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AI Watch
Adoption of Autonomous Machines

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Executive summary

This report provides an empirical analysis of the drivers and barriers to adoption of autonomous machines (AM) technologies by European companies. Based on this analysis, the report provides a series of policy recommendations to accelerate the uptake of AM and robots and emphasise its impact on the European economy.

Policy context

This report is part of AI Watch, the European Commission's knowledge service to monitor the development, uptake and impact of artificial intelligence (AI) in Europe. In December 2018, the European Commission and the Member States published a "Coordinated Plan on Artificial Intelligence" on the development of AI in the EU that mentions AI Watch's role in providing analysis and studies to support the plan. Moreover, the 2021 review of the Coordinated Plan on AI confirmed the role of AI Watch to support implementation and monitoring of the Coordinated Plan. In this context, and with an economic focus, this report contributes to two of the objectives of AI Watch: monitoring the uptake and technical developments of AI and monitoring its impact.

Key conclusions

The main takeaway of this report is that AM adoption is driven by several factors and has heterogeneous effects on companies depending on their characteristics.

Regarding the drivers of adoption, we find that firm size, employee knowledge of AI, the joint adoption of AM with complementary technologies (namely: robotic process automation, process optimisation technologies, computer vision, forecasting technologies, and creative and innovative activities) and having a low productivity level increase a firm's probability of adopting AM.

On the other hand, concerning barriers to adoption of AM, we can highlight three main findings. First, the most relevant barriers to AM adoption for non-adopters are cost of adoption and, to a lesser extent, lack of skills and data access. Specifically for large firms (those with 250 employees or more), liability and reputation risks, as well as data access, are the most important obstacles. Second, certain types of obstacles (namely: liability and reputation risks, data access and lack of funding) are more likely to be present in certain sectors of activity. Third, the more complementary technologies a firm adopts, the lower its probability of facing obstacles to AM adoption.

Policy recommendations

Based on the findings of the empirical analysis carried out, this report makes a series of policy recommendations along five axes:

- Focus on workforce skilling and upskilling
- Widen the scope of adoption-fostering policies to technology bundles
- Target firms in low-adoption sectors
- Prioritise reducing the cost of adoption
- Design policies that are tailored to the size of the company

1. Introduction

Artificial intelligence (AI)[2] has become an area of strategic importance with the potential to be a key driver of economic development. AI also has a wide range of potential social implications. As part of its Digital Single Market Strategy, the European Commission put forward in April 2018 a European strategy on AI in its Communication "Artificial Intelligence for Europe". The aims of the European AI strategy announced in the communication are threefold:

- To boost the EU's technological and industrial capacity and AI uptake across the economy, both by the private and public sectors
- To prepare for the socio-economic changes brought about by AI
- To ensure an appropriate ethical and legal framework

In December 2018, the European Commission and the Member States published a "Coordinated Plan on Artificial Intelligence" on the development of AI in the EU. The Coordinated Plan mentions the supporting role of AI Watch,[3] the European Commission's knowledge service, to monitor the development, uptake and impact of AI for Europe, which was launched in December 2018. AI Watch monitors: (i) the European Union's industrial, technological and research capacity with respect to AI; (ii) AI-related policy initiatives in the Member States; (iii) uptake and technical developments of AI; and (iv) the impact of AI. AI Watch has a European focus within the global landscape. In the context of AI Watch, the Commission works in coordination with Member States. From AI Watch's in-depth analyses, we will be able to understand better the European Union's areas of strength and areas where investment is needed. AI Watch will provide an independent assessment of the impacts and benefits of AI on growth, jobs, education and society.

Subsequently, in February 2020, the Commission unveiled its vision for a digital transformation, which strives to be beneficial to the entirety of European citizens. The Commission presented a White Paper proposing a framework for trustworthy AI based on excellence and trust.

In April 2021, the European Commission proposed a set of actions to boost excellence in AI, and rules to ensure that the technology is trustworthy. The proposed Regulation on a European Approach for Artificial Intelligence and the update of the Coordinated Plan on AI, including specific actions on robotics, aim to guarantee the safety and fundamental rights of people and businesses, while strengthening investment and innovation across EU countries. The 2021 review of the Coordinated Plan on AI[4] refers to AI Watch reports and confirms the role of AI Watch to support implementation and monitoring of the Coordinated Plan.

In this context, and as part of AI Watch, this report provides an empirical analysis of the drivers of and barriers to adoption of a key AI technologies by European companies: autonomous machines (AM)[5] (including robots[6]). Based on this analysis, the report provides a series of policy recommendations to accelerate the uptake of AM and reinforce its impact on the European economy.

The remainder of this report is structured as follows. **Section 2** summarises the main findings of the literature regarding the three areas on which this report focuses: (i) drivers of technology adoption and (ii) barriers to technology adoption **Section 3** uses recent data from a European Commission survey to empirically analyse these three issues with respect to the particular case of AM. **Section 4** concludes and sets out policy recommendations to accelerate the uptake of AM and reinforce its impact on the European economy.

[2] We define artificial intelligence as "a software that is developed with one or more techniques and approaches" such as machine learning or knowledge- and logic-based approaches "and can, for a given set of human-defined objectives, generate outputs such as content, predictions, recommendations, or decisions influencing the environments they interact with" (European Commission, 2021). For a full list of these techniques and approaches, see Annex I in European Commission (2021).

[3] AI Watch results and analyses are published on the AI Watch Portal.

[4] See https://digital-strategy.ec.europa.eu/en/library/coordinated-plan-artificial-intelligence-2021-review

[5] We define autonomous machines as apparatus whose core function is to replicate in the most efficient way some very repetitive tasks.

[6] We define "robots" as machines that are designed and created to operate under conditions in which human interaction is (at least) possible.

2. Factors influencing technology adoption: a literature review

The adoption of a technology such as AM is a complex process encompassing all the facets of a firm, from its infrastructure to its organisational structure and workforce skills.

Autonomous machines are self-governing machines that operate independently of direct human control. These machines are programmed to interact with their environment and make decisions without direct human intervention. Examples of autonomous machines include robots, self-driving vehicles and drones. Although research on AM has been part of the agenda of roboticists and AI scholars for some time, there has not been a unified definition of what "autonomy" means in artificial agents. Due to the existence of different definitions, it becomes difficult to assess or judge the degree of autonomy of most disruptive and sophisticated systems such as self-driving cars, industrial robots or game playing agents (Ezenkwu and Starkey, 2019). In any case, autonomous machines are extremely complex systems that integrate many pieces of technology and are still, for the most part, in the development phase and face many technical and non-technical challenges (Liu and Gaudiot, 2022.

As the data is issued from a survey concerning the use of technologies based on AI, hence the autonomous machines in object belong to the realm of AI-enhanced Robotics (Righi, 2022), with the following definition:

AI technological support for robotics: automation refers to an area close to robotics but with some substantial differences. While the term "robots" indicates machines that are designed and created to operate under conditions in which human interaction is (at least) possible, "automated machines" are apparatus whose core function is to replicate in the most efficient way some very repetitive tasks.

Nevertheless, the integration of AI technologies in automated machines allows the realisation of smart and partially self-regulating processes that may be very cost intensive because of their complexity and the physical resources/inputs involved. For this reason, the boundaries between "robotics" and "automation" are in many cases blurred and, depending on the initial perspective, a specific activity may be defined as more related to one instead of the other. Because of the continuity between these two areas, we can capture the part of "automation" that is closest to "robotics".

In this section, we provide a concise outline of how the literature has discussed three issues related to technology adoption, namely: **(i) drivers of technology adoption and (ii) barriers to technology adoption** in order to provide a review of the research context underlying our empirical analysis in Section 3. The focus on these three topics responds to two criteria. First, these are well-studied phenomena that can inform our understanding of the drivers and barriers to AM adoption. Therefore, they are particularly pertinent to the objectives of AI Watch. Second, these are topics that we are able to explore empirically with the existing data.

2.1 Drivers of technology adoption

There is a large body of economics literature investigating how the adoption of new technologies is promoted by specific firm characteristics such as size and age (Kamien and Schwartz, 1982). Because of their perceived positive impact in technology adoption, these characteristics are often called "drivers" of technology adoption. In what follows, we briefly summarise relevant results with respect to **firm size, workforce knowledge and skills, joint adoption of complementary technologies, sector of activity and productivity level**. The choice of these factors responds to two criteria. First, the first three are among the most relevant ones in the literature. Second, for all of them we have reliable data to analyse the impact of relevant firm characteristics on AM adoption. Furthermore, as AM is one of the key technologies in the context of Industry 4.0, i.e. the new paradigm for industry relying progressively more on connection, digitalisation and automation of processes, we also highlight relevant results in this specific context. Then, the aforementioned drivers will be the object of our empirical analysis in Section 3.2.

Firm size The size of the company is an important factor in the effective adoption of technologies (Awa and Ojiabo, 2016; Awa et al., 2016; Puklavec et al., 2018; Thomas & Barton, 2012). Larger companies are able to afford new technological changes and take advantage of economies of scale. On the other hand, although small

and medium-sized enterprises (SMEs) might be aware of the relevance of new technologies, their adoption capacity is much lower than that of large companies. Larger companies have the resources to develop the right strategic planning, business formalisation and control systems to support the adoption process (Yu & Schweisfurth, 2020). Therefore, there are clear connections between company size and the capacity to embrace new technologies. In the case of Industry 4.0 technologies, which also include AM, large companies show higher abilities to make use of such technologies (Colotla et al., 2016). Notwithstanding these results, some sector-specific studies (Matsepe & Van der Lingen, 2022; Romero, & Martínez-Román, 2015; Newby et al, 2014) have found that small firms have the same or a higher probability of adopting ICT technologies than large firms.

Workforce knowledge and skills Workforce skills and learning capabilities are considered fundamental for operating new technologies in the context of Industry 4.0 (Ghadge et al., 2020; Ghobakhloo, 2020; Kamble et al., 2018; Tornatzky & Fleischer, 1990). Employees with the right education and learning capabilities are more likely to adapt to new innovative schemes and to adopt new technologies (Lin & Ho, 2011). On the other hand, a lack of knowledge hampers efforts to adopt technology (Gunasekaran & Ngai, 2008; Teo et al., 2007). Therefore, technological skills in the workplace allow companies to effectively manage the risks derived from technological investment. Nevertheless, the impact of workforce skills on the adoption of Industry 4.0 technologies can also depend on company size. In a study exploring technology adoption by SMEs in the manufacturing sector, Hassan et al (2017) find that, contrary to what previous studies showed, employee knowledge does not promote adoption in the case of SMEs.

Joint adoption of complementary technologies Technologies are characterised by their complementary nature (Gossé et al., 2020). For instance, in the manufacturing sector, process optimisation could be enhanced and synergistically build on other AI technologies such as computer vision and anomaly detection. Hence, the propensity to adopt a new technology exhibits path dependence since it is influenced by the technologies already adopted and their complementarity with the new one to be adopted. Hence, the concept of **technological bundles**, i.e. groups of complementary technologies more likely to be adopted together, has emerged (Miller et al., 2017; 2019; and Lambert et al., 2015). These results illustrate the importance of technological bundles in the innovation process. Their analysis of the agriculture sector reveals that farmers managing large operational processes requiring precise agriculture techniques have a greater propensity to adopt technology bundles. Furthermore, farmers who engage in innovation may adjust their use of a technology as new complementary techniques become available. This reveals the importance of technology bundles in innovation.

