are not investing in AI. Panels b)-d): Shares of different firm characteristics for those SMEs who are investing in AI. "ICT and R&D" refers to information and communications technology and research and development. "Other services" includes real estate and professional/technical activities, education and health/social services as well as sports and recreation. "Single- or family-owned" indicates firms whose majority ownership stake is through single owners, family members or entrepreneurs. "Other firms or businesses" includes firms owned by other enterprises or business associates.

8 Firms’ response to competition in AI investment

In this section we briefly report the results of the randomised controlled trial designed by Baumann et al. (2025) and implemented within the SAFE to understand how firms decide whether to invest in AI. When analysing firms’ replies based on the trial, Baumann et al. (2026) find that firms’ decisions to adopt new technology are likely to be influenced not only by their own characteristics and constraints, but also by the competitive environment in which they operate.[17] Their results show that firms significantly underestimate the share of their competitors investing in AI. However, when provided with information on the actual investment behaviour of their competitors, they update their beliefs about the share of their competitors investing in AI in the future and, importantly, expect higher own future investment in AI.

8.1 How much did competitors invest in AI by June 2025?

The ad hoc module on AI investment introduced in the June 2025 survey data made it possible to calculate the proportion of firms that had invested in AI by June 2025 for each country, industry and size class. This granular breakdown enables us to analyse AI investment among a comparable group of firms, defined as competitors. These investment shares are summarised in **Table 1**.

In the December 2025 survey round, the randomised control trial introduced by Baumann et al. (2025) made it possible to examine the impact of information about domestic competitors’ past AI investments on firms’ expectations regarding future adoption. This trial leveraged the data presented in Table 1. Firms were first asked to report the proportion of comparable domestic firms that had already invested in AI up to June 2025 (prior belief). Following this, the sample was randomly divided into two equally sized groups. One group received information on the actual share of comparable firms that had invested in AI, as detailed in Table 1, while the other group did not receive this information. Next, firms were asked to report their expectations regarding the share of comparable domestic firms likely to invest in AI in the future (posterior belief). Lastly, firms provided their own anticipated AI investment rate. This experimental design allows us to trace the full causal chain – from the provision of information to belief updates and, ultimately, intended investment behaviour.

[17] For more details on the analysis derived from the randomised controlled trial, see Baumann et al. (2026).

Table 1
Share of firms that invested in AI technologies up to June 2025, by country, sector and size class

(percentages)

	Construction		Industry		Services		Trade	
	Less than 50 employees	50 or more employees	Less than 50 employees	50 or more employees	Less than 50 employees	50 or more employees	Less than 50 employees	50 or more employees
Austria	23	83	29	64	35	73	23	37
Belgium	26	26	12	59	31	53	19	89
Germany	18	30	31	48	35	53	19	47
Spain	24	50	30	55	37	56	18	13
Finland	24	75	31	38	28	65	25	44
France	7	55	13	34	20	38	12	30
Greece	12	17	18	66	22	11	7	41
Ireland	17	31	23	56	27	36	17	36
Italy	2	12	12	35	24	35	13	30
The Netherlands	13	76	28	27	38	60	14	19
Portugal	8	60	18	36	37	57	14	21
Slovakia	15	21	18	28	29	25	15	49

Source: Survey on the Access to Finance of Enterprises (SAFE).
Note: The table shows the weighted percentages of firms that invested in AI, by sector, country and firm size, up to June 2025.

8.2 Firms' assessment of shares of competitors investing in AI

Building on Baumann et al. (2026), we delve deeper into the responses from the randomised controlled trial to examine the heterogeneity in misperceptions, using the same firm characteristics analysed in the previous sections. Most firms tend to underestimate the share of their domestic competitors investing in AI (**Chart 27**). Misperceptions are measured by comparing actual AI adoption rates, based on the June 2025 SAFE round, with firms' perceived share of comparable competitors, as reported in the December 2025 survey. The results show that, on average, 80% of firms underestimate the share of AI investors in their peer group. The average degree of underestimation is 18 percentage points. This gap is smaller for SMEs than for large firms, at 14 percentage points compared with 25 percentage points (**Chart 27**, panel a). The difference may reflect the fact that large firms are more likely to view themselves as market leaders, which could lead them to underestimate the extent to which competitors are also investing in AI.

