

European enterprise survey on the use of technologies based on artificial intelligence

Final report

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Abstract (in English and French)

0.1 Abstract

This study aimed to conduct the first EU-wide survey on the uptake of artificial intelligence (AI) technologies among enterprises. A robust survey instrument was designed and fielded in the EU27, Norway, Iceland and the UK using Computer Assisted Telephone Interviewing to obtain representative country estimates. The survey reached a total of 9640 enterprises in January – March 2020 and measured five KPIs: AI awareness, AI adoption, AI sourcing, external and internal obstacles to AI adoption.

Awareness of AI is high across the EU (78%). Four in ten (42%) enterprises have adopted at least one AI technology, 25% have adopted at least two. While 18% have plans to adopt AI in the next two years, 40% have neither adopted AI nor plan to do so. Adoption at the level of each technology is still relatively low: from 3% for sentiment analysis to 13% for anomaly detection and process/equipment optimisation. The most common sourcing strategy is external, as 59% of EU enterprises that use AI purchase software or ready-to-use systems.

Three key internal barriers to AI adoption are difficulties in hiring new staff with the right skills (57%), the cost of adoption (52%) and the cost of adapting operational processes (49%). Reducing uncertainty can be beneficial, as enterprises find liability for potential damages (33%), data standardisation (33%) and regulatory obstacles (29%) to be major external challenges to AI adoption.

0.2 Résumé

Cette étude visait à mener la toute première enquête à l'échelle de l'UE sur l'adoption des technologies d'intelligence artificielle (IA) au sein des entreprises. Une technique d'étude robuste a été élaborée et déployée dans l'Europe des 27, en Norvège, en Islande et au Royaume-Uni basée sur une enquête téléphonique assistée par ordinateur qui a généré des résultats représentatifs des taux obtenus à l'échelle de chaque pays. L'enquête a porté sur 9 640 entreprises au total en janvier - mars 2020 et s'est axée autour de cinq ICP : la connaissance de l'IA, l'adoption de l'IA, l'approvisionnement en solutions d'IA, les obstacles externes et internes à l'adoption de l'IA.

Le niveau de connaissance de l'IA est élevé à travers toute l'UE (78 %). Quatre entreprises sur dix (42 %) ont adopté au moins une technologie d'IA, 25 % en ont adopté au moins deux. Tandis que 18 % envisagent d'adopter une solution d'IA au cours des deux prochaines années, 40% ne l'ont soit pas fait ou n'ont pas l'intention de le faire. Le niveau d'adoption de chaque technologie est relativement faible : de 3 % pour l'analyse de sentiments à 13 % pour la détection des anomalies et pour l'optimisation des processus/équipements. La stratégie d'approvisionnement la plus courante est externe, dans la mesure où 59 % des entreprises de l'UE qui utilisent l'IA achètent des logiciels ou des systèmes prêts à l'emploi.

Les trois principaux obstacles internes à l'adoption de l'IA sont la difficulté d'embauche de nouveau personnel possédant les compétences nécessaires (57 %), le coût de l'adoption (52 %) et le coût de l'adaptation des processus opérationnels (49 %). La réduction de l'incertitude pourrait être un élément bénéfique, les entreprises considérant en effet le risque de responsabilité pour dommages (33 %), la normalisation des données (33 %) et les obstacles réglementaires (29 %) comme les obstacles externes majeurs à l'adoption de l'IA.

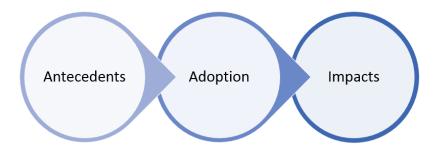
1 Executive Summary (in English and French)

1.1 Executive summary

This executive summary presents an overview of the results of the first EU-wide survey on the uptake of artificial intelligence (AI) technologies as part of a project commissioned by DG Connect. The assignment took place in two phases: a conceptual development phase and an execution phase. Phase I included a thorough review of the literature, scoping the definitions of AI-based technologies, identifying the relevant KPIs and developing an appropriate survey instrument.

To assess the state of play of artificial intelligence in European enterprises, a conceptual model was developed based on the literature review and tailored towards the objectives of this study. This model contains three interconnected phases that range from the moment a business becomes aware of a technology to the moment when the technology is embedded in several of its core processes.

The three phases of AI adoption



Each phase contains different dimensions on which Key Performance Indicators (KPIs) can be measured. Identifying the key performance indicators to measure was the second key stage of the process leading to the development of the survey instrument to explore the uptake of AI in businesses. During the second phase, the survey instrument was successfully fielded in the EU27, Norway, Iceland and the UK using Computer Assisted Telephone Interviewing (CATI) to obtain representative results at country level. The results of the AI survey, which reached a total of 9640 enterprises across the 30 countries surveyed, are presented in the following sections. They are structured based on the KPIs measured: awareness, adoption, sourcing, as well as external and internal obstacles to AI adoption.

1.1.1 Awareness of AI

At this stage of the digitisation of European businesses, **awareness of AI is almost universal** with 78% of enterprises stating that they know what the term Artificial Intelligence is and only 7% not aware and 15% unsure. At the more granular level, awareness of specific AI technologies is consistently high ranging between 87% for anomaly detection and 96% of enterprises aware of autonomous machines. Awareness of AI is clearly not a major barrier to the adoption of AI in Europe except amongst a small cohort of businesses.

1.1.2 Adoption of AI

However, awareness is only the first step towards **adoption of Al**¹ within an enterprise. Taking Europe as a whole, enterprises tend to fall into one of two camps, the 'adopters' (42%) who are currently using at least one Al technology and the non-adopters (40%) who do not currently use Al nor intend to use any of the Al technologies (at least in the following two years). The remaining 18% of enterprises represent a sizeable proportion who have plans to adopt Al in the next two years, despite currently not utilising Al solutions within their enterprise. The intensity of adoption also shows encouraging signs as a quarter (25%) of enterprises use at least two Al technologies.

At the aggregate level, large businesses are more likely to be adopters compared to smaller businesses, which is to be expected based on data from other sources, such as the DESI, which suggests the same pattern. Larger companies have the potential to benefit most from the adoption of AI given their larger economies of scale and potential return on investment. Therefore, it is unsurprising to find that almost double the proportion of large enterprises (39%) use two or more AI technologies compared to microsized (21%) and small enterprises (22%).

This aggregate level result does not reveal the full picture when it comes to estimating the level of adoption of AI technologies amongst European businesses. The survey digs deeper investigating the level of adoption of ten specific AI technologies. When adoption is considered at the **level of each technology**, adoption in the EU is still relatively low. It ranges from merely 3% of enterprises currently having adopted sentiment analysis to 13% for anomaly detection and process/equipment optimisation, despite 42% of businesses having adopted at least one of these ten AI technologies. Therefore, whilst the uptake of AI is relatively high amongst enterprises and differences in the adoption of specific technologies exist, there is no concentration of a specific technology that has particularly high uptake.

An association algorithm sheds light on which 'bundles' of AI technologies are most likely to be implemented by enterprises in combination. In conclusion, process optimisation is often coupled with another AI technology. As such, the use of this technology represents more a complementary set of tools than a real self-standing objective of utilising artificial intelligence within an enterprise.

1.1.3 Sector insights

Whilst the adoption of some technologies appears to be related to the adoption of another technology, the adoption of specific AI technologies or bundles of technologies is not universal across business sectors in Europe. Different sectors have different needs when it comes to AI technologies and which

¹ It is important to bear in mind that the approach of this survey was to include enterprises that have a minimum of 5 or more employees. Therefore, a proportion of micro-enterprises are excluded from the survey (and therefore from the results of this survey).

ones will serve their business most effectively. Al adoption (of at least one technology) is not surprisingly highest in the ICT sector (63%). Nevertheless, Al technologies clearly bring added value to a range of possible applications that tailor to a multitude of business contexts across sectors. If we exclude the ICT sector, the differences in Al adoption across sectors is not very pronounced, especially among businesses that adopt two or more technologies.

Related to the intensity of adopting different AI technologies the tendency is to use a range of AI technologies within specific sectors. Cluster analysis illustrates that there are forerunners that experiment with all kinds of AI technologies such as IT and the financial sectors. Conversely, sectors such as the construction sector are the lowest in terms of adopting a range of different AI technologies, possibly because the adoption of these AI technologies is less relevant.

The analysis also highlights that sectors do not adopt AI for the same purpose when considering which technologies are adopted by which sectors. Some sectors are using AI more for its ability to scale the understanding of human customers or partners (through natural language processing (NLP), sentiment analysis, etc.), while others use it to either take the human factor out of the equation (by automatising tasks) or to make their process more efficient. Association analysis illustrates that the industrial sectors use AI to optimise and automate processes, whereas service sectors have a more varied approach to adopting various AI technologies. The ICT sector combines different sets of AI technologies and seems to offer the most use cases for recommendation engines while the financial sector, which is also exposed to the risk of wire fraud, seems to utilise AI to automate fraud detection.

The similarity in the use of different AI technologies across industrial sectors indicates that the use of AI seems to be relatively homogeneous in comparison to the service sectors. AI adoption may already be exploited broadly among competitors within these industrial sectors.

1.1.4 AI sourcing strategies

The prospect of AI exploration is closely linked to where enterprises source their AI solutions². Looking at out-sourcing versus in-sourcing of AI solutions the data highlights that the most common sourcing strategies in the EU are external; 59% purchase software or ready-to-use systems and 38% hire external providers to develop AI applications. Only a minority developed AI fully in house (20%) or modified AI software (20% open source and 24% commercial). It is again the larger enterprises that have found the capacity to have fully customised sourcing of AI solutions for their business needs (28% developed fully in-house solutions in large enterprises compared to 16% of micro enterprises). When it comes to in-house solutions, unsurprisingly given their capacity, skills and profile, it is the more technical sectors (IT with 36%, other technical and/or scientific sectors with 28%) that are most likely to develop AI in-house.

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² Enterprises may use more than one sourcing strategy

1.1.5 Future AI adoption

The results illustrate interesting patterns in terms of the current adoption of AI in terms of intensity and the differences in the types of technologies used by enterprises of different characteristics. This leads us to ask: what will the **future of AI adoption** look like going forward? As already mentioned, 18% of enterprises that do not currently use AI plan to adopt at least one technology in the next two years. The 'adopters' seem to clearly value the benefits of utilising AI in their business operations given that more than half (56%) plan to use it more in the next two years. The remainder expect to continue using AI at a similar rate (37%) while only 4% plan to make less use of AI in the near future. This reflects a dichotomy of EU enterprises falling into two camps: adopters, the majority of whom will continue to use AI or use it more in the next two years, and non-adopters who do not use AI technologies, nor have plans to do so in the next two years with only a relatively small proportion of enterprises falling in the middle.

At the same time, on the level of specific AI technologies, whilst the EU will likely not see short term exponential growth in the use of AI overall given that only 18% of enterprises have plans to adopt AI in the next two years, the diversity in the adoption of AI technologies is set to continue at a fast pace. These findings suggest that the growth in the uptake of AI technologies is diversified across AI technologies and, depending on the barriers businesses currently face, is likely to result in a healthy growth reflective of the current uptake of these AI technologies.

1.1.6 Obstacles to AI adoption

Of course, the future of AI adoption is the measured intentions of enterprises to adopt the various AI technologies. Successful adoption of AI assumes that enterprises are able to overcome any **obstacles to adoption**, whether these are internal or external to the enterprise itself. The survey explored the degree to which various obstacles pose a major barrier for enterprises as well whether external or internal barriers pose the bigger challenge.

In the first instance, all barriers are relevant, although internal barriers are more commonly perceived as relevant compared to external obstacles. Amongst those that find barriers to be relevant to their enterprise, external barriers can negatively impact the adoption of AI technologies. However, enterprises generally find **internal obstacles to be a major challenge in comparison to external obstacles**. The core barriers to the uptake of AI technologies are challenges internal to an enterprise, which have to be addressed in order for adoption rates to go up. As a result, the two leading barriers that enterprises face are characterised as AI skills needs (lack of skills amongst existing staff 45%, difficulties hiring new staff with the right skills 57%) and the cost of implementation (cost of adoption 52%, cost of adapting operational processes 49%, lack of external/public funding 36%). The skills barrier is especially important given that it is not primarily related to size or sector but rather all enterprises compete in the same labour market and therefore face skills shortages. The two least challenging obstacles are reputational risks linked to the use of artificial intelligence (17%) and lack of internal data (20%).

Looking specifically at external barriers, while regulatory (29% state the need for new laws and regulation as a major barrier) and data standardisation efforts (33% find strict standards for data exchange to be a major barrier) seem important to enterprises, they might not necessarily be the barriers that make projects fail in the efforts to adopt AI in business practice. Reducing uncertainty can undoubtedly be highly beneficial for enterprises. However, they also seem to face other as important, if not more important, external issues in addition to the internal barriers already mentioned. The results draw attention in particular to the liability for potential damages when it comes to adopting AI technologies (33% across all enterprises, but the most recurrent barrier when looking at the level of individual technologies)³. This important barrier is followed by the lack of citizens' trust and access to public or external funding associated with the adoption of some technologies when looking at the most recurrent barriers at the level of each individual technology.