2.2 Barriers to technology adoption

The literature shows that adoption of new technologies can be hindered by obstacles such as legislative gaps, lack of data access or a weak infrastructure that prevents companies from fully exploiting their capabilities for digital transformation. In the context of our analysis, we focus on **the perception of such barriers and the factors influencing it** (Baldwin and Lin, 2002; Baldwin and Hanel, 2003; Galia and Legros, 2004; D'Este et al. 2012; D'Este et al. 2014; Pellegrino, G., 2018), which will be further empirically investigated in Section 3.3.

Innovators and non-innovators The perception of barriers to innovation is, interestingly, mostly reported by firms that are highly innovative. Most empirical studies on the perception of barriers stress a positive association between firms' perception of obstacles and their innovation propensity (Arundel, 1997; Mohnen and Rosa, 2002; Baldwin and Lin, 2002; Mohnen and Röller, 2005; Iammarino et al., 2009; Coad et al., 2016). However, as relatively recent studies suggest (Savignac, 2008, Blanchard et al. 2012; Pellegrino and Savona 2013), the positive correlation between innovators and barriers may be due to an inadequate selection of the sample: as two groups exist among non-adopters, potential innovators and firms not interested in innovation, the analysis on the perception of barriers should be restricted to the potential innovators, as they are likely to face them while adopting the technology. In this context, the concept of **revealed** and **deterring barriers** emerges (D'Este et al., 2012), based on whether the difficulties are encountered by a firm as a result and in the process of technology adoption (the former), or instead are obstacles that firms perceive as impediments to adoption (the latter).

Technological bundle effects We have seen above that AM tends to be adopted along with other complementary technologies in bundles. Therefore, when analysing barriers to AM adoption, it is pertinent to focus on technology bundles that include AM, rather than on AM alone. The literature indicates that the adoption of technological bundles can lead to stronger perception of barriers, due to the difficulties entailed by combining more than one technology (D'Este et al., 2012; de-Oliveira and Rodil-Marzábal, 2019). Previous research did not, however, disentangle the impact that certain technological bundles can play in the perception of barriers. On the other hand, the analysis we undertake in Section 3.3 sheds light on this point by investigating several technological bundles composed by AM and other complementary technologies.

2.3 The links between technology adoption and firm performance

The emergence of new and more sophisticated technologies such as AM has enhanced the impact of innovative processes on firm productivity. According to Crews (2019) and the Boston Consulting Group (CIGREF, 2018), in order to improve productivity and be more competitive, organisations will have to rely more and more on advanced digital technologies such as AI. Thus, digital transformation has an enormous potential for business value. In this section we focus on two angles: **productivity levels** and **size**. We will further explore them empirically in Section 3.4.

Productivity levels The use of new technologies disproportionally raises productivity in those firms that were already more productive (Ballestar et al., 2020; Stiebale et al., 2020). Specifically, Stiebale et al. (2020) report a considerable rise in total factor productivity (TFP) for the 20% of firms with the highest initial productivity after the adoption of industrial robots. In a related study, Dinlersoz and Wolf (2018) find that larger and more productive plants tend to be more automated. However, while robotisation[7] positively affects mark-ups[8] in large firms, small companies with initially low mark-ups suffer losses when adopting robots. Stiebale et al (2020) interpret that the adoption of robots seems to trigger a winner-takes-most dynamic in which large companies expand their mark-ups at the expenses of non-adopters and, to a lesser extent, of small firms adopting robots.

Firm size and productivity Regarding firm size, its effects on technology adoption are not always straightforward to predict. Economies of scale and adoption capacities influence the way firms exploit innovative processes. Some evidence indicates that both small and large firms experience productivity growth associated with the adoption of technologies, but large firms are likely to experience a more persistent growth than small firms. The main argument behind this conclusion is that large firms can more easily benefit from complementarities in the adoption of new technologies compared to small firms (Rochina-Barrachina et al., 2010).

[7] "Robotision" refers to the adoption of robots in general, which may not necessarily be AI-enhanced as in the present case.
[8] Mark-ups are defined the ratio between a product's price and its cost. The adoption of robots can lead to higher mark-ups both by reducing the cost of production and by allowing to produce more sophisticated products at a higher price.

3. Empirical analysis

In this section we delve into the empirical investigation of the three factors influencing technology adoption discussed in Section 2, providing an analysis of:

1. The drivers influencing the probability of firms' adoption of AM;
2. Firms' perception of barriers to adoption;

3.1 Data

Our data are issued from a European Commission survey entitled "European enterprise survey on the use of technologies based on artificial intelligence". The survey was designed and conducted in the EU27, Norway, Iceland and the UK, resulting in the participation of 9 640 companies. It was carried out between January and March 2020. The survey focuses on AI awareness (i.e. whether the company knows what AI is), present and future AI adoption (i.e. whether the company has adopted or plans to adopt AI technologies), AI acquisition path (i.e. how does the company acquire AI: through a purchased software, developing one in-house, etc.) as well as external (e.g. the need for new laws or regulations, lack of public or external funding, etc.) and internal (e.g. lack of skills, lack of internal data, etc.) obstacles to the adoption of those technologies (for further details, see Annex A).

The sample selection was made to be representative of the EU27, Norway, Iceland and the UK.[9] However, it is not devoid of the biases inherent in surveys, for instance the results depend on the accuracy of the responses declared by the respondents. Therefore, errors due to respondents misunderstanding a question (for example, considering they have adopted an AI-based software when in fact they have adopted a deterministic one) or failing to provide an accurate answer on behalf of the company (for example, the respondent declaring that access to data is the most relevant barrier, when most of the personnel involved with AI do not see it as such) might bias the results. In the context of surveys targeting the uptake of technologies, it is thus an effective mitigating strategy to address the survey also to the technical personnel within the company, rather than only the management. Lastly, some questions can only be answered through the subjective appreciations of the respondent. As a result, "this could mean that different respondents may have interpreted the question differently, which may have an impact on the reported figures" (IPSOS, 2019). To limit the influence of subjective appreciation, several surveys on technology adoption reformulate the questions by asking whether or not specific actions – considered as milestones for the uptake of a given technology – are undertaken in order to anchor the assessment to a concrete proxy rather than the estimation of the subject.

3.2 Adoption of AM technologies

In this section we analyse the probability of adoption of AM in EU companies, investigating the differences deriving from firm characteristics and context. Furthermore, we explore the possible relationships between the adoption of AM and the adoption of other AI technologies.

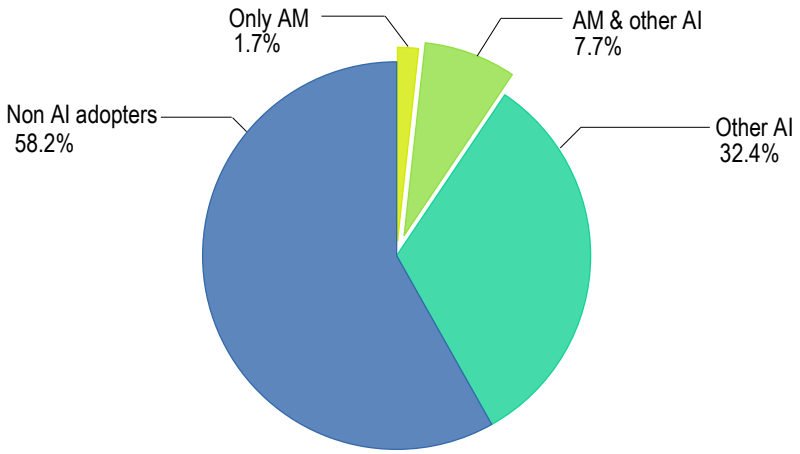
It should be noted that we can only observe whether the firm declares having adopted a given technology (be it AM or another AI technology), but not the intensity of adoption (e.g. how many AM per employee it has).

3.2.1 Probability of adoption of AM technologies

In Europe, the proportion of AM adopters is low when compared with non-AI adopters. Figure 1 illustrates the proportion of firms adopting AM in Europe, whether alone or in combination with other AI technologies. The other technologies surveyed are the following: natural language processing, computer vision, anomaly detection, sentiment analysis, forecasting, process optimisation, recommendation engines, robotic process automation (RPA), and creative activities.

[9] For the sake of succinctness, we use the term 'Europe' to refer to these countries hereafter.

Figure 1. Breakdown of AI technology adopters and non-adopters in the data



Only 9.42% of European firms adopt AM, either alone or in combination with another AI technology, while non-AI adopters account for 58.16% of the respondents.

Thus, in order to shed light on the factors influencing such imbalance between adopters and non-adopters, we investigate the effect of three variables on the probability of AM adoption using a probit regression (for the technical details, please refer to Annex B). The variables of our interest are:

- Employees' knowledge about AI technologies,
- Firm size,
- Sector of activity,
- Firm productivity

AI knowledge Firms whose employees report having knowledge about AI technologies are more likely to adopt autonomous machines and robots compared to firms whose employees report a lack of knowledge of AI technologies. We can hence confirm that, according to our results (cf. Figure 2 below), and in coherence with the literature (cf. Section 2.1), employees with the right competences and knowledge about AI technologies favour adoption of AM and robots.[10] Note that the survey from which these results are drawn only contains data about AI knowledge in general, as opposed to AM knowledge in particular. This is explained by two intertwined reasons. First, while our analysis focuses on AM, the survey's objective is to understand the uptake and effects of several AI technologies. Second, employee knowledge of AI in general favours the uptake of several AI technologies, as it provides a knowledge base on which individuals can develop specific AI-related knowledge. Consequently, as shown in Section 3.2.2, AM adoption is linked to the adoption of other complementary technologies that benefit from the same general AI knowledge.

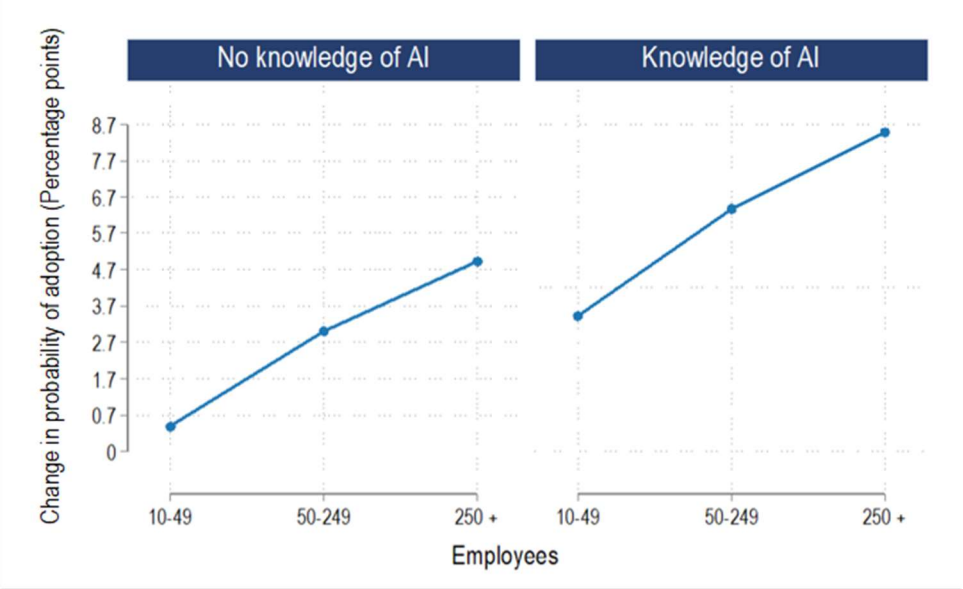
Firm size As outlined in the previous subsection, SMEs can also face difficulties in the adoption of AM due to weaker competitive advantages compared to larger firms. Absence of economies of scale, along with a limited financial capacity, complicate AM adoption by small size companies. This, in turn, could entail uncertainty regarding amortisation (Birkel et al., 2019).