Sectoral differences are also pronounced. Firms in services and industry exhibit larger misperceptions, on average, than firms in construction or trade. This may be because competitive benchmarks and technologies evolve more rapidly in these sectors, making it harder to assess rivals' investment behaviour accurately (**Chart 27** panel b). A more detailed breakdown within services shows that misperceptions are highest in accommodation and transport. By contrast, they are relatively low in ICT and R&D, at around 5 percentage points, consistent with the idea that digitally intensive and innovation-oriented sectors are better informed about frontier technologies and competitors' adoption patterns (**Chart 27**, panel c).

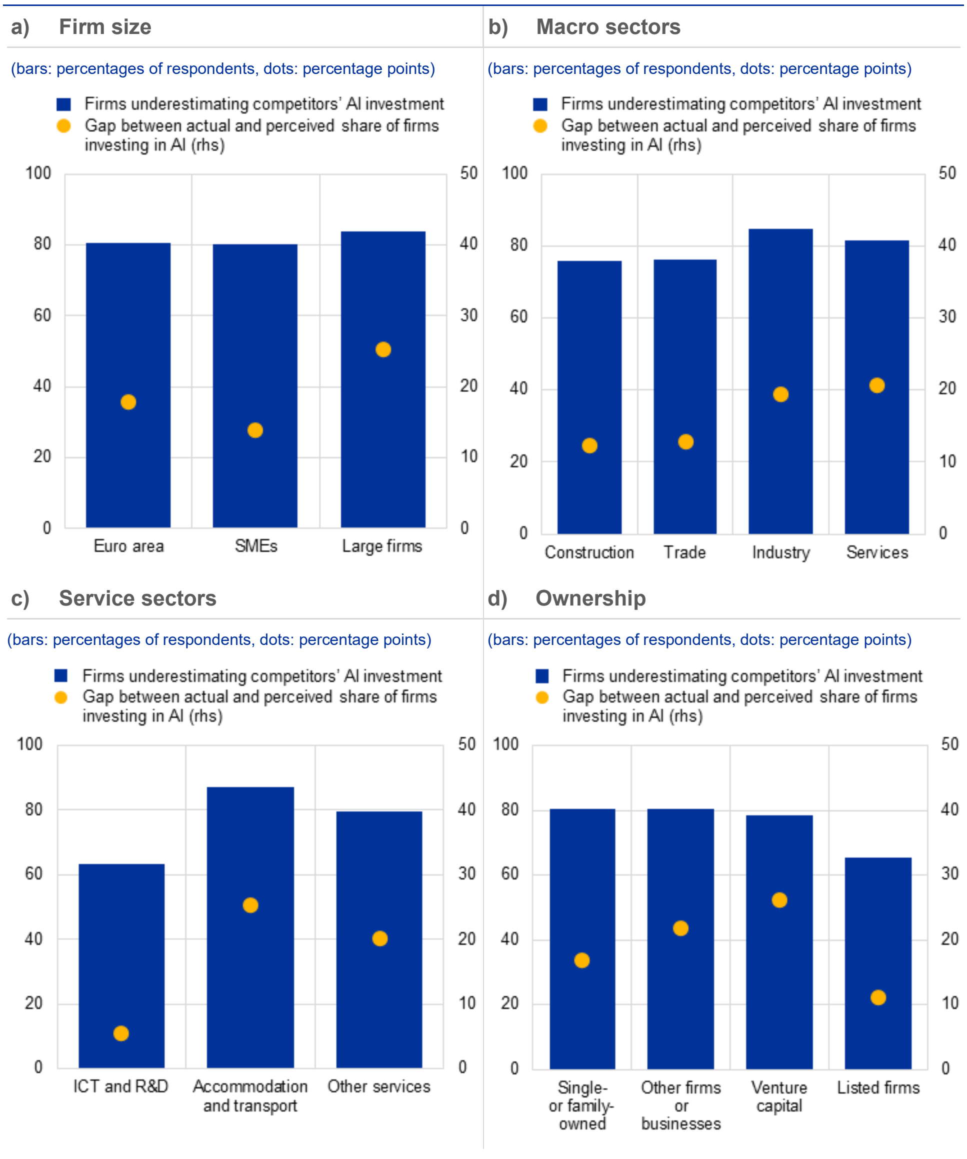
Misperceptions also vary by ownership type. Listed firms display the smallest misperception, on average, while venture capital-backed firms show the largest (**Chart 27**, panel d). This may reflect stronger disclosure requirements and greater market transparency for listed firms, whereas venture capital-backed firms may operate in more dynamic or less transparent competitive environments, where market information is harder to obtain or interpret, leading to greater misperceptions (EIB, 2024).