Businesses that have already adopted AI (i.e. the 'adopters' who have adopted at least one technology) are the ones least likely to find obstacles to be major barriers to adopting AI. Speculatively, this may be due to already having overcome key obstacles to becoming 'adopters' of AI and therefore, in retrospect, no longer seeing the obstacles as major barriers. Interestingly, non-adopters show a similar pattern to adopters in the proportion that they see the obstacles as major barriers, perhaps reflecting that a proportion of them have not yet gone through the process of adoption and therefore do not find the obstacles to be major barriers (yet). On the other hand, those who currently have not adopted AI technologies, but who plan to adopt in the next two years report the highest level of challenge across all obstacles (both external and internal). Theoretically, this could be related to these businesses being at the stage of adoption where they are currently facing barriers and obstacles to adopting AI as they make concrete attempts to adopt a given technology.

1.1.7 Next steps

The current findings provide the first EU-wide results from a business survey of enterprises to establish the incidence of the adoption of AI technologies as well as shedding light on both sourcing strategies and barriers to adoption. Furthermore, the patterns related to these key indicators identifying which technologies tend to be adopted together, the primary barriers experienced and by which types of enterprises. This provides an important baseline upon which future editions of this survey can be built bringing further insights as the changes in the adoption of AI technologies in the EU is tracked over the next years.

Future waves of the survey would benefit from nuancing the adoption of AI question even further to identify not only plans to adopt, but whether enterprises have made any attempts to adopt AI technologies or not as well as identifying the relevance of the given AI technologies for their business.

³ Liability for potential damages is the most recurrent barrier across all the technologies covered by the survey, though this is just indicative as the data does not allow for such fine-grained conclusions at the level of the technology itself as enterprises are not asked about barriers specific to a technology, but rather in general for the adoption of AI. It is therefore possible that the trends observed in relation to barriers experienced by enterprises that adopt or plan to adopt that one technology "leak" to the others because those two technologies are often used together.

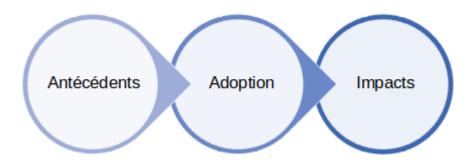
This is especially important in order to shed further light on the dichotomy of enterprises between 'adopters' and 'non-adopters' in order to further disaggregate non-adopters into those that have made attempts to adopt or not.

1.2 Résumé général

Ce résumé général vise à présenter une vue d'ensemble des résultats issus de la première enquête déployée à l'échelle de l'UE sur l'adoption des technologies d'intelligence artificielle (IA) dans le cadre d'un projet commandité par DG Connect. Le projet s'est déroulé en deux phases : une phase de développement conceptuel et une phase d'exécution. La phase I a inclus un examen approfondi de la documentation visant à élaborer les définitions relatives aux technologies reposant sur l'IA, à identifier les indicateurs clés de performance pertinents et à développer un instrument d'étude approprié.

Pour évaluer l'état de mise en œuvre de l'IA au sein des entreprises européennes, un modèle conceptuel a été développé sur la base de la documentation existante et adaptée aux objectifs de cette étude. Ce modèle contient trois phases interconnectées allant du moment où une entreprise prend connaissance de la technologie au moment où cette technologie est intégrée dans plusieurs de ses processus clés.

Les trois phases de l'adoption de l'IA



Chaque phase comprend différents aspects sur lesquels des indicateurs clés de performance (ICP) peuvent être appliqués. La deuxième étape clédu processus menant au développement des instruments de l'enquête a consisté à identifier les indicateurs clés de performance utilisés à des fins d'évaluation, afin d'examiner l'intégration de l'IA au sein des entreprises. Au cours de la deuxième phase, l'instrument d'étude a été déployé avec succès dans l'Europe des 27, en Norvège, en Islande et au Royaume-Uni à l'aide d'une interview téléphonique assistée par ordinateur (ITAO) qui permet d'obtenir des résultats représentatifs à l'échelle nationale. Les résultats de l'enquête sur l'IA qui a rassemblé 9 640 entreprises dans 30 pays au total, sont présentés dans les sections suivantes. Ces résultats sont structurés en fonction des ICP mesurés : connaissance, adoption, approvisionnement, mais aussi obstacles externes et internes à l'adoption de l'IA.

1.2.1 Connaissance de l'IA

À ce stade de la numérisation des entreprises européennes, la connaissance de l'IA est presque universelle : 78 % des entreprises déclarent savoir ce que signifie le terme Intelligence artificielle, 7 % ne le connaissent pas, et 15 % déclarent ne pas être sûres.

Plus précisément, la connaissance de technologies d'IA spécifiques est régulièrement élevée et varie de 87 % pour la détection d'anomalies à 96 % d'entreprises connaissant les machines autonomes. À l'évidence, la connaissance de l'IA ne constitue pas le principal obstacle à l'adoption de l'IA en Europe, hormis pour une petite cohorte d'entreprises.

1.2.2 Adoption de l'IA

Cependant, la connaissance n'est que la première étape vers **l'adoption de l'IA**⁴ au sein d'une entreprise. En considérant l'Europe dans son ensemble, les entreprises ont tendance à se diviser en deux catégories : les adeptes (42 %) qui utilisent actuellement au moins une technologie d'IA et les non-adeptes (40 %) qui n'utilisent pas actuellement de technologie d'IA et n'ont pas l'intention d'en utiliser une à l'avenir (du moins au cours des deux prochaines années). Les 18 % restants représentent une proportion considérable d'entreprises prévoyant d'adopter une solution d'IA au cours des deux prochaines années, même si elles n'en utilisent pas à l'heure actuelle au sein de leurs processus. L'intensité de l'adoption montre également des signes encourageants, puisqu'un quart des entreprises (soit 25 %) utilise au moins deux technologies d'IA.

Globalement, les grandes entreprises sont plus susceptibles d'adopter l'IA que celles de plus petite taille, ce qui est confirmé par des données issues d'autres sources, telles que l'indice DESI qui évoque la même tendance. Les entreprises de plus grande taille ont davantage le potentiel de tirer profit de l'adoption de l'IA compte tenu de leurs économies d'échelle et des possibilités de retour sur investissement. Par conséquent, il n'est pas surprenant de constater que le pourcentage de grandes entreprises (39 %) utilisant au minimum deux technologies d'IA représente le double ou presque du pourcentage des micro-entreprises (21 %) et des petites entreprises (22 %).

Ce résultat global ne dresse pas un tableau complet en ce qui concerne l'estimation du niveau d'adoption des technologies d'IA au sein des entreprises européennes. À cette fin, l'enquête approfondit l'examen pour se concentrer sur l'adoption de dix technologies d'IA spécifiques. Lorsqu'elle est étudiée au **niveau de chaque technologie**, l'adoption au sein de l'UE demeure relativement faible. Elle varie entre seulement 3 % des entreprises ayant actuellement adopté une "analyse de sentiment" et 13 % pour la détection d'anomalies et l'optimisation des processus/équipements, malgré les 42 % d'entreprises ayant adopté au moins l'une de ces dix technologies d'IA. Ainsi, bien que l'intégration de l'IA soit relativement élevée au sein des entreprises et que des différences existent en termes d'adoption de technologies spécifiques, aucune technologie spécifique ne bénéficie d'un taux d'adoption particulièrement élevé.

Un algorithme d'association permet de mettre en lumière les associations de technologies d'IA qui sont le plus susceptibles d'être mises en œuvre au sein des entreprises. En somme, l'optimisation du

⁴ Il est important de garder à l'esprit que l'approche utilisée dans le cadre de cette étude a consisté à inclure les entreprises ayant au minimum 5 employés. Par conséquent, une certaine proportion de micro-entreprises est exclue de l'enquête (et donc des résultats de cette enquête).

processus s'accompagne le plus souvent d'une autre technologie d'IA. Par conséquent, l'utilisation de cette technologie représente davantage un ensemble complémentaire d'outils plutôt qu'un objectif réel distinct visant à utiliser l'IA au sein d'une entreprise.

1.2.3 Résultats sectoriels

Alors que l'adoption de certaines technologies peut sembler liée à l'adoption d'une autre technologie, l'adoption de technologies d'IA spécifiques ou d'associations de technologies n'est pas universelle à travers l'ensemble des secteurs commerciaux en Europe. Chaque secteur a des besoins différents en matière de technologies d'IA et en ce qui concerne l'identification des technologies susceptibles d'avoir l'impact le plus efficace sur ses activités. Comme on peut s'y attendre, l'adoption de l'IA (au moins d'une technologie) est la plus élevée au sein du secteur informatique (63 %). Néanmoins, les technologies d'IA apportent une valeur ajoutée incontestable à toute une gamme d'applications possibles qui s'adaptent à une multitude de contextes commerciaux englobant plusieurs secteurs. Si nous excluons le secteur informatique, les différences en termes d'adoption de l'IA à travers les différents secteurs ne sont pas très marquées, notamment au sein des entreprises adoptant deux technologies supplémentaires.

En ce qui concerne l'intensité d'adoption des différentes technologies d'IA, la tendance qui se dégage consiste à utiliser une gamme de technologies d'IA au sein de secteurs spécifiques. Une analyse typologique révèle que les adeptes précoces qui essaient tous les types de technologies d'IA se situent au sein des secteurs informatiques et financiers. À l'inverse, des secteurs comme le bâtiment sont les moins enclins à adopter une gamme de technologies d'IA différentes, peut-être parce que l'adoption de ces technologies est moins pertinente pour leurs activités.

L'analyse révèle également que les secteurs n'adoptent pas l'IA pour les mêmes raisons. Certains secteurs utilisent l'IA davantage pour sa capacité à développer la compréhension des clients humains ou des partenaires à grande échelle (par le biais du traitement du langage naturel (TLN), de l'analyse de sentiments, etc.), alors que d'autres l'utilisent soit pour exclure le facteur humain (en automatisant les tâches) soit pour rendre leurs processus plus efficaces. L'analyse d'associations révèle que les secteurs industriels utilisent l'IA pour optimiser et automatiser leurs processus, alors que les secteurs des services ont une approche plus variée consistant à adopter différentes technologies d'IA. Le secteur informatique associe différents types de technologies d'IA et semble les utiliser le plus souvent pour des moteurs de recommandations, alors que le secteur financier également exposé au risque de fraude électronique semble utiliser l'IA pour automatiser la détection des fraudes.

La similitude d'utilisation des différentes technologies d'IA à travers les secteurs industriels indique que l'utilisation de l'IA semble être relativement homogène par rapport aux secteurs des services. L'adoption de l'IA peut déjà être largement exploitée pour se démarquer de la concurrence au sein de ces secteurs industriels.

1.2.4 Stratégies d'approvisionnement en solutions d'IA

La perspective d'une exploration de solutions d'IA est étroitement liée au **lieu d'approvisionnement en solutions d'IA**⁵ des entreprises. Lorsque l'on examine l'approvisionnement interne par rapport à l'approvisionnement externe en solutions d'IA, les données révèlent que les stratégies d'approvisionnement les plus courantes au sein de l'UE sont externes; 59 % des entreprises achètent des logiciels ou des systèmes prêts à l'emploi, alors que 38 % embauchent des prestataires externes pour développer des applications d'IA. Une minorité seulement des entreprises développe l'IA entièrement en interne (20 %) ou à l'aide d'un logiciel d'IA modifié (20 % Open source et 24 % commercial). Une fois encore, il s'agit de grandes entreprises ayant la possibilité de personnaliser entièrement leur approvisionnement de solutions d'IA par rapport à leurs besoins commerciaux (28 % de solutions d'IA développées entièrement en interne au sein des grandes entreprises, par rapport à 16 % des micro-entreprises). S'agissant des solutions internes, les secteurs les plus techniques sont les plus susceptibles de développer l'IA en interne (36 % pour l'informatique, 28 % pour d'autres secteurs techniques et/ou scientifiques), ce qui n'est pas surprenant compte tenu de leurs capacités, compétences et profils.

1.2.5 L'adoption de l'IA à l'avenir

Les résultats illustrent une tendance intéressante de l'adoption actuelle de l'IA en termes d'intensité et de différences dans les types de technologies utilisées par les entreprises présentant différentes caractéristiques. Ceci nous mène à poser la question : quel sera le visage de l'adoption de l'IA à l'avenir ? Comme nous l'avons déjà indiqué, 18 % des entreprises qui n'utilisent pas l'IA actuellement prévoient d'adopter au moins une technologie au cours des deux prochaines années. Les adeptes semblent voir clairement les avantages liés à l'utilisation de l'IA au sein de leurs opérations commerciales, étant donné que plus de la moitié (56 %) envisage d'avoir davantage recours à l'IA dans les deux prochaines années. La part restante devrait continuer à utiliser l'IA à un taux similaire (37 %), alors que 4 % seulement envisagent de réduire leur utilisation de l'IA à l'avenir. Ceci reflète une dichotomie entre les entreprises de l'UE qui se divisent en deux catégories : les adeptes, dont la majorité envisage de continuer à utiliser l'IA ou de l'utiliser davantage au cours des deux prochaines années, et les nonadeptes qui n'utilisent pas les technologies d'IA et n'envisagent pas de le faire au cours des deux prochaines années, avec une proportion relativement faible d'entreprises se situant entre ces deux catégories.