Figure 2 illustrates the effects of company size on the probability of AM adoption. The plot shows the marginal effects[11] of size over AM adoption probability. To assess the influence of companies having employees with the right competencies, we split the analysis into firms whose employees are knowledgeable about AI technologies

[10] Note that these employees could have acquired knowledge about AI before the adoption of AM or been hired before the adoption.
[11] The marginal effect gives the effect on the probability of adoption while holding all other variables constant.

and firms whose employees are not. The full results are also reported in Table S1 in the "Additional tables" section.

Figure 2. Change in the probability of adoption of AM technologies by firm size and employee knowledge of AI (compared to micro firms' probability)



Firms whose employees already have knowledge of AI technologies show a higher probability of adopting AM compared to those whose employees do not. Both graphs report a positive and relevant effect on the capacity of medium and large-sized companies to adopt AM and robots as compared to small firms. The analysis indicates that a firm with a size of 50–249 employees has a probability of adopting AM, which is 3.2 percentage points higher than a micro-firm of 5–9 employees. This difference increases to 5.4 percentage points when we compare with large firms (250+ employees). Hence, larger companies show clear advantages over SMEs. In this context, companies that enjoy higher economies of scale are able to adopt and exploit those technologies more easily than smaller companies with less resources. This may create a tighter competitive environment that leaves many small companies struggling to find ways to optimise their productive processes.

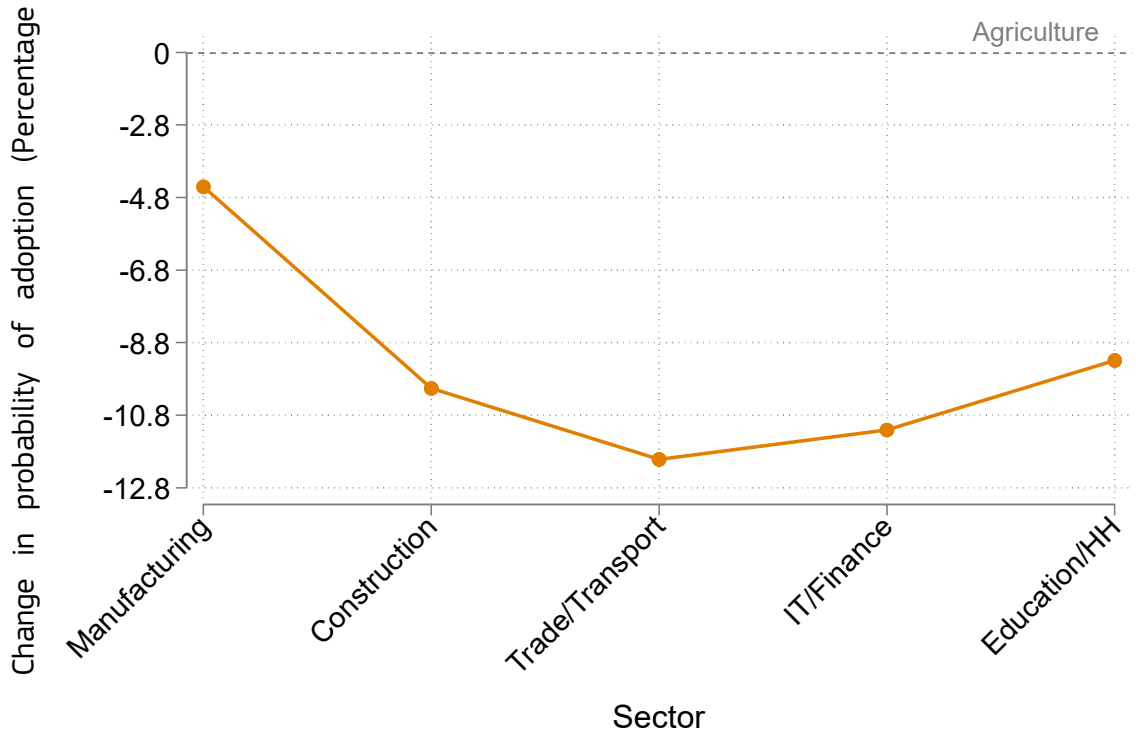
Sector of activity Figure 3 below shows the change in probability of adoption of AM technologies across sectors (the sectorial breakdown of the survey data can be found in Table A1). In this figure (as well as in those that follow, which differentiate results across sectors) we use the agriculture sector as a benchmark against which to assess how certain sectors can affect the probability of adoption of AM.[12]

We also find strong differences in AM adoption by sector. Figure 3 displays the fluctuation of probability of AM adoption across sectors. Companies operating in the construction, trade and transport, IT and finance, and education/human health sectors show lower probabilities of adoption than companies operating in agricultural activities. Firms working in the trade and transport sector show the lowest likelihood of adoption compared to firms competing in the agricultural sector. Concretely, a firm operating in the trade and transport sector has a probability of adopting AM technologies 12 percentage points lower than a firm engaged in agricultural activities. The risk of harm to persons that the activities of the transportation sector entail, and the consequent regulatory requirements to introduce AI-driven solutions, might explain this. On the other hand, many studies delve into the disruption brought about by robotic and autonomous processes in the agricultural sector, mainly by large-sized companies. Higher population projections and the effects of climate change put pressure on

[12] The choice of a sector as a benchmark is necessary when analysing the impact of a given sector on the probability of the outcome (in this case, adopting AM) using a probit model. Any sector can be chosen as a benchmark without altering the results, as the model evaluates relative changes in probabilities between sectors (i.e. how much more likely it is to adopt AM for a firm in sector A compared to a firm in sector B), as opposed to absolute probabilities (what is the average probability of adoption of AM by firms belonging to sectors A versus firms belonging to sector B).

farmers to increase and optimise production. Hence, in most European countries where the expansion of cropland is not possible, adoption of AM and robots is already very strong in the agricultural sector (Subeesh, A. & Mehta, C., 2021).

Figure 3. Change in probability of adoption of AM technologies across sectors (compared to the probability in the agricultural sector)



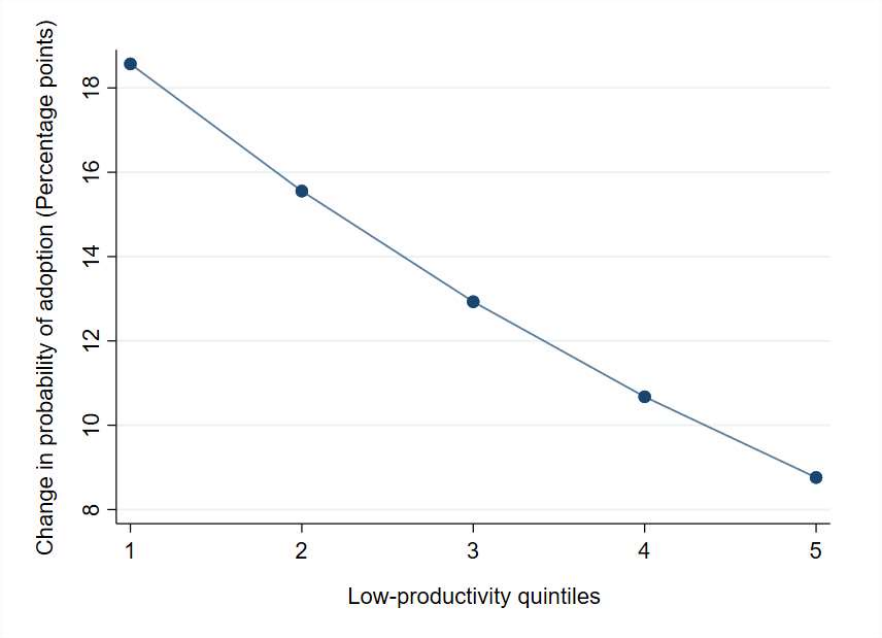
Firm productivity. In order to measure productivity, we use information on firms' operating revenues and their number of employees to construct a standard labour productivity metric: operating revenue per employee. It allows us to identify the labour productivity from a firm's primary business activities and, thus, to isolate the effect of primary activities on productivity. The indicator is in euros and corresponds to the last available date provided by the companies from the years 2016 to 2019. Although we are aware that this variable is not a perfect measure of productivity, it mitigates the lack of data on capital and allows us to obtain relevant information about the effect of AM on productivity. Given the data availability to build this indicator, and after eliminating outliers, the number of firms for which we analyse productivity levels is lowered to 6,304.

This indicator tells us how productive a firm is by indicating how much revenue each employee creates on average during a year. Consider two companies A and B that have the same number of employees and pay them the same wages. If company A's operating revenue is higher than company B's, this implies that the former manages to use its human resources more efficiently than the latter to produce and sell. The main advantage of this metric is that is allows to compare any type of firm using reliable and available data. The main disadvantage of this indicator is that, contrary to alternative ones such as capital productivity or the more comprehensive total factor productivity, it does not measure the productivity of another relevant production factor directly: capital. Following our example, it could be the case that the reason why company A has higher productivity is that its employees use more capital than company B's. For example, the former could use AM for production processes for which company B does not. In other words, firm A has more capital than firm B. Without knowing how much capital each firm has, disentangling the respective contributions of labour and capital to each firm's productivity is not possible. However, at the firm level, data on capital is less easily available and more unreliable than data on employees. This is because firms might use different accounting methodologies to produce it, which generates numbers that are not fully comparable.

When analysing the impact of productivity on the adoption of AM technologies for all the firms for which the productivity measure can be built (6,304), there are no statistically-significant results. However, the analysis of the data indicates that this

relationship exists for low-productivity firms[13]. In particular, after segmenting the sample into 5 quintiles of productivity, and controlling for all other firm characteristics, we can see that there is a negative relationship between a firm's productivity and its probability of adopting AM technologies for low-productivity (i.e., the 20% less productive firms) firms. Figure 4 below illustrates this finding.

Figure 4 Change in probability of adoption of AM technologies by productivity level for the 20% less productive firms



NB: low-productivity firms are the 20% (i.e., first quintile) less productive firms of the entire sample.

We believe that the negative relationship between firm-level productivity and AM adoption for low-productivity firms can be attributed to the efforts of the latter to catch up with their higher-productivity counterparts. The adoption of AM technologies may present an opportunity for these firms to improve their productivity levels. As the literature shows (cf. Section 2.3), the adoption of robots by a firm boosts its productivity.