Overall, the evidence suggests that firms systematically underestimate the extent of AI investment among competitors. Given the role of competitive pressures in shaping technology adoption, such underestimation may have significant implications for firms' strategic positioning and their ability to keep pace with technological change.[18]

[18] See also Cullen et al. (2025), who show that firms in Italy substantially underestimated competitors' AI adoption.

Chart 27

Firms' misperception of AI investment by domestic competitors



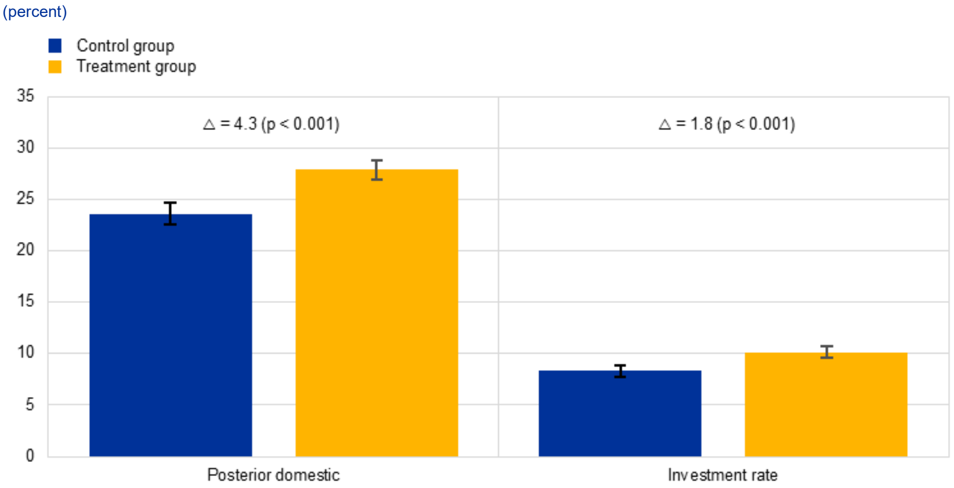
Source: Survey on the Access to Finance of Enterprises (SAFE).
Notes: Bars shows the weighted share of responding firms that underestimate the share of firms investing in AI within their category (size class, sector and country). Dots shows the average difference between the true and perceived investment share of firms. "ICT and R&D" refers to information and communications technology and research and development. "Other services" includes real estate and professional/technical activities, education and health/social services as well as sports and recreation. "Single- or family-owned" constitutes a majority ownership stake through single owners, family members or entrepreneurs.