Dans le même temps, au niveau de technologies d'IA spécifiques, alors que l'UE ne devrait pas connaître une croissance exponentielle à court terme de l'utilisation de l'IA dans l'ensemble, étant donné que 18 % seulement des entreprises prévoient d'adopter l'IA au cours des deux prochaines années, la diversité en termes d'adoption de technologies d'IA devrait se poursuivre à grands pas. Ces résultats suggèrent que la croissance en termes d'adoption de technologies d'IA est diversifiée avec plusieurs technologies d'IA. Ainsi, en fonction des obstacles auxquels les entreprises sont actuellement

⁵ Les entreprises peuvent utiliser plus d'une stratégie d'approvisionnement

confrontées, il devrait en résulter néanmoins une hausse franche traduisant l'adoption actuelle de ces technologies d'IA.

1.2.6 Obstacles à l'adoption de l'IA

Bien entendu, l'adoption future de l'IA est mesurée par l'intention des entreprises d'adopter les différentes technologies d'IA à l'avenir. Une adoption d'IA réussie suppose que les entreprises soient capables de surmonter les éventuels **obstacles à l'adoption**, que ceux-ci soient de nature interne ou externe à l'entreprise. L'enquête examine la mesure dans laquelle les différents obstacles représentent un frein majeur pour les entreprises, et si les obstacles externes ou internes constituent leur plus grand défi.

En premier lieu, tous les obstacles sont pertinents, même si les obstacles internes sont le plus souvent perçus comme étant pertinents par rapport aux obstacles externes. Parmi ceux indiquant que les obstacles rencontrés sont pertinents pour leur entreprise, il convient de noter qu'un certain nombre d'obstacles externes peuvent également nuire à l'adoption des technologies d'IA. Toutefois, les entreprises sont généralement d'avis que les obstacles internes constituent un défi plus important que les obstacles externes. Les principaux obstacles à l'adoption des technologies d'IA sont les obstacles internes à l'entreprise, qui doivent être résolus avant de pouvoir accroître le taux d'adoption. Par conséquent, les deux principaux obstacles auxquels une entreprise est confrontée sont décrits comme étant les besoins en matière de compétences relatives à l'IA (45 % indiquent un manque de compétences au sein du personnel existant, 57 % indiquent des difficultés d'embauche d'un nouveau personnel ayant les bonnes compétences), et le coût de mise en œuvre (52 % mentionnent le coût d'adoption, 49 % le coût d'adaptation des processus opérationnels, et 36 % le manque de financement externe/public). L'obstacle des compétences est particulièrement significatif étant donné qu'il n'est pas principalement lié à la taille ou au secteur mais qu'il concerne toutes les entreprises du marché et, par conséquent, le manque de compétences auxquelles elles sont confrontées. Les deux derniers obstacles en termes d'importance sont les risques pour la réputation liés à l'utilisation de l'IA (17 %) et le manque de données internes (20 %).

S'agissant plus particulièrement des obstacles externes, si les difficultés réglementaires (29 % indiquent le besoin de nouvelles lois et de réglementations comme un obstacle majeur) et les efforts en matière de normalisation des données (33 % des entreprises citent les normes strictes en matière d'échange des données comme un obstacle majeur) semblent importants pour les entreprises, ces obstacles ne sont pas nécessairement à l'origine de l'échec des efforts en matière d'adoption de l'IA au sein des processus d'entreprise. Réduire l'incertitude représentera sans aucun doute un avantage pour les entreprises. Toutefois, outre les obstacles internes déjà mentionnés, les entreprises semblent également être confrontées à des problèmes externes tout aussi importants, sinon plus. Les résultats mettent en évidence le risque pour les entreprises de responsabilité pour dommages lors de l'adoption de technologies d'IA pour les entreprises (33 % pour toutes les entreprises, mais il s'agit de l'obstacle

le plus souvent mentionné au niveau de chaque technologie)⁶. Cet obstacle important est suivi par le manque de confiance des citoyens et le manque d'accès à des financements publics ou externes associé à l'adoption de certaines technologies, lorsque l'on examine les obstacles les plus souvent mentionnés au niveau de chaque technologie.

Les entreprises qui ont déjà adopté l'IA (c.-à-d. celles qui ont adopté au moins une technologie) sont celles qui sont le moins susceptibles de trouver des obstacles significatifs à l'adoption de l'IA. On peut supposer que cela est dû au fait d'avoir déjà surmonté les principaux obstacles liés à l'adoption de l'IA, et par conséquent, en rétrospective, de ne plus les considérer comme des obstacles majeurs. Il est intéressant de noter que celles qui n'ont pas adopté d'IA affichent une tendance similaire aux autres en termes d'obstacles majeurs, ce qui indique peut-être qu'une partie d'entre elles n'a pas encore engagé le processus d'adoption et ne considère donc pas (encore) ces obstacles comme étant significatifs. D'un autre côté, les entreprises qui n'ont pas adopté de technologies d'IA à l'heure actuelle, mais envisagent d'en adopter au cours des deux prochaines années, font état d'un niveau élevé de difficulté pour tous les obstacles (à la fois externes et internes). En théorie, cela pourrait se rapporter au fait que ces entreprises en sont au stade d'adoption où elles sont confrontées actuellement à des obstacles et des barrières qui freinent leurs efforts en matière d'adoption d'une technologie donnée.

1.2.7 Étapes suivantes

Les résultats actuels constituent les premiers résultats à l'échelle de l'UE issus d'une enquête menée auprès des entreprises visant à déterminer l'incidence de l'adoption des technologies d'IA ainsi qu'à examiner à la fois les stratégies d'approvisionnement et les obstacles à l'adoption. De plus, les tendances liées à ces indicateurs clés ont permis d'identifier les technologies qui sont généralement adoptées ensemble, les principaux obstacles auxquels les entreprises font face et les obstacles par types d'entreprise. Ce résultat donne un point de repère important sur lequel les prochaines éditions de cette enquête pourront se fonder pour apporter un éclairage supplémentaire. L'adoption des technologies d'IA au sein de l'UE fera en effet l'objet d'un suivi au fil des prochaines années.

Les futures vagues d'enquêtes gagneraient à nuancer la question de l'adoption de l'IA davantage encore afin d'identifier non seulement la probabilité d'adoption, mais aussi si les entreprises ont tenté ou non d'adopter les technologies d'IA, ainsi que la pertinence des technologies d'IA spécifiques par rapport à leurs activités. Ceci est particulièrement important pour examiner de manière plus

⁶ Le risque de responsabilité pour dommages est l'obstacle le plus souvent mentionné pour toutes les technologies abordées dans l'enquête, même s'il ne s'agit là que d'une indication, les données ne permettant pas d'affiner des conclusions au niveau de la technologie en elle-même. Cela s'explique par le fait que les entreprises ne doivent pas répondre à des questions portant sur les obstacles propres à chaque technologie, mais sur les obstacles à l'adoption des technologies d'IA généralement parlant. Il est, par conséquent, possible que les tendances observées concernant les obstacles mentionnés par les entreprises adoptant ou envisageant d'adopter une technologie donnée «contaminent» une autre technologie, si ces deux technologies sont le plus souvent utilisées ensemble.

approfondie la dichotomie existant dans les entreprises entre les adeptes et les non-adeptes, et pour ventiler davantage les non-adeptes en non-adeptes ayant fait une tentative d'adoption ou non.

2 Introduction and methodology

2.1 Introduction

The present report summarises the analysis conducted on the EU-wide data collected on the uptake of AI technologies as part of the project "European enterprise survey on the use of technologies based on artificial intelligence" commissioned by DG Connect.

New technologies in general, and artificial intelligence (AI) in particular, have been growing rapidly in the last decade. The development of AI has benefited from large volumes of data and the increasingly powerful capacity of modern computers. High speed and wireless networks enable entirely new applications such as the Internet of Things (IoT) and new platform business models. Such new technologies are becoming increasingly important for businesses and individuals. Therefore, their development is expected to constitute a key driver for economic development in Europe.

Despite the importance of new technology in businesses, only limited data is available on this topic at the EU and Member State level. While a number of studies have been conducted, there is still a clear need for reliable, quantitative data on the uptake of new technology in businesses operating across the EU. The key objective of the project is to fill this information gap and obtain a reliable quantitative overview at Member State level on the status of Al-based technologies.

The assignment took place in two phases: a conceptual development phase and an execution phase. Phase I included a thorough review of the literature, scoping the definitions of AI-based technologies, identifying the key performance indicators (KPIs) and developing an appropriate survey instrument.

The quest for **an AI definition** in the context of the present study carried different objectives. First, it was a starting point for a clear delimitation of the scope of technologies to be covered in the survey. Second, it was helpful in ensuring a common understanding of the core concepts involved in the survey across the parties involved. And third, it was used in the survey itself, for the interviewers to be able to clarify toward the respondents what is meant with AI in the context of the questionnaire.

Defining artificial intelligence is a challenging task. As acknowledged by many authors and reports, the notion of artificial intelligence is a very elusive concept because intelligence itself is. Based on the literature review, it appeared that one key decision point for the present survey was to restrict the definition to systems that "learn".

Based on results from the literature review, complemented by discussions with relevant stakeholders (DG JUST, DG GROW, Eurostat, DG JRC, OECD), the following definitions were developed:

"Artificial Intelligence: is technology that tries to automate one or more (human) cognitive functions or processes. It provides predictions, recommendations or decisions to achieve specific objectives. It does so by continuously learning about its environment or results from its actions."

- "Artificial Intelligence system: is a system having an artificial intelligence as one of its components. It provides information about the environment as input for the artificial intelligence and uses the predictions, classifications, recommendations or decisions produced by this component to act on its environment."
- "Cognitive functions: are the intellectual processes by which one becomes aware of, perceives, or comprehends ideas. It involves all aspects of perception, language, remembering, reasoning and learning."

Whilst this provided a broad definition of AI, the survey seeks further refined information related to specific AI technologies. Based on the extensive review of the literature and existing taxonomies (for example, the taxonomies used in the European Commission Digital Scoreboard data repository), the project team developed a taxonomy of new digital technologies. For this study, the focus is on two perspectives: the application taxonomy that is based on high-level functionalities and secondly, the taxonomy based on the technology itself, i.e. classes of algorithms. The resulting taxonomy and therefore the AI technologies included in the survey to explore awareness and application of in European enterprises are:

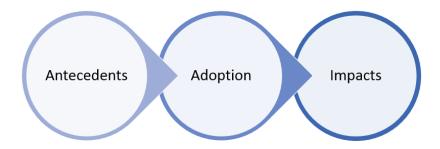
- 1. Speech recognition, machine translation or chatbots, also known as **natural language processing**.
- 2. Visual diagnostics, face or image recognition, also known as computer vision.
- 3. Fraud detection or risk analysis, also known as anomaly detection.
- 4. Analysis of emotions or behaviours, also known as sentiment analysis.
- 5. Forecasting, price optimisation and decision-making using machine learning algorithms.
- 6. **Process or equipment optimisation** using artificial intelligence.
- 7. **Recommendation and personalisation engines** using artificial intelligence to produce customised recommendations, via matching algorithms or information retrieval.
- 8. **Process automation** using artificial intelligence, including warehouse automation or robotics process automation (RPA).
- 9. Autonomous machines, such as smart and autonomous robots or vehicles.
- 10. **Creative and experimentation activities**, such as virtual prototyping, data generation, artificial music or painting.

To assess the state of play of artificial intelligence in European enterprises, a conceptual model was developed based on the literature review and tailored towards the objectives of this study. This model contains three interconnected phases that range from the moment a business becomes aware of a technology to the moment when the technology is embedded in several of its core processes.

A pictorial representation of the model is presented below. It starts with the antecedents, i.e. all the factors that lead an enterprise to want to adopt a technology as well as potential reasons that might hinder the adoption. Once the enterprise chooses to adopt a technology and manages to remove the

potential roadblocks on the path of its implementation, the adoption phase starts. After or in parallel to the implementation, the adoption might have led to measurable impacts.

The three phases of AI adoption



Each phase contains different dimensions on which Key Performance Indicators (KPIs) can be measured. Identifying the key performance indicators to measure was the second key stage of the process leading to the development of the survey instrument to explore the uptake of AI in businesses. The focus was to identify topics that are relevant in providing a better picture of the current state of AI adoption and would also directly or indirectly inform current and future policy on the topic.

The definition of KPIs was greatly facilitated by the development of the taxonomy and the conceptual model of AI adoption. This task required to translate the definitions of technologies and descriptions of KPI classes into indicators that are specific, measurable, relevant and time-bound (i.e. measurable at a clear moment in time). Once KPIs were derived, the project team reviewed each indicator with regards to their relevance to the study's objectives and measurability and therefore prioritised the KPIs to be included in the survey instrument.

Once the most relevant metrics were determined for each KPI that was to be included in this baseline survey of AI uptake, questions were designed linked to these metrics. The following KPIs are measured in the final questionnaire:

⁷ See e.g. Doran, G. T. (1981). "There's a S.M.A.R.T. way to write management's goals and objectives". Management Review. 70 (11): 35–36.