3.2.2 Joint adoption of complementary technologies

As mentioned above, in the survey, firms reported the adoption of several AI technologies apart from AM. Table 1 shows the proportion of firms adopting AM in combination with any of the other nine AI technologies. The technologies that present the highest percentages of firms having also adopted AM are robotic process automation (RPA) (40.9%) and process optimisation (35.9%). This confirms the importance of considering the existence of complementarities between technologies. In line with the studies developed by Miller et al. (2017) and Lambert et al. (2015), technology adoption is contingent upon to the adoption of other technologies that are complementary to it.

[13] See table S7 and table S8. Adoption of AM technologies may depend on a firm's level of productivity, while productivity itself may be affected by prior adoption of these technologies. This would require correcting for the presence of potential endogeneity bias in the estimation. Unfortunately, we were unable to correct for this bias due to the unavailability of appropriate instruments. Nonetheless, we believe that the presence of endogeneity is unlikely to alter the nature of our findings.

Table 1. AI technologies adopted with AM

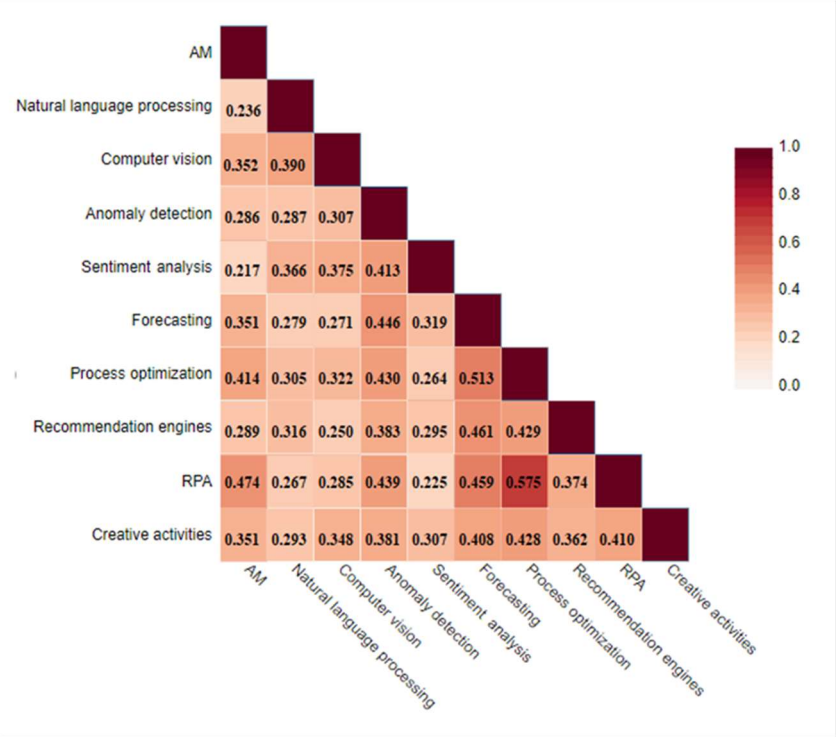
Technologies	Nº of firms	%
Natural language processing	166	20.34
Computer vision	213	26.10
Anomaly detection	229	28.06
Sentimental analysis	56	6.86
Forecasting	210	25.74
Process optimization	293	35.91
Recommendation engines	171	20.95
RPA	334	40.93
Creative activities	160	19.61

Thus, we study the relationship between technologies and the probability of joint adoption through a Multivariate Probit Model (MPM) for the ten categories of technologies described in the survey (for further details on the methodology, please refer to Annex B).

Error! Reference source not found.provides the error correlation matrix[14] of the MPM between the ten technologies. In the figure, the depth of colour designates the magnitude of the correlation: the deeper the colour, the stronger the correlation between the technologies. In this case, all ten categories are positively correlated (in red) to each other. This indicates that all AI technologies mutually reinforce each other at the firm level.

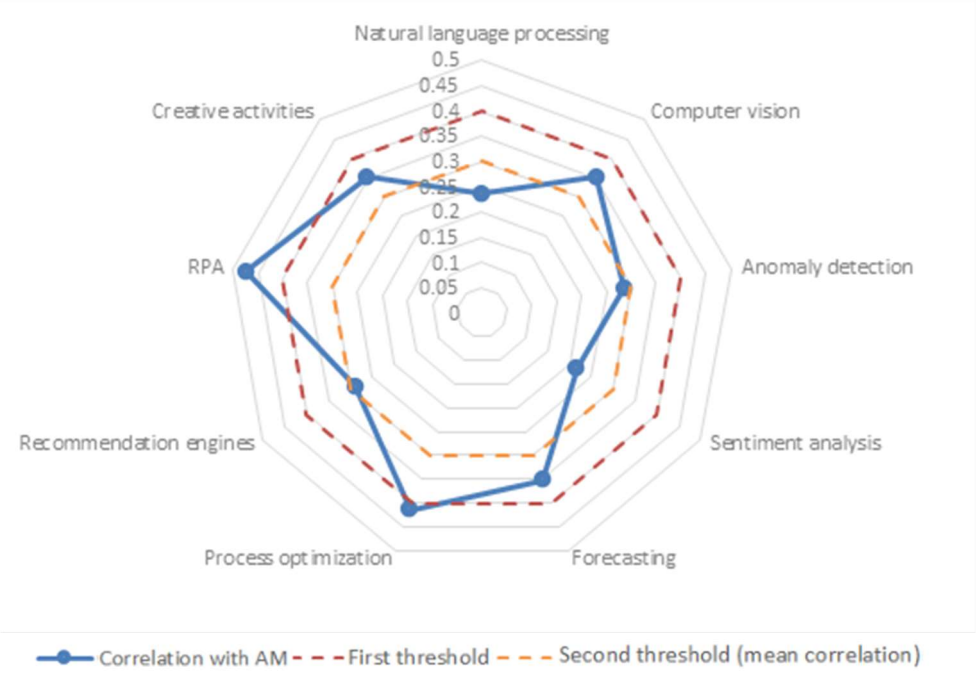
Figure 5. Correlation matrix between technologies

[14] The correlation between the errors of the 10 equations estimating the probability of adopting each of the 10 technologies studied provide a measurement of the extent to which the probability of adopting technology A depends on the probability of adopting technology B. Here, the term "error" refers to the part of the choice of the probability of choosing a certain technology that cannot be explained by the variables introduced in the model, such as firm size or sector of activity. If the errors of the equations estimating the probabilities of adopting technologies A and B are correlated, this indicates that there is some unobservable variable not present in the dataset (e.g. the fact that the two technologies are complementary in that their joint use is necessary to introduce a certain productive process) that explains that, to a certain extent, the choice of adopting technologies A and B are linked.



We have used a two-step approach to statistically determine which technologies appear to be most used together with AM. In the first step, adoption patterns were analysed using a MPM model. Next, the model offers an error correlation matrix for technology adoption (Figure 5). Using these correlation values, we are able to isolate clusters of technologies that are frequently used together. To cluster the technologies into bundles, we use a threshold correlation. In order to identify the existence of a bundle, the correlation between AM and other technologies must be above the mean correlation level (0.33). Five technologies are over this threshold. Among those technologies, two stand out as outliers, as their correlation coefficient is particularly high: process optimization and RPA. Hence, we choose the lowest correlation level of the two (process optimization: 0.414) as the second threshold level. This results in two bundles. The first bundle (correlation threshold: 0.4 or more) is composed by: RPA and process optimisation technologies. The second bundle (correlation threshold between 0.33 and 0.4) is composed by computer vision, forecasting and creative activities. Figure 6 illustrates the bundle selection according to both thresholds.

Figure 6. Bundles of technologies adopted together with AM – thresholds



The most natural relationship is with RPA and process optimisation technologies. The error correlation between AM and robots and those two technologies is over 0.5, indicating a considerable mutually reinforcing relationship. In other words, the adoption of AM and robots are in half of the cases accompanied by the adoption of RPA and process optimisation technologies. A sector where this synergy between RPA and process optimisation technologies naturally emerges is manufacturing: the automation of repetitive tasks entailed by RPA could also lead to optimising them, for instance by increasing their frequency or achieving a better coordination between different machines' tools (de Nigris et al, 2022). Similarly, forecasting, computer vision and creative and innovative activities also show a positive relationship, but less pronounced than RPA and process optimisation technologies. Again, a realm where this synergy can emerge is manufacturing: computer vision is often used to spot defects products and the stream of images collected can support forecasting applications, for instance recognising patterns in the production of defective objects, or creative applications, such as the personalisation of the product's design (de Nigris et al., 2022).

Considering the emergence of technology bundles from their correlations and the reinforcing relation some technologies have between them, in the next section we test the influence of bundles in the perception of barriers to adoption of AM and robots.

3.3 Barriers to adoption

With the aim of capturing the influence of the synergetic relations between technologies in our analysis, we consider how the adoption of specific bundles alters the perception of barriers to adoption.

Hence, we consider the two bundles displayed in the correlation matrix from Figure 6:

- **Bundle 1:** AM, RPA and process optimisation technologies.
- **Bundle 2:** AM, computer vision, forecasting technologies and creative and innovative activities.

In this way, we are able to discern the effects originated by the adoption of AM alone, on the one hand, and the additional effects created by the adoption of bundles including AM, on the other hand.

Following Savignac (2008), we restrict in this case the data sample used in the analysis to those companies that confirmed having adopted the technologies and to those who did not, but confirmed their intentions to do so in the future. This allows us to isolate the effect of those firms that aspire to innovate from those that do not when analysing how they perceive the barriers. This exclusion is based on the rationale that firms that do not have any intention to innovate do not experience the negative effects created by the barriers (D'Este et al.,

2012). Therefore, among a total of 5,038 non-adopters, we include in the analysis 1,528 firms who confirmed their intentions to innovate in the future. We consider those firms as potential innovators, independently of the fact that they have not adopted any technology yet.

Based on the questionnaire design, we classify the perception of barriers to adoption by considering five categories: (1) data access; (2) liability and reputation; (3) cost; (4) skills; and (5) internal data. In the analysis of their impact, we again focus on the adoption of the two technology bundles. Tables 2 and 3 show the ratio of firms reporting each of the aforementioned barriers as important. The tables compare two sub-samples: adopters, who face revealed barriers, and non-adopters, who in turn face deterring barriers, as defined in Section 2.2. For each variable, a means comparison test showed that the difference between the aforementioned ratios are statistically significant at the 0.01 level.