8.3 The impact of information about domestic competitors on firms' investment plans in AI

In this section we report the results of the analysis of Baumann et al. (2026) to show that firms update their beliefs about the share of competitors investing in AI and adjust their own planned behaviour in response to the information treatment (**Chart 28**). Firms in the treatment group which received information on competitors' actual AI investment report on average 4.3 percentage points higher beliefs about the share of future AI adopters among their competitors than firms in the control group, which did not receive this information. This indicates that respondents paid attention to the information provided and considered it relevant. Most importantly, the information treatment also affects firms' own planned investment behaviour. On average, treated firms report an expected AI investment rate almost 2 percentage points higher than that of firms in the control group. This suggests that informational frictions can materially slow the diffusion of new technologies such as AI: when firms underestimate competitors' investment in AI, they may also underinvest themselves. Conversely, providing accurate information about competitors' behaviour can strengthen incentives to invest. These findings align with experimental evidence from German and Italian firm surveys showing that providing accurate information about competitors' adoption rates raises firms' own adoption plans (Menkhoff, 2025; Cullen et al., 2025), and with the broader literature documenting the role of informational barriers in slowing technology diffusion (Kalyani et al., 2025). They also suggest that competitive pressures may be stronger than many firms perceive and that correcting misperceptions could help accelerate AI adoption across the euro area.

Chart 28

Treatment effects on posterior beliefs and AI investment rate



Source: Baumann et al. (2026).
Notes: The chart shows treatment effects on posterior belief about domestic adoption and on expected AI investment rate, comparing control and treatment groups. This reproduces Figure 4, Panel A from Baumann et al. (2026). The sample is restricted to firms with non-missing observations across all AI variables, as in Baumann et al. (2026).

9 Conclusion

This paper has harnessed the unique, harmonised firm-level data of the ECB and European Council’s SAFE to provide a comprehensive picture of AI adoption among euro area firms in 2025. Drawing on dedicated ad hoc modules fielded in the June and December 2025 survey rounds, the analysis covers adoption patterns and their determinants, financing channels, firm-level expectations, planned investment and perceptions of competitive pressure across 12 euro area countries.

AI adoption is widespread, but intensive integration remains limited. Approximately 70% of euro area firms report some degree of AI use, yet only 7% characterise their use as significant. This share is remarkably uniform across firm size classes, pointing to a common ceiling on intensive adoption that cuts across the SME-large firm divide. Pronounced cross-country heterogeneity is evident: adoption rates are highest in the Netherlands, Finland and Austria (above 80%) and lowest in Italy and Ireland (below 65%), with differences reflecting both the share of non-adopters and the depth of use among adopters. The evidence suggests that the challenges faced by firms varies by country: in high-non-adoption economies the priority is for firms to move from non-use to experimentation, while in more advanced adopter countries the key task is scaling up from experimental to intensive integration.

Firm characteristics shape adoption in systematic ways. Large firms are significantly more likely to use AI than micro and small firms, though the share of significant users is broadly similar across size classes. Younger firms – particularly those founded around or after the emergence of advanced LLMs in late 2022 – display substantially higher rates of intensive AI use, suggesting that these firms embedded AI into their business models from inception. Sectoral differences are striking. ICT and R&D firms exhibit the highest shares of significant adopters, while construction lags considerably. Ownership structure also matters, with listed and venture capital-backed firms being the most advanced users and family-owned or single-owned firms concentrated among non-users or infrequent adopters.

The primary motivation for adopting AI is the improvement of core and non-core business processes, a finding that holds broadly across countries, firm sizes, sectors and ownership structures. Personnel cost reduction and innovation-related motives play a secondary but meaningful role. Barriers are more heterogeneous: skill shortages are the most pervasive impediment, while data and privacy concerns and system incompatibility become more salient as firms advance along the adoption path. Among non-adopters and limited users, a perception that AI is irrelevant is particularly common among micro and small firms.

On the financing side, AI adoption relies primarily on internal funds, with subsidised bank loans and, to a lesser degree, bank loans providing complementary support. This pattern holds across size classes and sectors, though with notable nuances: for SMEs, all three sources are significantly associated with current AI use and planned investment, while for large firms, internal funds and subsidised bank loans dominate and bank lending plays no significant role in planned AI investment.