Table 1: Definition of KPIs to be measured in the survey

		KPI
	Technological base	Availability of quality data internally : Some algorithms and technologies, such as the neural networks or probabilistic graphical models, typically require large amount of data to be trained. This question determines the adequate availability of data inside the enterprise.
		Accessibility of quality external data: As for internal data, some techniques require large amounts of data that can be either found publicly or purchased from information provider. The availability and accessibility to those data might be crucial for an enterprise in its endeavour to implement an artificial intelligence solution.
Organisation		Usage of standards for data exchanges : Data standards and labels are increasingly being promoted through enterprises. While correlated to the availability of external data, they capture a different aspect of the transaction, namely the quality of the data.
		Availability of public resources about AI : Besides data, public powers can also provide enterprises with information and other types of resources to help them implement AI solutions. While not a barrier per se, it might be a way to speed up adoption of certain strains of AI or some application. The question is therefore whether a demand for such resources exists.
	Financial	Existence of financial constraints to AI adoption: One of the reasons enterprises might be unwilling or unable to adopt artificial
	resources	intelligence-based solutions might be that they do not manage to have access to financial resources needed to finance such endeavours.
	Institutional certainty	Existence of legal/regulatory barriers : Some enterprises might be unwilling to undertake the adoption of a technology as a consequence of the lack of existence or failures of a regulatory framework. As such, it is interesting to be able to capture the aggregated views of enterprises regarding such a topic.
Environment		Legal/regulatory uncertainty : Connected but not entirely overlapping with the previous point is the uncertainty existing in any system of rules. Such uncertainty might lead some enterprises to adopt a wait-and-see attitude towards certain technology, giving a signal to the public entities that timing in legislating or improving legislation might be decisive.
		Degree of comfort with potential liabilities : Beside the inherent uncertainty in the legal framework, the building up of potential (legal or otherwise) liabilities might be a concern to enterprises that might factor it or not in their perceived benefits/perceived costs assessment.
		Dase Organisation Financial resources Institutional

		Human resources	Ease of access to AI talents : An often-cited issue in the field of AI is the lack of skilled workforce in the field. The concepts involved in AI are advanced and require either formal or informal training. Identifying specific issues on the labour market is an important step to promote adoption of technologies by European enterprises.
	Extent of	Awareness	
	adoption	Pilot/ experimentation	Current stage of awareness and adoption of each application (cf. taxonomy) : Measuring the state of awareness and adoption of each application provides insights into the requirements of enterprises across industries and countries to be able to build a multidimensional map of AI adoption and be able to discuss synergies between sectors or geographical areas.
ptior	Scope of adoption	Which applications?	map or / ii daoption and se asie to also as syntengies seemeen sections of geographical areas.
Adop		Internal investment	Direction of planned investments in AI : This indicator was measured on a qualitative scale, asking about future adjustments to the current use of AI. This can be translated into intentions of future financial investment in AI.
	Sourcing	Sourcing strategy	Sources currently exploited : This KPI refers to the way enterprises carry out their implementation (in-house build, customised (open-source/commercial) packages, external supplier / integrator, AI as a service (cloud)). There are different impacts, for instance on the labour market, depending on whether the enterprise mainly relies on consultants or train their own workforce to implement the solutions. The same holds if enterprises use online solution and keep little infrastructure and software in place for their applications.

The draft survey instrument underwent in-depth cognitive testing in five languages across five EU Member States (Belgium, Spain, Poland, Sweden and Ireland) to ensure its validity. The target respondent in each enterprise was broadly defined as an employee who knows about the use of technology in the company.

The resulting data was analysed to provide relevant insights for each KPI studied. The preliminary results from this analysis are presented in this Final Report, including summaries of the key findings overall, per type of enterprise (adopters, non-adopters and those who plan to adopt AI), per company size, sector and region/country.

The report broadly follows the structure of the survey and is divided into five key chapters, focusing on the following topics/KPIs:

- 1) The adoption of Al
- 2) Sourcing strategies for the adoption of AI
- 3) External obstacles to the adoption of AI
- 4) Internal obstacles to the adoption of AI
- 5) In-depth analysis of the obstacles to AI adoption by technology and by country.

2.2 Methodology

2.2.1 Sampling design

The target sample unit for this survey was an enterprise, which is defined by Eurostat as:

An enterprise is an organisational unit producing goods or services which has a certain degree of autonomy in decision-making.⁸

An enterprise refers to a business that may comprise one or more premises (establishments). As establishments often do not have dedicated financial reporting and the liberty to make their own financial decisions (e.g. about investments in new technologies), they were excluded from the target universe. To filter out establishments, only "headquarters" offices were selected in each country. The enterprises were targeted on country level, which means that large international enterprises may be included several times in the sample, based on their presence in multiple target countries. As the accurate sampling of the statistical unit "enterprise" can be challenging, some limitations to this approach should be noted. The selection of headquarters offices only guarantees that each enterprise has only one chance to be included in the gross sample at country level. Apart from filters applied on country, company size (see below) and enterprise unit (headquarters), no additional consolidation of legal units took place. In cases where a large enterprise is surveyed, it is therefore assumed that the validity of the answers applies to the whole enterprise at country level.

The survey targeted European enterprises of four different sizes, ranging from micro to large enterprises and operating in a wide variety of NACE activity sectors⁹ with some exclusions¹⁰. Enterprise size was determined based on the number of employees¹¹ and businesses with zero to four employees were excluded from the target population¹²:

- 1) micro (5-9 employees)
- 2) small (10-49 employees)
- 3) medium (50-249 employees)
- 4) and large (250+ employees).

Given the subject of the survey, it was expected that the most knowledgeable respondent could hold different functions within the company. To ensure results can be generalised to the total target universe of enterprises, the main **target respondent** definition had a broad scope. It was defined as *an employee who is familiar with how technology is used within the firm*. Initially, the topic of Artificial Intelligence was mentioned during the introduction to the survey. Results from the soft launch indicated, however, that many respondents seem reluctant to respond to the survey when the

⁸ https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Glossary:Enterprise

⁹ From **Sector A** (Agriculture, Hunting and Forestry) to **Sector Q** (Extraterritorial Organisations and Bodies). For a full list please visit: https://ec.europa.eu/eurostat/documents/3859598/5902521/KS-RA-07-015-EN.PDF, page 57.

¹⁰ **Section O, division 84:** Public administration; **Section T, divisions 97 and 98:** Activities of Households as Employers; Undifferentiated Goods and Services Producing Activities of Households for Own Use; **Section U, division 99:** Activities of Extraterritorial Organisations and Bodies

¹¹ The number of employees refers to official statistics on the number of persons employed.

¹² The exclusion of micro enterprises with zero to four employees was based on the fact that they represent a very large proportion of the total universe of enterprises and could thus bias the results.

term Artificial Intelligence is mentioned specifically. As the purpose of the survey is to measure the uptake of AI in general, higher non-response from enterprises that are not aware of or do not use AI could bias the results. Therefore, the introduction was altered to refer to technology in general.

2.2.2 Sampling frame

The overall target responses¹³ for all 30 countries was set at 9640 enterprises. We drew the gross sample¹⁴ disproportionally to the universe when it comes to enterprise size, to ensure that enough large and medium enterprises are targeted and allow comparisons across enterprise size. The final raw sample was drawn at random for each country and per enterprise size (micro, small, medium and large) due to the disproportionality stated above. It was released in batches and consisted of three batches in total, which were used in a continuous manner (the previous batch had to be exhausted before a new sample batch was used). The table below presents the target distributions per country and company size.

Table 2: Target responses per country and company size

Country	Large (>250	Medium (50-249	Small (10-49	Micro (5-9	Total N per
Country	employees)	employees)	employees)	employees)	country
Austria	23	80	100	130	333
Belgium	22	100	130	140	392
Bulgaria	15	85	145	135	380
Croatia	17	35	70	76	198
Cyprus	1	10	15	15	41
Czechia	32	85	100	100	317
Denmark	30	80	130	140	380
Estonia	3	20	110	114	247
Finland	15	50	160	144	369
France	60	110	200	180	550
Germany	54	160	160	180	554
Greece	12	50	125	126	313
Hungary	20	60	80	100	260
Ireland	20	60	85	90	255
Italy	15	100	230	250	595
Latvia	10	60	80	100	250
Lithuania	5	40	75	75	195
Luxembourg	5	15	45	45	110
Malta	1	5	10	5	21
the Netherlands	100	130	130	140	500
Poland	50	120	125	120	415
Portugal	30	80	125	126	361
Romania	32	100	135	121	388
Slovenia	10	50	85	94	239
Slovakia	5	15	90	100	210
Spain	55	110	130	114	409
Sweden	23	80	150	126	379
Norway	30	100	140	150	420
Iceland	3	10	27	32	72
the UK	125	125	125	112	487
Total	823	2125	3312	3380	9640

¹³ The target responses refer to the number of complete responses the survey aims to achieve, depending on the response rates.

¹⁴ The gross sample refers to the total sample drawn from the target universe of enterprises to conduct the survey. The gross sample drawn was approximately 20 times larger than the number of target responses.

The universe from which the sample was drawn was Orbis¹⁵, which is considered the most comprehensive source for comparative business statistics in Europe. It relies on official sources that are enriched with multiple external data sources and allows matching and use of additional data (e.g. enterprise revenue). The database is systematically scanned for duplications based on phone number, enterprise name and address and is updated continuously (in real time for some parameters). In some target countries with a limited population of enterprises and no access to official business registers (Malta and Cyprus), the available sample frame is rather limited. Another limitation of the database is reduced coverage of micro and small companies with respect to large enterprises. Despite these limitations, Orbis was considered the optimal choice of sampling frame for this study as it allows for a consistent sampling approach across all surveyed countries.

2.2.3 Data collection method

Computer Assisted Telephone Interviewing (CATI) was used as a data collection methodology in all 27 EU Member States, Iceland, Norway and the UK. Adopting a CATI methodology for survey administration ensured a streamlined sampling approach that delivers robust and representative estimates of the overall target universe of enterprises across the 30 countries surveyed. CATI interviews were conducted by national interviewers making use of a unified fieldwork system used in all countries covered by the survey. This allowed for centralised scripting of the questionnaire, fieldwork monitoring, data collection, data checks and data storage.

Once the questionnaire was finalised, it was scripted in a central data collection system (IBM Dimensions). The scripting was done in two steps: master scripting and the translation overlays. After the first step, a checking syntax was used to determine whether all filters, randomisations, value range restrictions, recodes were scripted correctly, and to verify that all data is captured completely. The master script was then tested manually by several experienced script testers capturing different filters and randomisations. After the translation overlays, the translated versions of the questionnaire were tested manually in a second testing phase. Simultaneously to first scripting phase (master scripting), the final version of the questionnaire was **translated** in the local language(s) of each country. Each translated language version of the questionnaire was checked by a separate reviewer.

Prior to starting the main fieldwork, the field teams were briefed extensively. The local fieldwork managers received an oral briefing in English via a conference call from the Ipsos central project team, while local teams were provided with a written briefing document including the survey background and specifics. The local fieldwork managers briefed the interviewers in detail in each local language, stressing on key response maximization and recruitment techniques, as well as the ESOMAR/GDPR guidelines.

2.2.4 Achieved sample and response rates

The main fieldwork was conducted between 16 January 2020 and 9 March 2020. In total 9640 interviews were completed across all 30 countries, with 8661 interviews completed within the EU27. In several countries with the lowest population of enterprises, the quota on enterprise size was relaxed to allow the total sample size per country to be reached. Response rates¹⁶ based on the gross

¹⁵ https://www.bvdinfo.com/en-gb/our-products/data/international/orbis

¹⁶ Response rates are computed as the number of enterprises who answered the survey divided by the number of contacted enterprises in the gross sample.

sample used varied between 5% (in a majority of target countries) and 19% in Malta. The average response rate was 7% of the gross sample across all surveyed countries, corresponding to 93% non-response rate overall.

The fieldwork was particularly challenging in Malta, due to the low number of enterprises available in the sample frame, which resulted in only 21 achieved interviews - a sample size that is unlikely to present reliable estimates for this country. The interviews were realised within the expected survey length of on average 10 minutes.

2.2.5 Data quality controls

The fieldwork progress and interview quality were monitored daily. A minimum of 10% of the interviews were subject to quality control via live listening in or listening in to recordings. In addition to local quality controls, the Ipsos central team performed strict data quality controls, including interviewer performance, straight lining, and item non-response.

To maximise the chance of reaching establishments, potential respondents were called during what's generally seen as standard business hours in each respective country. Calling was spread over different days and different times of the day. At least 8 contact attempts (and maximum 10) per valid telephone number were made.

2.2.6 Weighting

To ensure overall representativeness of the sample allowing us to draw conclusions at EU level, the achieved sample was weighted to the universe proportions based on enterprise size for each country using data from Eurostat's Structural Business Statistics¹⁷. Given quota were set on the company size per country, the deviations observed between the target population and achieved sample were limited for most countries. This ensured very high weighting efficiency across the surveyed countries, ranging between 79% and 100%. Only in the countries where we needed some flexibility on quota per enterprise size to be able to reach the country targets, the deviations are slightly higher but still well within the norm with Malta having the lowest weighting efficiency of 79%.

2.2.7 Additional data and analysis

After the weighting, the collected data was linked to key indicators available in the ORBIS database (e.g. sectors NACE codes, number of employees, revenue etc.) using unique enterprise identifiers. These additional variables were used for verification purposes in the in-depth analysis, which is part of this report. They are also available in the final datafile.

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¹⁷ https://ec.europa.eu/eurostat/web/structural-business-statistics

3 Adoption of Artificial Intelligence technology across the EU

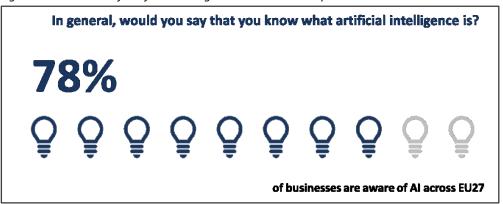
Key findings

- Overall, self-reported awareness about AI among EU enterprises is consistently high across sectors and enterprises of different sizes.
 Differences in awareness are limited with the highest variation in awareness observed across specific EU Member States.
- Enterprises fall generally into two categories either adopters (four in ten)
 or non-adopters who have no plans to adopt AI (four in ten), with just under
 one-fifth of enterprises being non-adopters that plan to adopt AI in the next
 2 years.
- Adoption of AI technologies is only slightly correlated with size and sector, with large companies and those operating in the ICT sector being most likely to adopt AI.
- Some regional differences in adoption are observed but the largest variation is recorded at the country level.