Table 2. Ratio of firms reporting obstacles to adoption (Bundle 1)

	Total	Deterring	Revealed
Data access	0.72	0.77	0.69
Liability and reputation	0.64	0.69	0.61
Cost adoption	0.89	0.93	0.87
Lack of skills	0.73	0.79	0.69
Lack of internal data	0.45	0.51	0.41

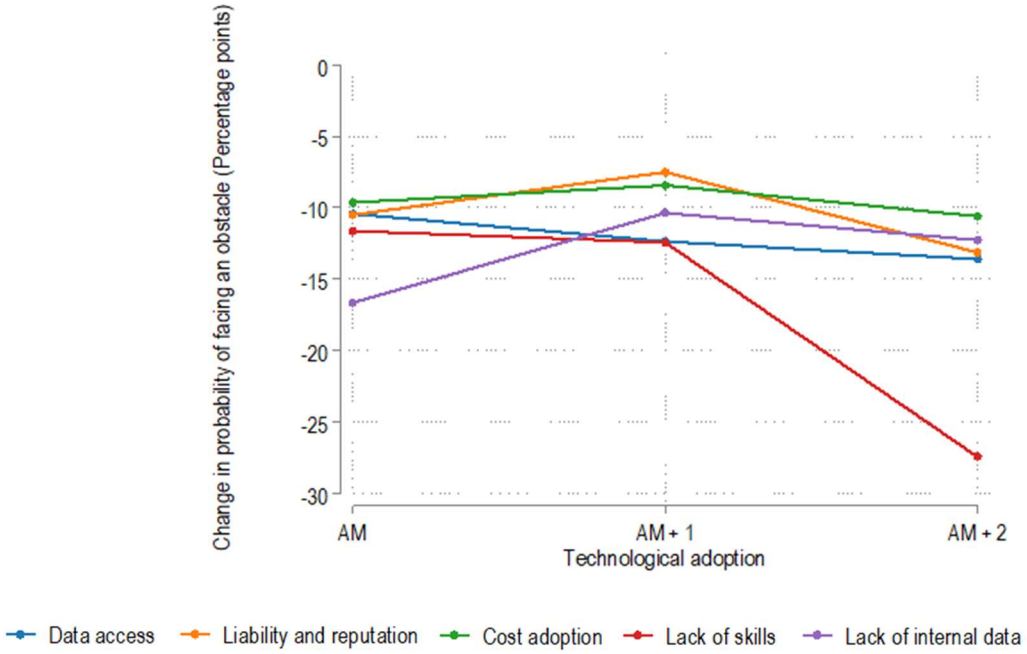
Table 3. Ratio of firms reporting obstacles to adoption (Bundle 2)

	Total	Deterring	Revealed
Data access	0.73	0.78	0.70
Liability and reputation	0.65	0.71	0.62
Cost adoption	0.89	0.93	0.87
Lack of skills	0.73	0.81	0.67
Lack of internal data	0.45	0.49	0.43

In both bundles, "cost of adoption" is the category among all obstacles to adoption that firms consider as the most important one or with a higher impact over their decisions. This was already the case when considering all of the technology categories. On the other hand, and despite the considerable number of firms reporting it, the lack of internal data seems to be a comparatively minor barrier for innovators and potential innovators when compared to the other obstacles reported. Both tables also show that differences exist in perceived barriers between adopters and potential adopters. For instance, deterring barriers appear to be more frequent than revealed ones. A possible source of this discrepancy may come from a substantial difference between the two cohorts, as adopters, having successfully deployed a given technology, have most likely overcome a series of obstacles which still stand as possibility for potential adopters. Hence the importance of distinguishing the influence of the different types of barriers, in line with the literature (D'Este et al., 2012; de-Oliveira and Rodil-Marzábal, 2019; Pellegrino, G., 2017).

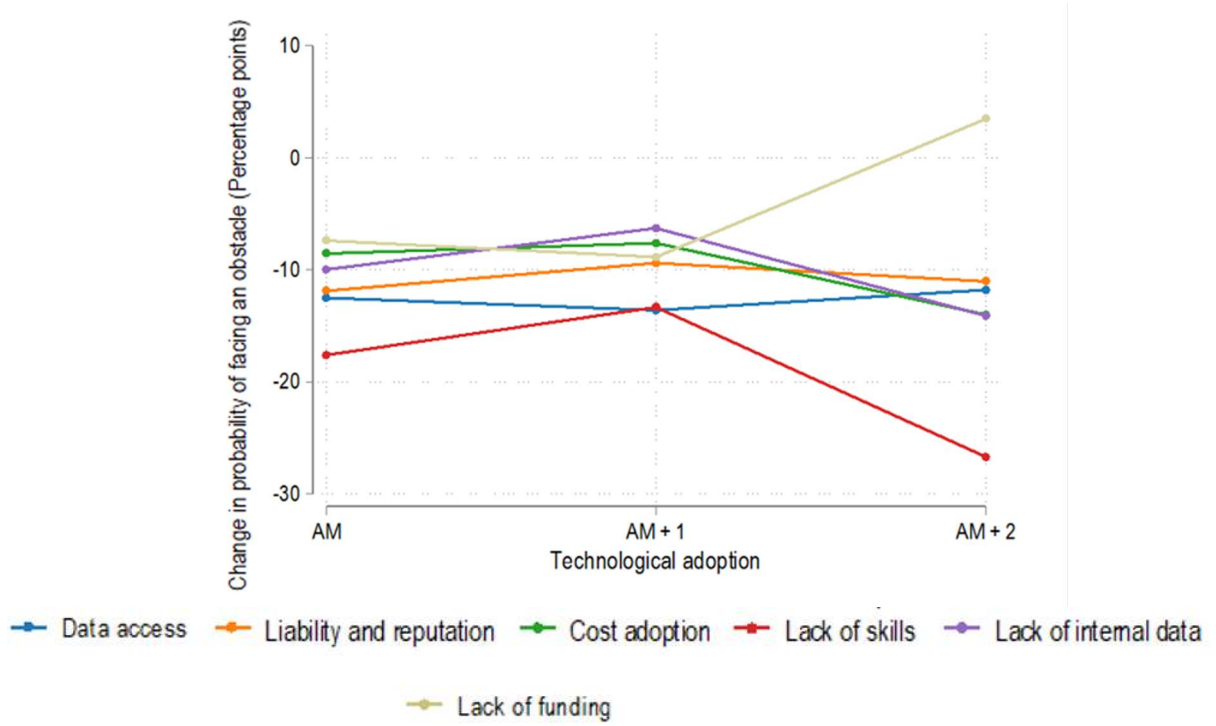
We obtained the probability of facing an obstacle through a multivariate ordered probit model for the two technology bundles (for the complete results, refer to Tables S3 and S6 in the additional tables section). Contrary to previous results (D'Este et al. 2012; Pellegrino and Savona 2013), our analysis highlights a complex and non-linear relationship between obstacle perception and technology adoption, linked to the type of barrier. Figure 7 displays the likelihood of facing obstacles to adoption as firms adopt more and more technologies of Bundle 1, while Figure 8 displays the probability of facing obstacles to adoption as firms adopt more technologies of Bundle 2.

Figure 7. Change in the probability of facing an obstacle to adoption (compared to non-adopters' probability) for different adoption levels (Bundle 1)



Note: The three cohorts in the graph are: AM: the adoption of only AM technologies; AM+1: the adoption of AM with one technology among RPA or process optimization; and AM+2: the entire bundle. All are compared to the non-adopters of the bundle. Only statistically significant obstacles to adoption depicted.

Figure 8. Change in the probability of facing an obstacle to adoption (compared to non-adopters' probability) for different adoption levels (Bundle 2)



Note: The three cohorts in the graph are: AM: the adoption of only AM technologies; AM+1: the adoption of AM with one technology among computer vision, forecasting technologies or creative and innovative activities; and AM+2: the adoption of AM in a bundle with two or three of those technologies. All are compared to the non-adopters of the bundle. Only statistically significant obstacles to adoption depicted.

As we expected from the preliminary analysis, the impact of barriers to adoption and the propensity to engage in innovation differ according to the barrier and the adopted technologies and we can observe the strongest difference between barriers linked to the human factor, technical barriers and financial ones.

As per the former, the barriers linked to the human factor, the effect of the adoption of both bundles is more pronounced in the case of lack of skills among employees. As companies adopt AM with an additional technology from any of the two bundles (AM+1), the likelihood to report the lack of skills among employees decreases with respect to non-adopters. Concretely, in Bundle, 1 it decreases by 11.2 (only AM) or 12 (AM +1) percentage points. In Bundle 2 the effect is even higher when firms only adopt AM, showing a decrease in their probability of facing an obstacle of 17.6 percentage points. This suggests a learning effect from the deployment of progressively more sophisticated techniques, with the exception of the adoption of AM with an additional technology in the Bundle 2. Thus, companies adopting technologies belonging to the same bundle report to have more skilful employees than the rest.

On the other hand, we observe the probability of facing a barrier of a technical nature linked to data is overall steady across the different cohorts with a slight decreasing tendency, which is natural as different technologies in the bundles feed on similar data streams and, hence, the likelihood of data being a stumbling block diminishes the more technologies are adopted. Nevertheless, the barrier linked to the lack of internal data is more strongly felt in the passage from standalone AM adoption to the adoption of an additional technology, and this may be linked to the difficulty of integrating different data streams, especially in the presence of silos within the company.

Finally, a non-linear relationship emerges when companies face obstacles such as liability and reputation and cost of adoption in the adoption of both bundles. Compared to non-adopters, firms that adopt AM or any of the AM bundles are overall less likely to report the aforementioned obstacles. Nevertheless, differences also arise among adopters: firms engaging in more advanced technological deployment with the usage of AM in combination with technologies from any of the two bundles display a higher likelihood to report those barriers than firms only adopting AM. This effect is not directly associated to innovation, contrary to what some authors

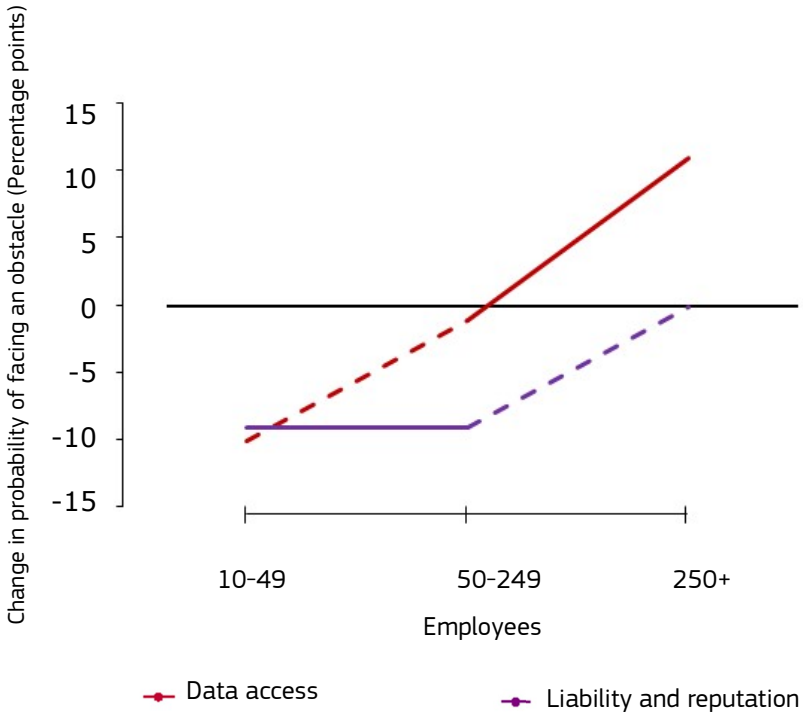
suggest (D'Este et al., 2012) since once firms adopt the entire bundle (AM+2), the likelihood to report one of these barriers sharply decreases again.