A key contribution of this paper is the evidence it provides on how AI adoption intensity shapes firms' forward-looking expectations. Firms with significant AI adoption report substantially higher expectations for turnover growth and fixed asset investment, consistent with a self-reinforcing dynamic in which deep adopters perceive their competitive positions as strengthening. Only significant users anticipate higher selling prices, pointing to a non-linear relationship between adoption depth and pricing behaviour. No statistically significant differences in wage or input cost expectations are found across adoption categories.

On productivity, AI adoption is positively associated with firm-level performance in the ICT and R&D sector, where even low-intensity use raises current productivity, while only significant use predicts higher expected productivity – suggesting a non-linear link between adoption depth and forward-looking performance gains.

Regarding employment patterns, our findings currently show no evidence of labour shedding, with AI seemingly complementing rather than replacing workers at this stage. However, as these results are based on a snapshot, they cannot provide insights into potential longer-term shifts or displacement risks.

Regarding expected AI investment, firms currently using AI plan to allocate significantly higher shares of their total investment to AI than non-users: significant users expect to devote around 20% of total investment to AI, compared with only 4% among non-users. This reinforcing cycle is evident across ownership structures and age groups, with listed and venture capital-backed firms leading at early adoption stages and privately owned firms exhibiting the highest planned investment intensity at advanced stages.

Taken together, these findings underscore that the productivity impact of AI in the euro area remains uncertain and will depend on the speed and breadth of adoption as well as the technology's intrinsic costs and benefits. This makes policies targeting diffusion – particularly among SMEs, laggard countries and sectors currently constrained by skills gaps and financing barriers – the most consequential lever available to policymakers.

A natural avenue for future research is to deepen the analysis of how euro area firms finance their investments in AI. While the present paper has documented the extent and patterns of AI adoption across the euro area, the question of how firms fund these investments remains largely open, both in this paper and in the broader literature. Data limitations have so far constrained the analysis to traditional banking products, but the diversity of AI-related expenditures – spanning technology purchases, digital infrastructure and workforce development – calls for a more comprehensive examination of the financing landscape. Unlike conventional capital expenditure, AI investment combines tangible components, such as servers and hardware, with largely intangible ones, including software licences, cloud services and organisational capabilities. Intangible assets are inherently difficult to pledge as collateral, which tends to raise the cost of external financing and push firms toward internal funds. Whether this dynamic is empirically borne out for AI adopters in the euro area – and whether it varies systematically by firm size, sector or country – are open empirical questions with direct policy relevance.

A possible approach to addressing these questions would be to first identify the scope of firms' intended AI investments, distinguishing between technology purchases, infrastructure investments, predictive analytics and workforce AI development. Next, it would be essential to collect detailed information on the various financing instruments firms plan to use for these expenditures. This analysis should extend beyond internal funds, bank loans and credit lines to include leasing and hire-purchase arrangements, corporate bonds and equity financing.

By mapping financing choices to investment types at the firm level, this expanded analysis could shed light on whether AI investment faces distinct financing constraints compared with conventional capital expenditures. It could also explore whether non-bank financing instruments – still underdeveloped in Europe compared with other advanced economies – are beginning to play a larger role in supporting technological adoption. These insights would have direct implications for ongoing policy discussions on deepening European capital markets and reducing financing barriers to enable the digital transition.

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Annalisa Ferrando
European Central Bank, Frankfurt am Main, Germany; email: Annalisa.Ferrando@ecb.europa.eu

Sara Lamboglia
European Central Bank, Frankfurt am Main, Germany; email: Sara.Lamboglia@ecb.europa.eu

Judit Rariga
European Central Bank, Frankfurt am Main, Germany; email: Erzsebet-Judit.Rariga@ecb.europa.eu

Maurice Schmidt
European Central Bank, Frankfurt am Main, Germany; email: Maurice_Pascal.Schmidt@ecb.europa.eu

Postal address 60640 Frankfurt am Main, Germany
Telephone +49 69 1344 0
Website www.ecb.europa.eu

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