3.1 Awareness of AI

The first indicator we explore is the extent to which enterprises are aware of Artificial Intelligence as a prerequisite to adoption.¹⁸ At the EU27 level¹⁹, close to eight out of ten of enterprises in the EU (78%) indicate that they know what artificial intelligence is, while the remainder are either unaware (7%), or not sure (15%).

Figure 1: Awareness of Artificial Intelligence across all enterprises in the EU27



Base question Q0: In general, would you say that you know what artificial intelligence is?
Base size: EU27, N=8661. (Base size represents only EU27 Member States, excluding the UK, Iceland and Norway).

¹⁸ It is important to note that awareness is a subjective indicator (answered by one person working within the enterprise who knows about the use of technology) and the question asked was general in nature. This could mean that different respondents may have interpreted the question differently, which may have an impact on the reported figures.

¹⁹ All results are reported on the EU27 level, unless indicated otherwise.

Looking at awareness by specific AI technology, overall the majority of businesses are aware of AI, with minor differences across technologies: ranging between 87% for anomaly detection (fraud detection and risk analysis) and 96% for autonomous machines.

The self-reported awareness varies further across company sizes: between 85% in large enterprises with more than 250 employees to 74% in micro-sized enterprises with 5 to 9 employees. The economic sectors which report the highest level of awareness about AI are ICT (91%) and education (88%), followed by finance and manufacturing (both 81%). Least awareness about AI is observed in the agriculture, forestry and fishing, water and electricity supply, and food sectors (all 71%).

3.2 The adoption of Artificial Intelligence

Altogether, roughly four in ten EU enterprises (42%) use at least one of the AI based technologies asked about. This includes 17% of enterprises that use one type of AI technology and 25% of enterprises that use two or more AI technologies. The use of specific technologies, however, is rather dispersed across enterprises where the uptake of any single technology is consistently under 15% of all enterprises (See Section 3.2.1).

When it comes to potential future uptake, slightly less than one in five enterprises (18%) do not use AI technology, but plan to do so in the near future (next 2 years), while the remaining 40% do not use AI and do not have concrete plans to use it.

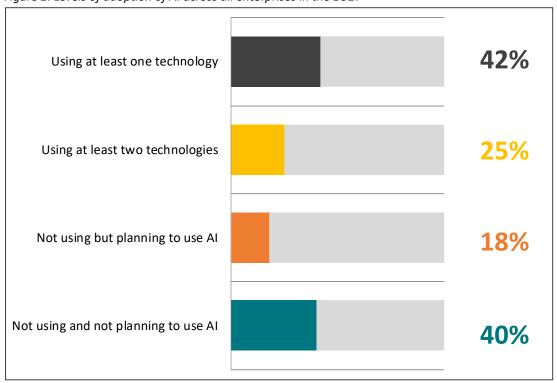


Figure 2: Levels of adoption of AI across all enterprises in the EU27

Base question Q1: What is the current state of adoption in your firm for [Al technologies]?; Base size: EU27, N=8661. (Base size represents only EU27 Member States, excluding the UK, Iceland and Norway).

These figures are broadly in line with a recent (2018) global survey of 2135 businesses run by McKinsey, which found that 47% of surveyed enterprises had embedded at least one AI application

into their business. ^{20,21} To put these results in the context of other new technologies, the 2019 Digital Economy and Society Index (DESI) report²² measured the integration of digital technologies in EU businesses when it comes to business digitisation (electronic information sharing, radio frequency identification (RFID), social media, e-Invoices and cloud computing) and e-commerce (SMEs selling online, e-commerce turnover and selling online cross-border). While AI uptake still lags behind business digitisation and e-commerce, this first EU-wide data suggests that a considerable proportion of enterprises already use at least one of the many AI technologies available with the level of adoption spread well across different technologies.²³

Among enterprises already using artificial intelligence, more than half (56%) plan to use it more²⁴ in the next two years. Most of the remaining adopters (37%) plan to continue using AI at a similar level as they are currently using it. Only 4% of enterprises already using AI plan to make less use of AI in the next 2 years. These figures point to a dichotomy: 1) **the adopters (42% of all businesses)** of which a large majority (93%) plan to use it more or at least at the same pace in the near future; 2) **the non-adopters (40% of all businesses)** that neither use nor state that they have plans to use AI technology in the next two years. The second groups (non-adopters) is likely to contain both businesses that need AI but do not use it but also a large number of enterprises that do not see useful applications for AI technologies in their business.²⁵

The number of AI technologies that businesses currently adopt is linked to their plans to use AI more or less in the future. This relationship is exemplified further in proportions in the visual below. Enterprises using one technology (42%) are more likely to state that they plan to use AI at the same rate in the future compared to those using three (32%) or more (30%) technologies. With respect to plans to use AI more in the future, the opposite is true: 68% of enterprises using at least four compared to 52% of those using one AI technology.

 $^{^{20}\,\}underline{\text{https://www.mckinsey.com/featured-insights/artificial-intelligence/ai-adoption-advances-but-foundational-barriers-remain}$

²¹ It should be noted that this comparison is only indicative. The survey conducted by McKinsey employed a different methodology (online) and a broader definition of AI, not looking at specific technologies.

²² European Commission (2019). DESI Report 2019 – Integration of Digital Technology. https://ec.europa.eu/newsroom/dae/document.cfm?doc_id=59979

²³ It should be noted that due to methodological differences in data collection, analysis and reporting, the figures reported in the present study are not directly comparable with the DESI report. As such, any comparisons are simply indicative and used to provide context.

²⁴ Based on Q5 from the Survey: "Finally, when it comes to using artificial intelligence in the next 2 years, which applies best to your company?" – answer options: 1) We have plans to use it less, 2) We have plans to use it about the same, 3) We have plans to use it more.

²⁵ Future surveys would benefit from further distinguishing between these two groups.

Figure 3. The intensity of AI adoption across all enterprises in the EU27 by number of sourcing channels

		 Plans to use Al less	Plans to use Al about the same	Plans to use Al more
usage	One technology	6%	42%	52 %
y of Al	Two technologies	4%	41%	55%
Intensit	Three technologies	4%	32%	64%
At	least four technologies	2%	30%	68%

Base question Q1: What is the current state of adoption in your firm for [Al technologies]?; Base size: EU27, N=8661. (Base size represents only EU27 Member States, excluding the UK, Iceland and Norway).

3.2.1 AI adoption by type of application

To measure the level of adoption of AI across different applications, respondents were asked whether their business uses various AI based technologies based on a clear taxonomy of ten applications of AI, which was developed during the extensive preparatory phase of this study. As visualised in the figure below, the enterprises' adoption levels of each of the different AI technologies varies between 3% and 13%. Most prevalent is the use of AI for anomaly detection (fraud detection or risk analysis), and for process or equipment optimisation, with 13% of EU enterprises currently using each of these two technologies. Relatively widespread is also the use of AI for process automation, including warehouse automation or robotics process automation (RPA), which 12% of enterprises currently use. Sentiment analysis is the least adopted technology with only 3% of enterprises using it.²⁶

06 7

²⁶ These results are broadly in line with the global AI survey by Mckinsey (2018), where machine learning was reported as the most commonly used application of AI. However, direct comparisons are not possible to make as the taxonomy of technologies surveyed differs between the two studies.

Figure 4: Levels of adoption by specific AI technology across all enterprises in the EU27

Al technologies	_	Currently use it	Plan to use it
Process or equipment optimisation		13%	11%
Anomaly detection		13%	7%
Process automation		12%	11%
Forecasting, price optimization and decision-making		10%	10%
Natural language processing	~_~~~	10%	8%
Autonomous machines		9%	7%
Computer vision	0	9%	7%
Recommendation/personalisation engines			7%
Creative and experimentation activities		7%	4%
Sentiment analysis		3%	3%

Base question Q1: What is the current state of adoption in your firm for [Al technologies]?; Base size: EU27, N=8661. (Base size represents only EU27 Member States, excluding the UK, Iceland and Norway).

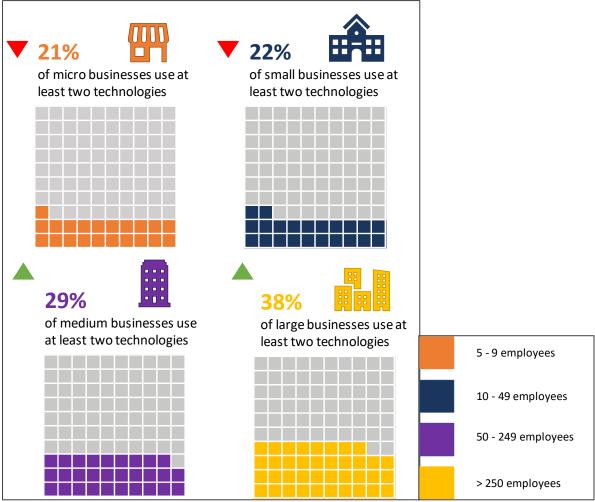
An interesting trend can be observed by comparing current use and plans to use by specific technology. For most technologies, a sizeable proportion of enterprises have plans to use specific technologies in the next two years compared to current levels of adoption. For example, process or equipment optimisation and process automation are currently used by 13% and 12% of all businesses, respectively. Strikingly, an additional 11% of businesses plan to start using these technologies in the next two years. This trend is observed across all surveyed technologies with plans for future usage ranging between 3% and 11%, while current usage ranging between 3% and 13%. As enterprises were asked to indicate planned usage for a short period in the future (the next 2 years), these figures suggest very good potential for growth across all AI technologies surveyed.

3.2.2 AI adoption by company size

Al adoption varies significantly based on company size, with large enterprises being most likely to use at least one technological application of Al. Over half (55%) of enterprises with 250 employees or more currently use at least one Al technology, compared to slightly less than four in ten (38%) micro-sized enterprises with between 5 and 9 employees. This gap across company sizes is in line with the DESI

report studying digitisation of businesses and e-commerce use.²⁷ Differences related to company size are slightly more pronounced when focusing on enterprises using two or more AI technologies. While 39% of large enterprises with 250+ employees use two or more AI technologies, this figure is only 21% for micro-sized enterprises with 5-9 employees, 22% for small enterprises 10-49 employees, and inbetween (30%) for medium-sized enterprises with 50-249 employees.

Figure 5: Levels of adoption of AI across all enterprises in the EU27 by company size (at least two t echnologies)



Base question Q1: What is the current state of adoption in your firm for [Al technologies]?
Base:EU27, N=8661. (Base size represents only EU27 Member States, excluding the UK, Iceland and Norway).

The gap between medium-sized and large enterprises is not extremely high, however, suggesting that they are not far behind in exploring the opportunities for growth AI technologies can offer. It can be due to multiple factors, such as investment possibilities (e.g. to build solutions or hire skilled employees) as well as advantages due to the scale of operation. These are discussed in more detail in Chapters 5 and 6 exploring the external and internal obstacles to the adoption of AI.

3.2.3 AI adoption by sector

²⁷ European Commission (2019). DESI Report 2019 – Integration of Digital Technology. https://ec.europa.eu/newsroom/dae/document.cfm?doc_id=59979 When looking at different economic sectors (presented in the visual below), AI adoption is most common among businesses active in ICT (63%), ahead from the next highest sector by 14%. It is followed by education (49%), human health, social work, and manufacturing (all 47%). Businesses active in accommodation (42%), real estate (42%) and other technical/scientific sectors (43%) score about average. At the other end of the spectrum in terms of AI uptake, are businesses active in waste management (31%), construction, transport and food (all 36%). These differences are broadly in line with sector differences in the adoption of new technologies reported by the DESI. ^{28,29}

Plans to use AI technologies in the next two years also varies by sector. Possibly linked to the already high proportion of AI adopters, businesses in the ICT sector are the fourth least likely (12%) to state that they have plans to use AI in the near future, after oil and gas (6%), social work (10%) and recreation activities (11%). The highest growth prospects are foreseen in the finance and insurance sector (27%), waste management (27%) and education (21%). Most other sectors fall close to the global average (18%) of businesses that plan to use AI in the next two years.

At least one AI At least two AI At least one AI At least two AI Sector (Part I) Plans to use Sector (Part II) Plans to use technology technology technologies 42% 15% Agriculture, forestry and/or 39% 24% 18% 22% Accommodation Profishing Recreation activities 47% 27% 16% Manufacturing 63% 43% 12% 36% 23% 16% Construction 27% 40% 20% Finance, insurance 38% 6% 19% Oil and gas 🔞 📶 42% 18% 23% Real estate Waste management 31% 21% 27% Other technical and/or scientific 43% Water and electricity supply 28% 17% sectors 45% 49% 21% 21% Education Trade, retail 38% 22% 20% 47% 19% 29% Human health Transport 36% 22% 20% 47% 10% Social work Food 36% 26% 20%

Figure 6: Levels of adoption of AI by sector

Base question Q1: What is the current state of adoption in your firm for [Al technologies]?; Base: EU27, N=8661. (Base size represents only EU27 Member States, excluding the UK, Iceland and Norway).