Lastly, we remark that the barrier for lack of funding displays a sharp increase in case of adoption of the entire bundle (Figure 8). As this barrier is linked to the possibilities of raising external or public funding (IPSOS, 2019), this increase may suggest stronger difficulties in getting financial support in a context of a more advanced technological adoption setting than in early stages of the digitalisation journey.

Regarding the impact of firm size, our analysis shows that this significantly affects the perceptions of obstacles to adoption (Figure 9). In the adoption of both bundles we observe a similar pattern: small-size companies (10-49 employees) are less likely to report data access (9 percentage points) and liability and reputation barriers (8.7 percentage points) compared to micro enterprises (5-9 employees). However, large-sized companies (250+ employees) are 10 percentage points more likely to experience data access barrier issues compared to micro enterprises.

A possible explanation is that small and large-sized companies use the technologies from bundles 1 and 2 in different ways. The latter tend to have more sophisticated products and processes that rely on Big Data to a larger extent to usufruct technologies such as AM. For example, large-sized companies could be more likely to train AI algorithms with datasets obtained from third parties than small firms, who would more likely rely on a "plug and play" AI software. Therefore, it is more likely for large-sized firms to face an obstacle to adoption related to access to data. Moreover, brand image tends to be more relevant to large companies, as they are more likely to use technologies from bundles 1 and 2 to mass produce differentiated high-quality products than small firms. Therefore, large-sized firms are more likely to face liability and reputation obstacles.

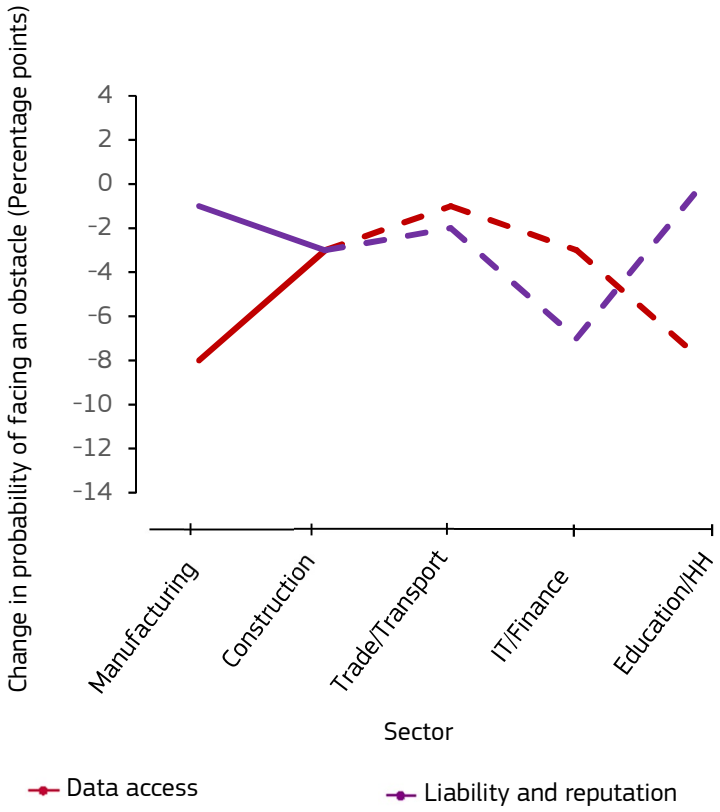
Figure 9. Probability of facing an obstacle (compared to the probability of micro-firms) by number of employees (both bundles)



Note: Non-statistically significant firm sizes dashed.

Lastly, the perception of barriers also shows some differences by sector. As seen in Figure 10, companies in the manufacturing sector adopting Bundle 1 show a lower likelihood to perceive data access and liability barriers than companies in the agricultural sector (by 8.5 percentage points). Companies from other sectors, in turn, are neither more nor less likely to face an obstacle to AM adoption than the agriculture sector. Therefore, regarding Figure 10 and the subsequent figures by sector, we only comment on the sectors for which results are statistically significant.

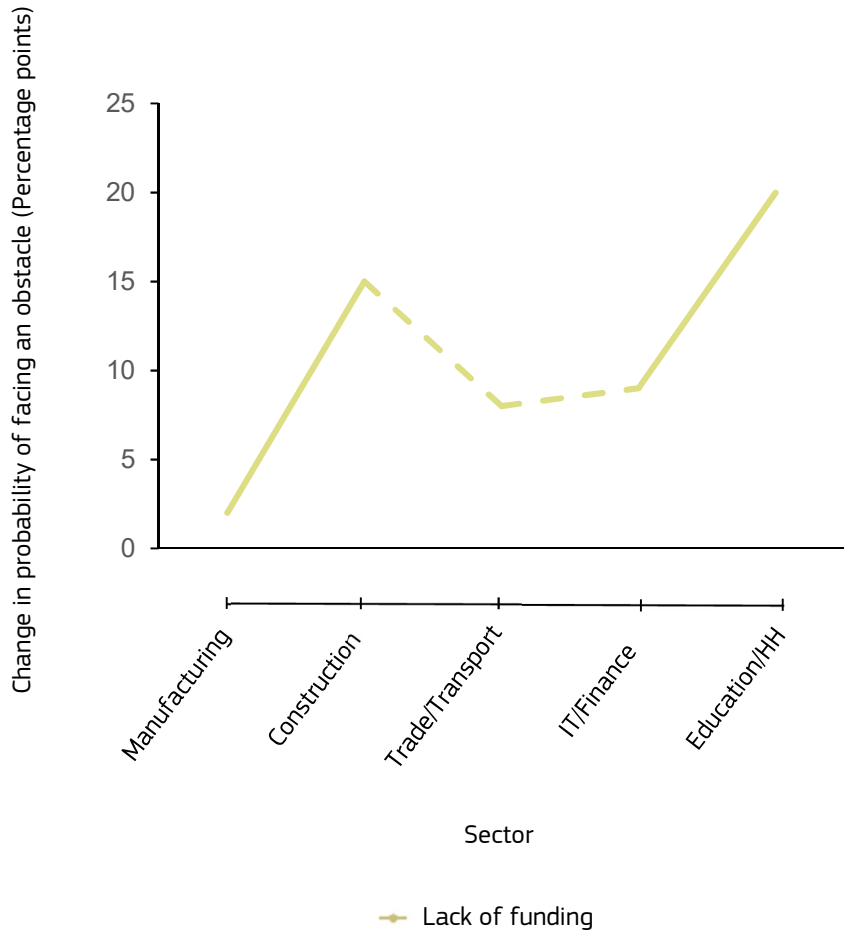
Figure 10. Change in probability of facing an obstacle to AM adoption (compared to the probability in the agricultural sector) by sector (Bundle1)



Note: only statistically significant sectors coloured.

Figure 11 displays the likelihood of facing an obstacle depending on the sector for firms adopting Bundle 2. Companies in the construction and educational/human health sector mention a higher likelihood to perceive lack of funding as a barrier than companies in the agricultural sector. This likelihood is much higher for companies whose main activity is related to education and human health (20.2 percentage points higher).

Figure 11. Change in probability of facing an obstacle to AM adoption compared to the agricultural sector by sector (Bundle 2)



Note: only statistically significant sectors coloured.

4. Conclusions and policy recommendations

Despite the rapid pace of technological change, the adoption rate of autonomous machines and robots in the EU is relatively low. Only close to 9.5% of EU companies claim adoption. In contrast, in 2018 the world average sector-level adoption rate was estimated to be of 17.5%. Several types of barriers hold back adoption (cost, lack of internal and external data, insufficient workforce skills and liability, reputation concerns and lack of funding), which are particularly felt by small firms. Notwithstanding such hurdles, as shown by the literature, companies that manage to adopt AM technologies benefit from productivity increases.

The empirical analysis carried out in this report allowed us to have a better understanding of the drivers and barriers to adoption of AM by European firms. The main takeaway is that **AM adoption is a multifactorial process that plays out and impacts companies differently depending on their characteristics**. Consequently, this report calls for **a holistic and targeted policy design to accelerate the adoption of AM and its economic impact**. In particular, we set out a series of policy recommendations structured around the following five axes.

Focus on workforce skilling and upskilling

Companies whose employees report knowledge of AI technologies have a higher probability of adopting AM regardless of other characteristics of the firm (size or sector). Hence, policies aiming at skilling and upskilling the workforce could act as a booster to the uptake of AM and its most complementary technologies (i.e., technological bundles); this crucial role played by training is also echoed the results of several studies with a sectorial focus, for instance, in manufacturing (de Nigris et al, 2022) and health (de Nigris et al, 2020).

More concretely, **in the short run**, the deployment of one-stop shops to support companies by providing (among other services) training and skills development such as **European Digital Innovation Hubs**[15] can function as a basis for responding to this need. This can be **complemented with other firm-level (up-)skilling policies** such as incentives for employers to develop training programmes for employees with skills similar to those required for AM use; online trainings and courses to supplement individual skill gaps; and strengthening the bridges between university graduates with the skills needed to adopt AM (e.g., mathematics or computer science) and companies. The Digital Skills and Jobs[16] platform and the AI4EU[17] stand as examples of such endeavours. **In the long run**, policies should focus on **ensuring that university and tertiary education programmes provide the necessary competences for graduates to develop AM skills, and that they are able to attract enough students across Member States**. In this sense, programmes aiming at developing university-industry collaborations are key, such as the European Network of AI Excellence Centres.[18]

Widen the scope of adoption-fostering policies to technology bundles

The empirical analysis carried out in this report confirmed that, as is generally the case with other technologies, AM adoption benefits from the adoption of other complementary technologies that form "technology bundles". **Consequently, policies aimed at increasing the uptake of AM should widen their scope to also target its complementary technologies**: RPA, process optimisation technologies, computer vision, forecasting technologies, and creative and innovative activities. Therefore, firm-level policies could benefit from assessing in which AM-complementary technologies a company is lagging behind, and focus on their adoption together with AM.

Target firms in low-adoption sectors

[15] See https://digital-strategy.ec.europa.eu/en/activities/edihs
[16] https://digital-skills-jobs.europa.eu/en
[17] https://www.ai4europe.eu/
[18] https://www.elise-ai.eu/

Our analysis shows that barriers to AM adoption (be it alone or together with other complementary technologies) vary across sectors. Trade/Transport, IT/Finance and Construction are three sectors that appear as particularly low adopters.

Therefore, **policymakers could target** firms located in the three aforementioned sectors, and **in particular Trade/Transport and IT/Finance, as they present the lowest AM adoption levels.**

Prioritise reducing the cost of AM adoption

Not all barriers to adopting AM and its complementary technologies are equally important. Our results show that the cost of adoption stands out as the most relevant one. Therefore, policies should focus on alleviating the economic burden of adopting AM and its complementary technologies faced by companies. Policies such as tax breaks for adopters and public co-financing innovation projects involving AM and its complementary technologies can help lift this barrier. Lack of internal skills and data access, on the other hand, appear as the second most relevant obstacles to AM adoption. In this regard, policies aimed at fostering data sharing in line with the Data Act[19] should continue to be developed. This includes, but is not limited to, the development of Common European Data Spaces[20] as well as sectoral data-sharing policies that supplement the provisions of the Data Act.

Design policies that are tailored to company size

Our analysis shows that small companies are the type of firms that adopt AM the least. Therefore, **policy design should focus on prioritising smaller firms and tailoring its instruments to their specificities**. The fact that these companies present the highest potential to boost AM adoption calls for avoiding a one-size-fits-all AM uptake policy.

In the case of large firms (firms with at least 250 employees), liability- and reputation-related obstacles appear as the most relevant obstacles to AM adoption. In that respect, policies aiming at providing legal certainty in terms of the application of liability rules to AI-driven products and services should foster the adoption of AI technologies by large firms with the highest capacity to bring these technologies to the common European market. **The ongoing adaptation and harmonisation of civil liability rules and the Product Liability Directive** to the specific challenges of AI are encouraging steps in that direction.

[19] See https://digital-strategy.ec.europa.eu/en/policies/data-act
[20] See http://dataspaces.info/common-european-data-spaces/#page-content

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List of figures and tables

Additional tables

TABLE S1: Estimated probability of adopting AM technologies

Explanatory variables	*AM Adoption*		*AM Adoption VCE(Robust)*	
	Coefficient	Marginal effects	Coefficient	Marginal effects
AIknowledge	0.171***	0.027	0.175***	0.028
	(0.049)		(0.052)	
Branch	0.048	0.008	0.096	0.015
	(0.043)		(0.051)	
Employees				
10 – 49	0.032	0.005	0.012	0.002
	(0.048)		(0.047)	
50 – 249	0.194***	0.032	0.197***	0.032
	(0.052)		(0.054)	
250+	0.276***	0.048	0.310***	0.054
	(0.072)		(0.073)	
Sector				
Manufacturing	-0.172*	-0.042	-0.188**	-0.045
	(0.089)		(0.090)	
Construction	-0.469***	-0.098	-0.488***	-0.100
	(0.095)		(0.096)	
Trade/Transport	-0.608***	-0.118	-0.628***	-0.120
	(0.088)		(0.089)	
IT/Finance	-0.560***	-0.112	-0.566***	-0.112
	(0.094)		(0.095)	
Education/	-0.421***	-0.091	-0.439***	-0.093
	(0.102)		(0.104)	
constant	-1.121***		-1.165***	
	(0.092)		(0.136)	
CountryDummies	No		Yes	
VCE(Robust)	No		Yes	
Numberofobservations	8,662		8,662	
Loglikelihood	-2622.303		-2553.898	
LRtest	163.24			
Waldchi2			275.41	

TABLE S2: Spearman's rho coefficients

Technologies	1	2	3	4	5	6	7	8	9	10
AM		0.236	0.352	0.286	0.217	0.351	0.414	0.289	0.474	351
Natural language processing	0.236		0.390	0.287	0.366	0.279	0.305	0.316	0.267	0.293
Computer vision	0.352	0.390		0.307	0.375	0.271	0.322	0.250	0.285	0.348
Anomaly detection	0.280	0.287	0.307		0.413	0.446	0.430	0.303	0.439	0.381
Sentimental analysis	0.217	0.366	0.375	0.413		0.319	0.264	0.295	0.225	0.307
Forecasting	0.351	0.279	0.271	0.446	0.319		0.513	0.461	0.459	0.408
Process optimization	0.414	0.305	0.322	0.430	0.269	0.513		0.429	0.575	0.428
Recommendation engines	0.289	0.316	0.250	0.383	0.295	0.461	0.429		0.374	0.362
RPA	0.474	0.267	0.285	0.439	0.225	0.459	0.575	0.379		0.410
Creative activities	0.351	0.292	0.348	0.381	0.307	0.408	0.428	0.362	0.410	

TABLE S3: Estimated probability of adopting AM technologies (Bundle 1)

Explanatory variables	Data access	Liability and reputation	Cost adoption	Lack of skills	Lack of internal data
Bundle1					
AM	-0.296***	-0.259***	-0.369***	-0.246***	-0.352***
	(0.080)	(0.081)	(0.092)	(0.078)	(0.081)
+1	-0.354***	-0.216**	-0.250**	-0.308***	-0.193**
	(0.088)	(0.088)	(0.101)	(0.086)	(0.088)
+2	-0.418***	-0.349***	-0.435***	-0.609***	-0.167
	(0.108)	(0.109)	(0.122)	(0.108)	(0.111)
AI knowledge	-0.153*	-0.217**	-0.117	-0.144	-0.019
	(0.092)	(0.093)	(0.103)	(0.092)	(0.095)
Branch	0.044	0.087	0.083	0.030	-0.044
	(0.084)	(0.085)	(0.095)	(0.082)	(0.085)
Employees					
$10-49$	-0.187**	-0.157*	-0.037	0.049	-0.121
	(0.081)	(0.082)	(0.091)	(0.081)	(0.084)
$50-249$	-0.011	-0.157*	-0.104	0.056	-0.045
	(0.087)	(0.087)	(0.097)	(0.085)	(0.089)
250+	0.328***	0.129	0.166	0.163	-0.133
	(0.118)	(0.119)	(0.134)	(0.116)	(0.121)
Sector					
Manufacturing	-0.327**	-0.271*	0.169	-0.133	0.241
	(0.141)	(0.141)	(0.155)	(0.140)	(0.151)
Construction	-0.198	-0.055	0.0240	-0.014	0.020
	(0.152)	(0.151)	(0.166)	(0.150)	(0.162)
Trade/Transport	-0.107	-0.017	0.112	-0.055	0.189
	(0.142)	(0.141)	(0.155)	(0.139)	(0.150)
IT/Finance	-0.166	-0.162	-0.108	-0.151	0.248
	(0.154)	(0.153)	(0.167)	(0.151)	(0.162)
Education/HH	-0.217	0.114	0.151	-0.121	0.017
	(0.169)	(0.169)	(0.185)	(0.166)	(0.180)
Country Dummies	Yes				
Number of observations	1,402				
Loglikelihood	-6423.8662				
LR test	530.35				

TABLE S4: Estimated probability of facing obstacles in Bundle 1 (Marginal effects)

Explanatory variables	Data access	Liability and reputation	Cost adoption	Lack of skills	Lack of internal data
Bundle1					
AM	-0.103	-0.105	-0.092	-0.112	-0.167
+1	-0.122	-0.075	-0.081	-0.120	-0.104
+2	-0.134	-0.131	-0.102	-0.270	-0.123
AIknowledge	0.052	0.073	0.007	0.057	0.031
Branch	0.024	0.013	0.001	0.006	-0.015
Employees					
$10-49$	-0.092	-0.087	-0.022	0.008	-0.018
$50-249$	-0.002	-0.085	-0.017	0.033	-0.008
250+	0.11	0.005	0.038	0.058	-0.009
Sector					
Manufacturing	-0.085	-0.0123	0.034	-0.082	0.036
Construction	-0.034	-0.036	-0.009	-0.051	-0.053
Trade/Transport	-0.012	-0.026	0.016	-0.039	0.020
IT/Finance	-0.037	-0.074	-0.002	-0.071	0.028
Education/HH	-0.089	0.003	0.014	-0.074	-0.075

TABLE S5: Estimated probability of adopting AM technologies (Bundle 2)

Explanatory variables	Data access	Liability and reputation	Cost adoption	Lack of skills	Lack of internal data	Lack of funding
Bundle2						
AM	-0.382***	-0.338***	-0.328***	-0.410***	-0.222***	-0.200**
	(0.080)	(0.080)	(0.092)	(0.078)	(0.081)	(0.082)
+1	-0.378***	-0.200**	-0.427***	-0.396***	-0.081	-0.207**
	(0.089)	(0.089)	(0.102)	(0.087)	(0.089)	(0.091)
+2	-0.409***	-0.371***	-0.556***	-0.717***	-0.297**	0.057
	(0.117)	(0.118)	(0.128)	(0.118)	(0.124)	(0.120)
AI knowledge	-0.167*	-0.223**	-0.119	-0.159 *	0.020	-0.014
	(0.092)	(0.093)	(0.103)	(0.092)	(0.095)	(0.097)
Branch	0.043	0.084	0.094	0.021	-0.047	0.160 **
	(0.084)	(0.085)	(0.095)	(0.078)	(0.085)	(0.086)
Employees						
10 – 49	-0.189**	-0.157*	-0.049	0.039	-0.115	0.003
	(0.082)	(0.082)	(0.092)	(0.081)	(0.084)	(0.084)
50 – 249	-0.016	-0.153*	-0.110	0.061	-0.055	-0.136
	(0.087)	(0.087)	(0.097)	(0.086)	(0.089)	(0.090)
250+	0.287**	0.109	0.151	0.118	-0.127	0.057
	(0.118)	(0.119)	(0.133)	(0.115)	(0.121)	(0.123)
Sector						
Manufacturing	-0.331**	-0.263*	0.183	-0.147	0.219	0.087
	(0.142)	(0.141)	(0.155)	(0.140)	(0.151)	(0.150)
Construction	-0.198	-0.039	0.023	-0.012	0.003	0.366**
	(0.152)	(0.151)	(0.165)	(0.150)	(0.162)	(0.159)
Trade/Transport	-0.139	-0.047	0.067	-0.101	0.118	0.200
	(0.142)	(0.141)	(0.155)	(0.140)	(0.150)	(0.149)
IT/Finance	-0.192	-0.166	-0.103	-0.153	0.216	0.211
	(0.153)	(0.153)	(0.165)	(0.151)	(0.161)	(0.161)
Education/HH	-0.239	0.120	0.105	-0.148	-0.013	0.529***
	(0.169)	(0.169)	(0.184)	(0.166)	(0.180)	(0.174)
Country Dummies	Yes					
Number of observations	1,402					
Loglikelihood	-7722.0177					
LR test	676.91					

TABLE S6: Estimated probability of facing obstacles in Bundle 2 (Marginal effects)

Explanatory variables	Data access	Liability and reputation	Cost adoption	Lack of skills	Lack of internal data	Lack of funding
Bundle2						
AM	-0.124	-0.119	-0.086	-0.176	-0.106	-0.076
+1	-0.135	-0.094	-0.076	-0.133	-0.069	-0.091
+2	-0.117	-0.111	-0.140	-0.267	-0.148	0.032
AIknowledge	0.057	0.073	0.003	0.059	0.031	0.012
Branch	0.024	0.013	-0.004	-0.001	-0.016	0.025
Employees						
10 – 49	-0.091	-0.088	0.022	0.005	-0.018	0.011
50 – 249	-0.005	-0.087	-0.018	0.034	0.005	-0.038
250+	0.102	0.002	0.034	0.037	-0.011	-0.063
Sector						
Manufacturing	-0.088	-0.117	0.026	-0.076	0.033	0.023
Construction	-0.038	-0.034	-0.010	-0.041	-0.056	0.151
Trade/Transport	-0.022	-0.037	-0.02	-0.047	-0.004	0.083
IT/Finance	-0.048	-0.079	-0.013	-0.065	0.019	0.091
Education7HH	-0.0102	-0.06	-0.003	-0.075	-0.085	0.202

TABLE S7: Estimated probability of low-productivity firms adopting AM technologies