Even sectors at the bottom of the spectrum, however, stay not far from the overall figure across all EU enterprises (42%), showing that sector differences are not substantial. When looking specifically at enterprises using two or more AI technologies, sector-related differences vary between 19% for oil and gas to 43% for the ICT sector. Excluding the ICT sector, this variation is only between 19% (oil and gas) and 29% for human health.

3.2.4 AI adoption by country³⁰

Compared to sector and size differences, the **country level differences in AI adoption** are decidedly larger (see Figure below). The proportion **of enterprises having adopted at least one AI technology** range from less than one third (27%) in Cyprus and Estonia to roughly double that proportion (61%) in

²⁸ European Commission (2019). DESI Report 2019 – Integration of Digital Technology. https://ec.europa.eu/newsroom/dae/document.cfm?doc_id=59979

²⁹ It should be noted that due to methodological differences in data collection, analysis and reporting, the figures reported in the present study are not directly comparable with the DESI report. As such, any comparisons are simply indicative and used to provide context.

³⁰ In this section, all 30 surveyed countries are considered, in contrast to previous sections.

Czechia. Other countries where many enterprises report adopting at least one AI technology are Lithuania and Bulgaria (both 54%), and Austria and Luxembourg (both 51%). Other countries in which the AI uptake of enterprises is low are Malta (31%) and Slovakia (29%). When looking at EU regions, no broader pattern emerges.

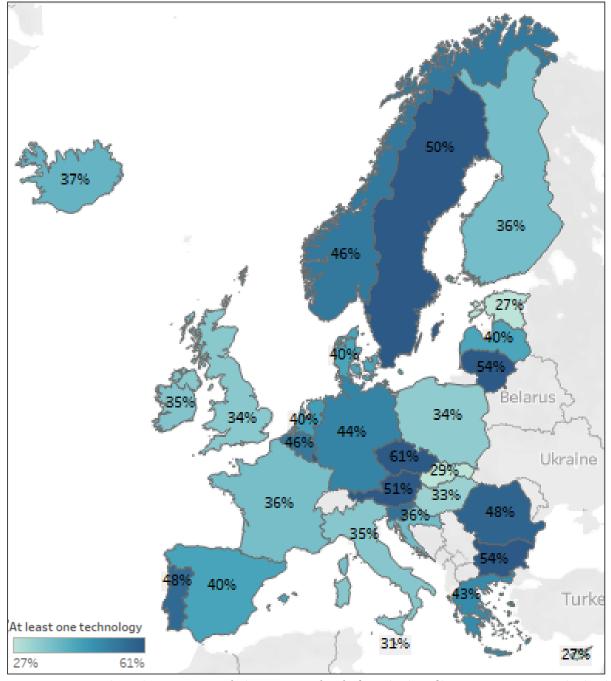


Figure 7: Levels of adoption of AI by country (at least one technology)

Base question: Q1: What is the current state of adoption in your firm for [AI technologies]?; Base:EU27, Norway, Iceland and the UK, N=9640.

Focusing on **enterprises using two or more AI technologies**, similar country-level differences are observed: The adoption of two or more AI technologies is highest in Czechia (40% of enterprises in this country use at least two AI technologies), followed by Austria (37%) and Lithuania (34%). The uptake of two or more AI technologies is particularly low In Malta (2% of enterprises in this country

use at least two AI technologies), Ireland (14%), and Cyprus, Estonia and Slovakia (15% in all three countries).

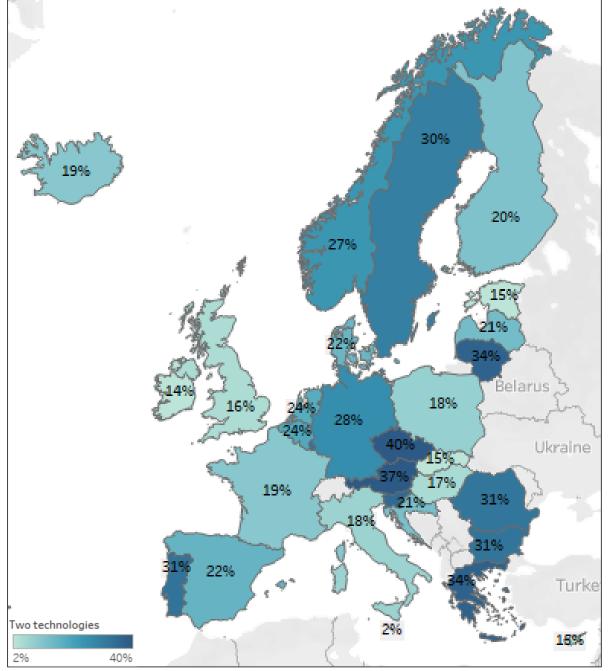


Figure 8: Levels of adoption of AI by country (at least two technologies)

Base question: Q1: What is the current state of adoption in your firm for [AI technologies]?; Base:EU27, Norway, Iceland and the UK, N=9640.

While plans for future AI adoption vary little between enterprises of different sizes, variations are higher across countries. The proportion of enterprises that do not use AI, but plan to use AI in the future, is highest in Malta (31%) and the Netherlands (27%). In Czechia, on the other hand, just 1% of enterprises not using AI planned to use AI in the future. This likely correlates with the fact that AI uptake in Czechia is currently already high, while in Malta it is low, as reported above.

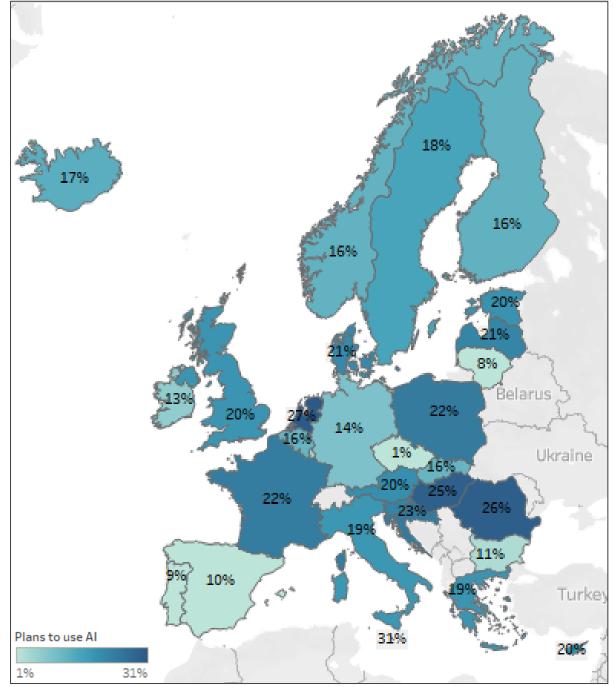


Figure 9: Plans to adopt AI in the next 2 years by country

Base question Q1: What is the current state of adoption in your firm for [AI technologies]?; Base:EU27, Norway, Iceland and the UK, N=9640.

3.3 In-depth analysis of AI adoption by sector and country using unsupervised learning techniques

In this section, findings from an in-depth analysis using unsupervised learning techniques³¹ are reported. The main focus is on clustering and association techniques on the following three topics:

- Analysis 1: technology adoption by industry sector
- Analysis 2: associations between applications that are usually adopted (bundled) together
- **Analysis 3:** the obstacles encountered by country (presented in Chapter 7, Section 7.2)

This analysis does not attempt to answer a specific question but rather to help form a useful mental framework for later analysis. Relatively broadly understood and adopted techniques are used. Therefore, the key objective is to inspire further ideas and introduce potentially useful concepts for policy making as well as to serve as an invitation to apply other relevant techniques with the same purpose. The aim is to group industry sectors and countries into "clusters" sharing some common characteristics. Due to the relative complexity of the analyses, the methodology used and the key theoretical foundations are presented first, providing links to relevant resources to aid the understanding and interpretation of the results.³²

3.3.1 Methodology

The analysis process followed consists of the following steps:

1. "Reorganize" (or rotate) the answers to be able to concentrate the information on a smaller number of dimensions. This is done through <u>principal component analysis</u> (PCA), a classical statistical technique. This technique is used to "concentrate" as much information (or variance) as possible on two dimensions in order to be able to produce a summary in a regular chart. The axes of this new chart represent "mixes" of the original dimensions to which we attempt to give business signification (by analysing the proportion of each of the original dimensions contained in each of these new dimensions).

This step is useful in this as it makes the interpretation of the results easier (if the principal components are interpretable, meaning that they make business sense). Indeed, the analysis of clusters may be done in a two-dimensional space and therefore visually represented instead of in a 9-dimensional space that inevitably make any attempt at interpreting the center of each cluster, for example, as arduous task.³³

2. Using the coordinates of each sector in this new dimensional basis, we use a clustering technique (called <u>K-Means</u>) that aims to group the observations into "clusters" of points that

³¹ These techniques are usually used to "let the data speak for itself" and allow unearthing insights that are frequently overlooked by a simple visual analysis.

³² The commented notebooks containing the code used to produce the results are available upon request.

³³ A potential drawback is that, doing so, we lose a part of the information contained in the data. However, this is seen by some practitioners as a noise filter and as such, a useful feature (since we "filter out" weaker signals in the data, keeping only the general direction). The discussion of such topic is, however, not the objective of this report.

are close to one another. This technique produces a pre-determined number³⁴ of classes that constitute the outcome of such an analysis.

This procedure is standard to perform such kind of analysis and is grounded in both classical statistical and mathematical literature (for the principal component analysis³⁵) and the computer science one (for the K-Means algorithms³⁶). A vision of the results obtained for the first two analyses is provided in the following sections. Furthermore, both the PCA components retained and a visual representation of the charts containing the observations are included for illustration purposes.

3.3.2 Technology Adoption per Industry

For the clustering of industries by their pattern of technology adoption, adoption was represented as a binary variable that takes the value 1 if the company currently uses the technology or plan to use it in the two years, and 0 if it neither use nor plan to use it for the moment.

Principal components

After transformation, the first two components of the dataset contain 65%³⁷ of the total variance of the set. The principal components extracted from the decomposition are presented in Table 2 as well as on Figure 9 below.

Table 3: Principal components extracted

Technology	X	Υ
NLP	0.489	0.317
Computer vision	0.073	-0.171
Anomaly detection	0.492	-0.193
Sentiment analysis	0.157	0.054
Forecasting	0.409	-0.138
Process optimisation	0.292	-0.373
Recommendation engines	0.422	0.272
Process automation	0.081	-0.649
Autonomous machines	-0.145	-0.414
Creative activities	0.175	-0.073

³⁴ This number was chosen according to heuristics based on some measure the "clustering error" (called inertia). The kink method was used as a first estimation of the optimal number of clusters.

³⁵ See, for example Friedman, J., Hastie, T., & Tibshirani, R. (2001). *The elements of statistical learning* (Vol. 1, No. 10)., chapter 14.5, New York: Springer series in statistics.

³⁶ Ibid. chap 13.2.

³⁷ The spread of the variance between the different components can be found in Annex D

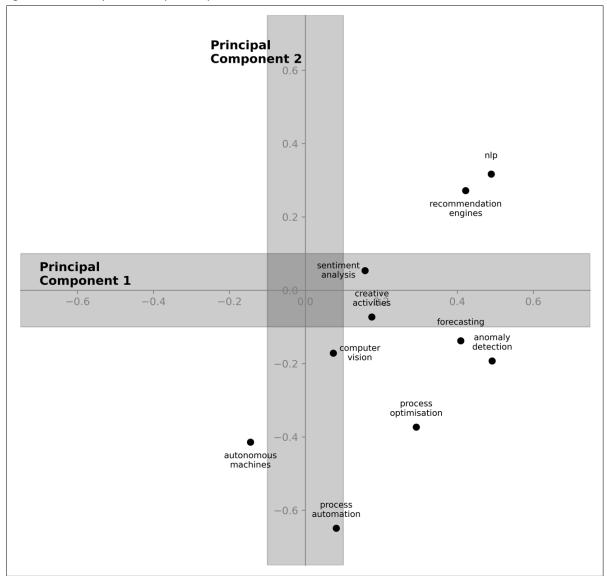


Figure 10. Scatter plot - Principal components extracted

These figures lead to the following interpretation. The **first principal component** loads positively on nearly all technologies. This dimension can be interpreted as **a measure of the intensity of AI use among dominant AI technologies**. Therefore, we can say that the higher the value on this first dimension, the more AI tech the industrial sector uses.

The **second component** (the one containing most variance and the most relevant way to approach differences between industries) is a **measure of the applications mix prominently observed in the industry**. The enterprises located on the upper part of the graph are those that tend to use more Natural Language Processing, Recommendation Engines and Sentiment Analysis, which are technologies that we associate more with consumer facing services. On the other hand, enterprises on the lower part of the graph are those that will tend to use more applications such as Process Optimisation or Automation and Autonomous Machines. We associate those technologies with manufacturing and operational processes that take place inside businesses.

Clusters

The result of the K-Means analysis is presented in the figure below. The letter corresponds to the NACE 1^{st} level sector.³⁸

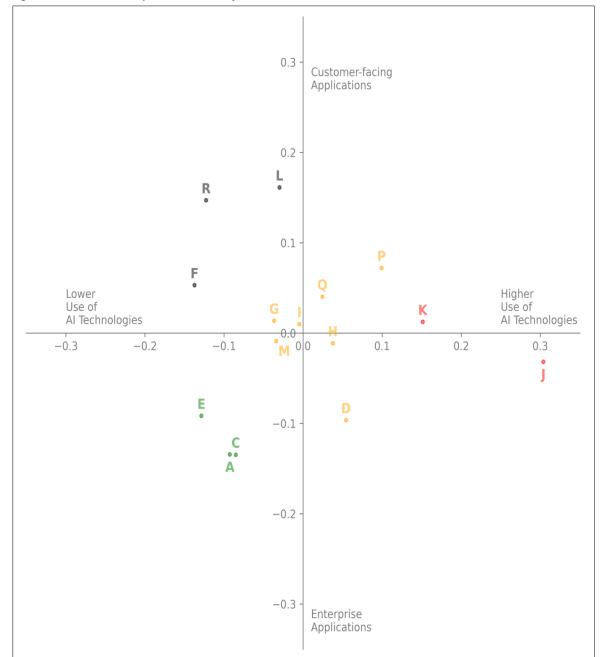


Figure 11. K-Means analysis – overview of results

The clusters are elaborated on further below:

1. **Red**: Information and communication technologies (J) and Financial and insurance activities (K). Those make heavy use of AI but have a balanced profile in terms of the type of application.

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³⁸ Sectors are listed in Annex C.

- 2. **Green**: Agriculture, forestry and/or fishing (A), Manufacturing (C) and Waste Management (E).³⁹ Those sectors tend to use AI mainly in its manufacturing and processes applications (see above) and they use it slightly less than the average.
- 3. **Grey**: Construction (F), Real estate activities (L) and Recreation activities (R). Those sectors make relatively little use of AI and use nearly exclusively the NLP, sentiment analysis and recommendation engines.
- 4. **Yellow**: The last cluster contains all other sectors. They are close to the mean on both axes and as such do not show a clear tendency. Although most are slightly more on the "customerfacing technologies" side, the Electricity and Water supply (D) is an exception that uses more "enterprise technologies".

While not surprising, this analysis has the merit of proposing a typology of sectors. There are **sectors** that experiment with multiple AI technologies (the Information technologies and the Financial and Insurance sectors) and there are **sectors for which AI may be less relevant** (such as the Construction and Waste Management sectors). However, the results further demonstrate that not all sectors use AI for the same purposes. There are some sectors such as Real estate and Recreation activities that use it more for its ability to **scale their understanding of customers or partners** (through NLP, sentiment analysis, etc.), while others such as Agriculture, forestry and/or fishing and Manufacturing use it to either take human out of the equation (by automatizing tasks) or **increase the efficiency of their processes**.

3.3.3 Association analysis – bundles of AI technologies

As a second analysis, an association algorithm⁴⁰ was used with the objective to identify "bundles" of Al technologies or applications that are usually implemented together. All applications enterprises are planning to implement were considered. The focus was placed on bundles that have a relatively large support (or prevalence in more than 10% of all enterprises).

Before looking at the results of the association analysis, please find the adoption rates of application by sector in Table 3 below. To compute these adoption rates, we considered respondents who are at least aware of the technology and we take the distinction between current users (Use) and future adopters (Plan) into account.

³⁹ Note that, depending, due to some randomization aspect of the K-Means clustering method, Trade, retail (G) and Transport (H) are sometimes assigned to this cluster.

⁴⁰ Referred to as "Frequent Pattern Growth" and usually used by supermarkets to perform market basket analysis.

Table 4 – Technologies' adoption rates by sector

	Ano dete	maly ction	Autono mach		Comput	er vision	Crea activ		Forec	asting	N	LP	Pro auton	cess	Pro optimi			mendation gines		timent alysis
	Use	Plan	Use	Plan	Use	Plan	Use	Plan	Use	Plan	Use	Plan	Use	Plan	Use	Plan	Use	Plan	Use	Plan
Α	19%	8%	19%	9%	15%	9%	9%	3%	12%	9%	5%	6%	16%	12%	14%	12%	8%	6%	4%	3%
С	15%	7%	15%	10%	8%	6%	9%	5%	11%	10%	9%	5%	18%	15%	17%	13%	9%	7%	1%	1%
D	12%	13%	8%	7%	7%	8%	7%	9%	21%	9%	10%	12%	15%	17%	16%	20%	12%	5%	1%	1%
E	8%	15%	8%	9%	11%	14%	1%	9%	3%	12%	13%	8%	7%	25%	11%	13%	3%	0%	3%	0%
F	12%	7%	8%	6%	10%	8%	9%	3%	7%	8%	8%	6%	8%	8%	12%	11%	7%	7%	3%	2%
G	15%	8%	6%	5%	7%	6%	5%	3%	12%	15%	9%	8%	11%	14%	12%	11%	10%	9%	3%	4%
н	16%	12%	9%	10%	10%	8%	6%	2%	16%	13%	10%	12%	10%	12%	15%	12%	12%	9%	1%	5%
I	19%	8%	9%	6%	8%	8%	3%	4%	18%	10%	11%	8%	11%	10%	14%	12%	11%	7%	3%	3%
J	28%	11%	7%	5%	17%	10%	13%	5%	18%	19%	25%	12%	15%	14%	20%	16%	18%	14%	5%	6%
К	18%	23%	3%	6%	7%	6%	3%	4%	13%	17%	15%	13%	12%	14%	12%	15%	11%	13%	3%	3%
L	10%	10%	8%	3%	16%	1%	4%	2%	5%	14%	16%	13%	10%	5%	13%	5%	14%	10%	2%	1%
М	14%	8%	9%	7%	10%	10%	9%	6%	9%	9%	9%	9%	15%	8%	14%	15%	12%	8%	4%	4%
P	15%	13%	9%	8%	9%	9%	18%	12%	15%	5%	18%	13%	12%	4%	18%	10%	15%	9%	7%	6%
Q	19%	8%	10%	6%	10%	8%	10%	4%	10%	7%	15%	13%	15%	7%	16%	12%	11%	11%	5%	3%
R	10%	4%	5%	4%	10%	5%	6%	3%	9%	11%	9%	10%	7%	7%	8%	9%	12%	6%	2%	1%

The main conclusion is that process optimisation is often coupled with another technology. As such, this application is more a complement than a self-standing objective of artificial intelligence. This might be of interest to help cast some light on the correlations between the effect of barriers between those technologies.

The three most frequent bundles of at least two technologies are reported in the table below:

Table 5 – Most common technology bundles

Bundle	Support (or prevalence)
Process Automation	
Process Optimisation	22.73%
Anomaly Detection	21.020/
Process Optimisation	21.02%
Forecasting	20.25%
Process Optimisation	20.25%

To dig a bit deeper, the analysis was repeated per industry, using the same process and keeping only bundles having a support (or prevalence) of at least 15% in this sub-population⁴¹. The results are presented in the table below:

Table 6 – Most common technology bundles by sector

Industry	Bundle	Support
Agriculture, forestry and/or fishing	Autonomous Machines Computer vision	22.57%
Manufacturing	Process Automation Process Optimisation	26.96%
Electricity and Water supply	Process Automation Process Optimisation	28.64%

⁴¹ Enterprises being, as one would expect, a bit more homogeneous inside an industry, it might make sense to be a little more selective as to the minimum threshold for inclusion here.

	Forecasting Process Optimisation	17.37%
	Forecasting Process Automation	16.43%
Waste management	Process Automation Process Optimisation	21.79%
Transport	Forecasting Process Optimisation	23.11%
	Anomaly Detection NLP	34.56%
	Forecasting Process Automation	26.65%
	Forecasting Process Optimisation	19.53%
Information and communication	Anomaly Detection Process Optimisation	18.21%
technologies	Anomaly Detection Recommendation Engines	17.68%
	Forecasting Recommendation Engines	17.41%
	NLP Process Optimisation	17.41%
	Process Optimisation Recommendation Engines	17.15%

	Anomaly Detection Forecasting	16.89%
	NLP Recommendation Engines	15.57%
	Forecasting NLP	15.30%
Finance, insurance	Anomaly Detection Forecasting	26.56%
	Anomaly Detection Process Automation	24.38%
Education	Creative Activities NLP	28.15%
	Creative Activities Process Optimisation	

These bundles hint at examples of use cases in each of the studied sectors. Most of the industrial sectors use AI to optimise and automate processes, with sectors with high variation in demand and storage constraints (such as the Energy and Water supply) adding the forecasting of demand into the mix. Services sectors, on the other hand, have more varied suggested use cases. IT, as one might expect, combines the largest set of applications' bundles with an important use of Recommendation Engines coupled with other applications such as NLP or Anomaly detection. The Financial and Insurance sector, on the other hand (which is also vulnerable to the risk of wire fraud) seems to utilise AI to automate fraud detection.

Also noteworthy is the fact that Education seems to combine the most "creative" aspects of AI (where virtual prototyping applications also fit according to this taxonomy) in combination with other technologies. It may be worthy to further investigate this possibility as such technologies are often at the cutting edge of AI research because they often require an important modelling effort and significant skills to deploy.

The relative similarity of bundles across industries seems to indicate that the use cases are already relatively established. The available data does not allow to further explore the specific underlying technologies constituting those bundles (e.g. are all businesses using the same type of algorithms to

optimise their processes?) and the applications seem to be relatively homogeneous at least among the different industrial sectors (as opposed to service). This suggests that AI adoption might therefore be in a less "prospective" than expected with some use cases already being exploited broadly across different competitors in specific industries.

4 Sourcing of Artificial Intelligence

Key findings

- The most common sourcing strategy, followed by six in ten enterprises, is to apply AI technology by purchasing software or ready-to-use systems. A further four in ten enterprises hire external providers to develop AI technology. Other methods to acquire or develop AI are less common.
- Enterprises using two AI technologies or more and larger enterprises (two groups which overlap) have an above average preference for developing AI in-house. This is also the case for IT and other technical / scientific enterprises – these are also more likely than enterprises in other sectors to modify existing commercial or open source software or systems.
- Northern and Western European enterprises are relatively more likely to have modified commercial software or systems to obtain AI compared to other regions. Eastern and Southern European enterprises relatively often purchased ready-to-use AI software or systems.

4.1 AI sourcing strategies

Artificial intelligence software or systems can be acquired via different sources, which vary in terms of whether there are sourced in-house or externally but also with respect to the level of customisation required by specific AI solutions. Businesses opt most frequently for external sourcing of AI technologies, by purchasing software or ready-to-use systems – close to six in ten enterprises (59%) have used this source to acquire AI technology as shown in the figure below. Enterprises also relatively often resort to another external sourcing strategy: hiring external providers to develop AI technology (38% of enterprises opt for this approach). While this strategy is also external, it requires a high level of customisation, which appears to be less popular overall compared to ready to use systems that require no customisation. The development of AI solutions in-house, either fully, by modifying commercial systems or by modifying open-source systems is less widespread, with about one in five enterprises (between 20% and 24%) having opted for each of these three options.

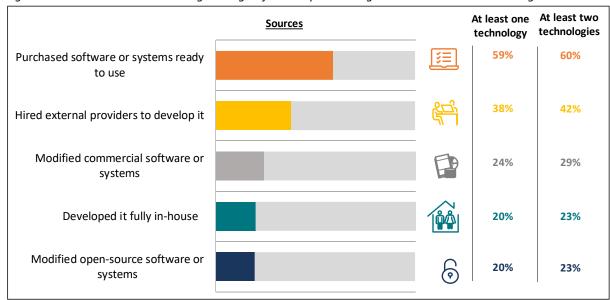


Figure 12: Most common Al sourcing strategies for enterprises using at least one or two technologies

Base question Q2: Artificial intelligence software or systems can be acquired via different sources. Which of the following have been used by your firm? Please confirm all that apply.; Base size: EU27, N=3624.

The intensity of AI adoption is also relevant to consider in the context of AI sourcing strategies. The data obtained suggests that the level of intensity of AI adoption is linked to business's choice of internal or external sourcing strategies but also, to some extent, to the level of customisation in sourcing AI technologies. Some key differences can be observed when considering businesses at the two extremes of the spectrum. While those that currently use only one AI technology represent 40% of all businesses that indicated they purchased software or systems ready to use, those that use four or more technologies represent only 20%. This is the largest difference across the two groups across all types of sourcing strategies reported. These differences are likely to stem at least partly from the approaches businesses of different sizes take in sourcing AI, as discussed in the following section.

Differences when it comes to internal sourcing channels (full in-house development or modification) are considerably smaller, indicating that businesses using only one AI technology prefer external sourcing channels and ready to use systems rather than custom solutions, in particular.

Figure 13. Sourcing strategies by the intensity of AI adoption

	Intensity of AI usage	One technology	Two technologies	Three technologies	At least four technologies
v	Ve purchased software or systems ready to use	39%	26%	15%	20%
Sourcing strategy	We hired external providers to develop it	33%	25%	17%	24%
Sourcing	We developed it fully in-house	32%	26%	18%	25%
,	We modified open-source software or systems	32%	22%	17%	29%
	We modified commercial software or systems	30%	28%	17%	25%

Base question Q2: Artificial intelligence software or systems can be acquired via different sources. Which of the following have been used by your firm? Please confirm all that apply.; Base size: EU27, N=3624.

4.2 AI sourcing strategies by company size, sector and region

A certain preference for developing AI technologies in-house was also visible among large enterprises: 28% of EU enterprises with more than 250 employees had developed AI technology fully in house, compared to 16% of micro-sized enterprises with between 5 and 9 employees that had opted for this approach to acquire AI technology.