AM adoption	(1)	(2)	(3)	(4)	(5)
Productivity	-0.276***	-0.277***	-0.282***	-0.302***	-0.318***
	(0.094)	(0.094)	(0.095)	(0.096)	(0.100)
AI knowledge		0.051	0.047	0.028	-0.087
		(0.289)	(0.289)	(0.286)	(0.296)
Branch			0.273	0.160	0.189
			(0.314)	(0.318)	(0.319)
Company size					
$10-49$				-0.058	-0.181
				(0.224)	(0.232)
$50-249$				0.530**	0.295
				(0.239)	(0.255)
250+				0.188	0.051
				(0.436)	(0.452)
Sector					
Manufacturing					0.207
					(0.436)
Construction					-0.860*
					(0.499)
Trade/Transport					-1.069**
					(0.491)
IT/Finance					-0.838*
					(0.504)
Education					-0.242
					(0.480)
Country Dummies	Yes	Yes	Yes	Yes	Yes
Number of observations	1,255	1,255	1,255	1,255	1,255

TABLE S8: Estimated probability of low-productivity firms adopting AM technologies (Marginal effects)

AM adoption	(1)	(2)	(3)	(4)	(5)
Productivity	0.185	0.155	0.129	0.106	0.087
Country Dummies	Yes	Yes	Yes	Yes	Yes
Number of observations	1,255	1,255	1,255	1,255	1,255

TABLE S9: Estimated probability of adopting AM, PO RPA technologies

Explanatory variables	*Only AM Adoption*	*PO Adoption*	*RPA* Adoption
	Coefficient	Coefficient	Coefficient
AIknowledge	0.388***	0.212***	0.254***
	(0.101)	(0.046)	(0.049)
Branch	0.036	0.038	-0.011
	(0.097)	(0.046)	(0.047)
Employees			
$10-49$	0.166*	-0.029	0.038
	(0.087)	(0.042)	(0.044)
$50-249$	0.225**	0.122**	0.168***
	(0.102)	(0.048)	(0.049)
250+	-0.180	0.209***	0.469***
	(0.199)	(0.068)	(0.066)
Sector			
Manufacturing	-0.120	0.144	0.152
	(0.155)	(0.097)	(0.093)
Construction	-0.644***	-0.035	-0.250**
6 (0.169)	(0.099)	(0.098)	
Trade/Transport	-0.628***	-0.026	-0.179**
	(0.157)	(0.094)	(0.091)
IT/Finance	-0.669***	0.079	-0.048
	(0.176)	(0.097)	(0.095)
Education	-0.572***	0.027	-0.045
	(0.205)	(0.106)	(0.104)
constant	-1.762***	-1.121***	-1.334***
	(0.258)	(0.129)	(0.129)
CountryDummies	Yes	Yes	Yes
VCE(Robust)	Yes	Yes	Yes
Numberofobservations	4,893	8,662	8,662
Loglikelihood	-611.591	-3247.218	-3110.806
Waldchi2	145.37	177.95	273.24

Annex A: Survey data

Our data is issued from a European Commission survey entitled "European enterprise survey on the use of technologies based on artificial intelligence". The survey was designed and conducted in the EU27, Norway, Iceland and the UK, resulting in the participation of 9,640 companies. It was carried out between January and March 2020. The survey focuses on AI awareness (i.e. whether the company knows what AI is), present and future AI adoption (i.e. whether the company has adopted or plans to adopt AI technologies), AI acquisition path (i.e. how does the company acquire AI: through a purchased software, developing one in-house, etc.) as well as external (e.g. the need for new laws or regulations, lack of public or external funding, etc.) and internal (e.g. lack of skills, lack of internal data, etc.) obstacles to the adoption of those technologies (for further details, see Annex A).

The sample selection was made to be representative of the EU27, Norway, Iceland and the UK.[21] However, it is not devoid of the biases inherent in surveys. The results depend on the accuracy of the responses declared by the respondents. Therefore, errors due to respondents misunderstanding a question (for example, considering they have adopted an AI-based software when in fact they have adopted a deterministic one) or failing to provide an accurate answer on behalf of the company (for example, the respondent declaring that access to data is the most relevant barrier, when most of the personnel involved with AI do not see it as the most relevant one) might bias the results.

The data base contains information obtained from the report carried out for the European Commission by IPSOS in 2020 called "European enterprise survey on the use of technologies based on artificial intelligence". The database includes variables such as the size of the firm, a sector classification and location (see Table A1 below). The survey offers a complete and representative analysis, with four different company size categories, with a higher percentage of companies belonging to small-sized firms with no more than 50 employees. We restrict the analysis to six recoded sectors; however, the survey offers a full sector identification. With the intention to make a simpler and cleaner analysis, we decide, without loss of generality, to maintain the sector recode in the study. A series of internal and external obstacles are included in the analysis. Among the external obstacles, the lack of access to data and the strict standards for data exchange stand out from the rest, as a problem for more than 70% of the interviewees. The lack of external funding and general trust amongst citizens can also be highlighted with some concern. In general, the internal obstacles seem to be more relevant to interviewees. The cost of adoption and the complexity of the algorithms adopted generates uncertainly and lack of trust. The lack of skills stands out as one of the main problems. A deeper analysis is carried out to further study the root of the problem. Finally, the lack of a quality structure concerns more than the 80% of the interviewers.

[21] For the sake of succinctness, we use the term 'Europe' to refer to these countries hereafter.

Table A1. Descriptive statistics of the survey data

Variables	Categories					
	Yes	No				
Knowledge of AI	78.24%	21.76%				
AI adopters	41.84%	58.15%				
AM adopters	9.42%	90.58%				
Barriers to adoption						
Data access	65.85%	34.15%				
Liability and reputation	58,8%	41,2%				
Cost of adoption	83.25%	16.75%				
Lack of skills	66%	34%				
Lack of internal data	41.9%	58.1%				
Lack of funding	39.7%	60.3%				
	$5-9$	$10-49$	$50-249$	$250+$		
Firms size	35,14%	35,28%	21,81%	7,76%		
	Agriculture	*Manufacturing*	*Construction*	*Trade/ Transport*	*IT/ Finance*	*Education/ Human health*
Sector	3.87%	19.66%	15.4%	33,94%	18,16%	8.97%
	0	1	2+			
Number of branches	72.6%	14.6%	12.8%			
Number of observations	8,603					

Table A2. Perception of barriers to adoption by sector

Barriers to adoption	Data access	Liability and reputation	Cost adoption	Lack of skills	Lack of internal data	Lack of funding
Sector						
Agriculture	21%	55%	81%	67%	42%	34%
Manufacturing	22%	55%	84%	67%	43%	39%
Construction	19%	53%	81%	64%	40%	39%
Trade/Transport	21%	62%	83%	67%	42%	39%
IT/Finance	29%	62%	85%	65%	45%	40%
Education/HH	27%	62%	84%	64%	36%	47%
Number of observations	8,603					

A3. AM adoption by sector

	AM adoption
Sector	
Agriculture	6.21%
Manufacturing	29.24%
Construction	14.19%
Trade/Transport	26.82%
IT/Finance	14.55%
Education/HH	8.99%
Number of observations	1,402

Annex B: Methodology for the probability of adoption analysis

B.1 Probit model for the probability of adoption

We introduce a univariate model based on a Probit regression to model a dichotomous dependent variable that takes the value 1 if the firm adopted AM, and 0 if otherwise. To take into account the factors characterising the adoption decision we control for four firm and industrial variables.

Following the IPSOS questionnaire, we include in our analysis variables concerning:

- the knowledge of the employees about AI technologies,
- the sector in which they operate
- the number of employees.

Previous evidence reveals the importance of employees' learning capabilities[22] in the adoption patterns. Companies whose employees have technological knowledge and innovative skills possess advantages in the adoption of new technological advances as compared with companies with an unqualified workforce (Ghadge et al., 2020; Ghobakhloo, 2020; Hassan et al., 2017; Kamble et al., 2018; Tornatzky & Fleischer, 1990). We include AI knowledge by employees as a control variable for employees' abilities. However, those workforce skills may not always be properly exploited due to practical constraints, especially of SMEs (Hassan et al., 2017). For this reason, we include firm size as a control variable. A large body of literature evidences the importance of firm size in the adoption of new technologies. Large companies possess better resources to develop and financial capacity to support the adoption of new technological processes (Yu & Schweisfurth., 2020). Since those effects may also apply to the adoption of specific and innovative technologies such as AM in our case, we include the variables in the analysis. Moreover, in order to control for the possible differences between sectors and countries, we introduce variables accounting for the firm's sector and country. By doing this, we are able to isolate the role that the sector of activity and the country of the firm has on predicting whether it is an AM adopter or not.

B.2 Multivariate Probit Model for joint adoption of technologies

Table S2, in the additional tables section, shows Spearman's rho coefficients from the econometric results of the Multivariate Probit Model (MPM). The MPM is a natural extension of the probit model that allows to run more than one equation with correlated disturbance terms. Therefore, the model allows to capture the possible correlations between disturbance across the different equations. Those correlations are given by the Spearman's rho coefficients. Therefore, we consider appropriate to account for the possible spill-overs adoption patterns may create. In our case, the MPM includes ten equations estimating the adoption of the ten AI technologies.

[22] Ashkenas *et al.* (1995, p. 177) define learning capability as "the ability of the organization to learn the lessons of its experience and to pass those lessons across boundaries and time. Without this capability, the organization will tend to recreate its own solutions rather than leverage its investments in change and improvement".

Annex C: Robustness checks

In this section we discuss a robustness check for each analysis and how they affect the results. As mentioned above, we are not able to control reverse causality and we base our main analysis in a correlation relationship. However, those results still offer remarkable results. With the aim to verify our hypothesis, we run several robustness checks applied to our analysis.

Adoption of AM technologies and robotics

The first robustness check involves reporting alternative specifications on the effects of adopting a technology. Since we have tested what affects the probability of adopting AM technologies, we consider it as reasonable to base our robustness check on testing what affects the adoption of similar technologies. To do that, we consider those technologies with the highest correlation with AM in the MPM analysis. We run two probabilistic analyses to verify our hypothesis with the adoption of process optimisation (PO) and RPA technologies. Despite being two different technologies, we expect similar outputs in both cases due to the correlation in the adoption of those two technologies and AM technologies.

Results are displayed in Table S9. The estimations for the adoption of both technologies, columns 1 and 2, confirm our main findings. We confirm the positive impact of technological knowledge and company size on the technology adoption. However, effects related to sector become non-significant in the adoption of PO technologies. As with the adoption of AM technologies, the probability of adopting RPA technologies by companies operating in construction or trade or transport show a lower likelihood of adoption compared to firms competing in the agricultural sector.

We expected similar effects on AI knowledge or firm size, but we did not expect same trends regarding the sector due to the specific uses of each technology. Technology adoption is adapted in this case to sector dependences. As we expected differences in the adoption of AM by sector, we also must expect differences in the adoption of different technologies by a company operating in the same sector.

The effects by country confirm similar difficulties in the adoption of technologies by countries as with Ireland or Hungary. Nevertheless, as for the sector effects, we cannot strongly rely on this robustness check due to the differences that countries have in the adoption of different technologies. We may be able to compare extreme situations due to the advances or lack of resources of a country. However, we cannot compare the effects on the adoption of PO and RPA with the effects on the adoption of AM in most of the countries.

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