Figure 14: Most common AI sourcing strategies by company size (enterprises using at least one AI technology)

	44		<u></u>	
<u>Sources</u>	Micro	Small	Medium	Large
Purchased software or systems ready to use	59%	57%	60%	58%
Hired external providers to develop it	35%	36%	38%	47%
Modified commercial software or systems	23%	23%	26%	28%
Developed it fully in-house	16%	29%	22%	28%
Modified open-source software or systems	19%	19%	18%	28%
5 - 9 employees 10 - 49 employees	50 - 249	employees	> 250 er	nployees

Base question Q2: Artificial intelligence software or systems can be acquired via different sources. Which of the following have been used by your firm? Please confirm all that apply; Base size: EU27, N=3624

Some noteworthy differences per sector are also observed. For instance, the proportion of enterprises that acquire AI technologies by developing these in-house ranges from 36% of enterprises in the IT and 28% in other technical and/or scientific sectors to only 8% of enterprises in the social work sector

and 12% in both the human health sector and the sector for agriculture, forestry and fishing. The IT and other technical and/or scientific sectors are also most likely to modify existing commercial or open source software or systems to adopt AI technologies. No pronounced differences are observed across sectors when it comes to purchasing ready to use systems and hiring external providers to develop AI solutions.

There are also noticeable regional and country differences in terms of how enterprises acquire Al technologies. Notably, Northern and Western European Member States are slightly more likely to purchase modified commercial software or systems – this figure ranges from 27% in Northern Europe to 21% in Southern Europe. Enterprises in Eastern and Southern European countries, on the other hand, more often than average purchase ready-to-use software or systems – this figure varies from 65% in Southern Europe and 63% in Eastern Europe to 54% in both Northern and Western Europe.

4.3 AI sourcing by multiple channels

In addition to the type of sourcing strategy applied, it is interesting to consider how businesses source the adoption of AI technologies.⁴²

The number of sourcing channels used by businesses is positively associated with the number of AI technologies adopted. While 62% of enterprises that are currently using one AI technology also use only one sourcing channel or strategy and only 13% use three or more channels, this is true for 41% and 32%, respectively, of those using four or more AI technologies.

Figure 15. The intensity of AI adoption by the number of souring channels (enterprises using at least one AI technology)

		Sourcing	One channel	Two channels	Three or more channels
sage	One technology		62%	25%	13%
of AI us	Two technologies		53%	27%	20%
ntensity	Three technologies		44%	29%	27%
	least four technologie	s 💝	41%	28%	32%

Base question Q2: Artificial intelligence software or systems can be acquired via different sources. Which of the following have been used by your firm? Please confirm all that apply; Base size: EU27, N=3624.

A similar trend can be observed when looking at the number of sourcing channels used to acquire AI technologies with respect to plans for future use of AI. Businesses that plan to use AI less in the near

⁴² In Q5 of the Survey on AI technologies, businesses could indicate multiple AI sourcing channels. The number of different channels indicated by each enterprise was computed and is reported in this section.

future are more likely to use a single sourcing channel (70%) compared to those who plan to use AI at the same rate (58%) or more (49%). The reverse is true when comparing these groups' usage of three or more sourcing channels. The use of three or more sourcing channels is much more common amongst businesses that plan to use AI more (24%), compared to those that plan to use it less (11%).

Figure 16. Future AI usage by the number of sourcing channels (enterprises using at least one AI technology)

	Sourcing	One channel	Two channels	Three or more channels
Plans to use Al less	×	70%	19%	11%
Plans to use AI the same		58%	26%	16%
Plans to use Al more	•	49%	27%	24%

Base question Q2: Artificial intelligence software or systems can be acquired via different sources. Which of the following have been used by your firm? Please confirm all that apply; Base size: EU27, N=3624.

Company size is also an important predictor of the likelihood of using multiple sourcing channels, which is not surprising given that larger enterprises are more likely to adopt multiple AI technologies compared to their smaller counterparts. The majority of micro (57%) and small (56%) enterprises use only one sourcing strategy, while this is true for roughly four in ten large enterprises with more than 250 employees (41%). The reverse is evident when considering the use of multiple (three or more) sourcing channels, with only micro (17%) and small (19%) enterprises reporting such broad use compared to 32% of large (250+ employees) enterprises.

Figure 17. Company size by the number of sourcing channels (enterprises using at least one AI technology)

		Sourcing	One channel	Two channels	Three or more channels
4.1	Micro	4	57 %	26%	17%
Company size	Small		56%	25%	19%
Comp	Medium		49%	30%	22%
	Large		41%	27%	32%

Base question Q2: Artificial intelligence software or systems can be acquired via different sources. Which of the following have been used by your firm? Please confirm all that apply; Base size: EU27, N=3624.

5 External obstacles to the adoption of Artificial Intelligence

Key findings

- Strict standards for data exchange and the need for new laws or regulation are considered relevant as external obstacles to the adoption of AI technologies by the largest proportion of firms in the EU.
- Non-adopters tend to perceive external obstacles as less likely to be relevant to their business, compared to adopters as well as those who plan to use AI in the next two years.
- The key external barriers most often perceived as a major obstacle to AI
 adoption are lack of public or external funding, strict standards for data
 exchange, and liability for damage caused by AI.
- Sector and size differences regarding external obstacles to AI uptake are limited.
 Country and regional differences were larger. Enterprises in Southern and
 Western Europe were more likely to see lack of public funding, strict data
 standards and the need for new regulation as major external barriers to
 adopting AI compared to firms based in the North and East regions.

5.1 Introduction

What obstacles prevent enterprises in the EU from adopting artificial intelligence? What are the barriers that enterprises who currently adopt AI had to overcome and still find relevant? To answer this question, both enterprises that adopt AI, non-adopters as well as those who plan to adopt AI in the next two years were asked to what degree their business experiences potential external (meaning located outside the enterprise itself) obstacles to using AI. The specific barriers studied were:

- 1. The need for new laws or regulation
- 2. Strict standards for data exchange (e.g. data protection laws)
- 3. Reputational risks linked to using AI
- 4. Liability for damage caused by AI
- 5. Lack of access to high quality private data
- 6. Lack of access to or availability of public data
- 7. Lack of public or external funding
- 8. Lack of trust among citizens.

To determine relevance, respondents were asked to note whether a specific challenge or barrier was applicable to their enterprise. If a specific obstacle was relevant, respondents were asked to indicate whether it represented:

- 1. no challenge or barrier
- 2. a minor challenge or barrier
- 3. a major challenge or barrier.

In this section, we discuss which external barriers are perceived as most relevant and which are most likely to be viewed as a major challenge by enterprises. Comparisons are drawn between enterprises that currently use AI (adopters), those that currently do not use and do not plan to use AI (non-adopters) as well as those who do not currently use AI but have plans to use it in the next 2 years (plan to adopt). In addition, we discuss differences by company size, sector and country.

5.2 External obstacles to AI adoption by relevance

Looking at the full sample of enterprises interviewed, some variation in the perceived relevance of specific obstacles is observed, ranging between 58% and 77% of the interviewed enterprises in the EU. Specifically, enterprises are most likely to assign strict standards for data exchange as a relevant obstacle (77%) to the adoption of AI technologies, followed by the need for new laws or regulation (69%). Lack of access to high quality private data is considered relevant by the smallest proportion of businesses (58%), followed by liability for damage caused by AI (59%).

Figure 18: Relevance of external obstacles to use of AI in the EU27 – overall, adopters, non-adopters and those who plan to use AI

Obstacles by relevance		Overall	Adopters	Non-adopters	Plan to use
Strict standards for data exchange		77%	83%	72%	81%
The need for new laws or regulation		69%	76%	64%	73%
Lack of public or external funding		65%	71%	60%	69%
Lack of trust amongst citizens	S. Color	65%	71%	61%	69%
Lack of access to or availability of public data		62%	68%	58%	65%
Reputational risks linked to using artificial intelligence		61%	69%	56%	64%
Liability for damage caused by artificial intelligence		59%	66%	54%	64%
Lack of access to high quality private data		58%	64%	54%	61%

Base question Q3: I will name potential EXTERNAL obstacles to the use of artificial intelligence. Please indicate all that your company has experienced as a challenge or a barrier. Base size: EU27, N=8661. (Base size represents only EU27 Member States, excluding the UK, Iceland and Norway).

Some differences are observed in the perceived relevance of specific external barriers between adopters, non-adopters and those who plan to use AI in the next 2 years. Overall, the ranking of specific barriers is consistent across the three groups. However, non-adopters are less likely than adopters to find any of the obstacles relevant to their enterprise. This is not surprising as AI technology's lack of immediate relevance or applicability for the business is likely a key reason many enterprises have not adopted or do not plan to adopt it. However, it is interesting that those who plan to use AI in the next 2 years (but do not use it yet) found overall comparable levels of relevance as AI adopters for all eight external barriers surveyed.

Consistently with the overall figures, all three groups (adopters, non-adopters and those who plan to use AI) are most likely to state that strict standards for data exchange is a relevant obstacle for them - ranging between 72% for non-adopters and 83% for adopters (81% for those who plan to use AI). It is followed by the need for new laws or regulation, which 76% of adopters (73% who plan to use AI) find relevant compared to 64% of non-adopters.

5.3 Major obstacles to AI adoption

Considering only the enterprises who found specific obstacles to the adoption of AI relevant⁴³, the top three perceived as a major external challenge or barrier by roughly one third of enterprises overall are: lack of public or external funding (36%), strict standards for data exchange (33%), and liability for damage caused by AI (33%). These three external obstacles are interesting to see on top as they represent three very different factors that can impact the adoption of AI: funding, legal barriers and financial or other risks associated with the use of AI technologies. One specific challenge or barrier that seems to stand out is liability for damage caused by AI: while it seems to not be as universally relevant, this barrier seems to pose a major challenge when it is applicable to the business context in which enterprises operate.

Figure 19: External challenges as a major obstacle to use of AI in the EU27 – overall, adopters, non-adopters and those who plan to use AI

External obstacles Lack of public or external funding	i e	Overall 36%	Adopters 35%	Non-adopters	Plan to use
Strict standards for data exchange		33%	34%	33%	37%
Liability for damage caused by artificial intelligence		33%	27%	38%	43%
The need for new laws or regulation		29%	29%	29%	34%
Lack of trust amongst citizens	(C)	28%	26%	30%	34%
Lack of access to high quality private data		27%	26%	27%	31%
Lack of access to or availability of public data		21%	20%	22%	24%
Reputational risks linked to using artificial intelligence	right The second	17%	16%	18%	19%

Base question Q3: I will name potential EXTERNAL obstacles to the use of artificial intelligence. Please indicate all that your company has experienced as a challenge or a barrier. Base size: EU27, N=8661. (Base size represents only EU27 Member States, excluding the UK, Iceland and Norway).

Looking at differences between adopters, non-adopters and those that plan to use AI, some interesting patterns emerge as shown in the visual above. When it comes to relevance, adopters are most likely overall to find specific obstacles relevant. When it comes to perception of the level of challenge an obstacle poses, those who plan to use AI in the next 2 years report the highest level of

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⁴³ Enterprises who responded that a specific barrier is applicable to their business.

challenge across all eight external obstacles (33%) compared to adopters (29%) and non-adopters (27%). This overall trend is consistent across all external barriers but the differences are more pronounced for some. For example, while only 27% of non-adopters find liability for damage caused by AI to be a major barrier to adopting it, this was true for 43% of those who plan to adopt AI in the next 2 years and 38% of AI adopters. A similar trend, although less pronounced is observed for lack of public or external funding (ranging from 34% of non-adopters to 42% of those who plan to use AI) and lack of trust among citizens (26% of non-adopters vs 34% of those who plan to use AI). These differences suggest that those who plan to use AI in the near future expect to experience specific external obstacles, which have so far prevented them or continue to prevent them to do so. Across all three groups, reputational risks linked to using AI and lack of access to or availability of public data remained the two obstacles least likely to pose a major challenge to the adoption of AI.

5.4 Major obstacles to AI adoption by company size

More variation is visible when looking at enterprises of different sizes, particularly when comparing large enterprises (with 250 or more employees) to micro, small and medium-sized enterprises. Most notably, four in ten (40%) large enterprises experience strict standards for data exchange (e.g. data protection laws) as a major external barrier to AI adaption, while the comparable figure for enterprises of all sizes combined is only one third (33%). Large enterprises are also more likely (33%) to state that the lack of access to high quality private data is a major barrier to AI adoption compared to smaller enterprises combined (26%). The opposite can be observed for challenges linked to the lack of public or external funding, which is perceived as a major barrier by micro, small and medium enterprises (37% on average) compared to large enterprises (32%).

Figure 20: External challenges identified as a major obstacle to use of AI in the EU27 – by company size

External obstacles	Micro	Small	Medium	Large
Lack of public or external funding	37%	36%	38%	32%
Liability for damage caused by artificial intelligence	34%	31%	33%	38%
Strict standards for data exchange	33%	32%	34%	40%
The need for new laws or regulation	31%	29%	28%	28%
Lack of trust amongst citizens	29%	27%	28%	30%
Lack of access to high quality private data	26%	26%	27%	33%
Lack of access to or availability of public data	23%	20%	20%	23%
Reputational risks linked to using artificial intelligence	19%	17%	16%	19%
5 - 9 employees 10 - 49 employees	50 - 2	249 employe	es	0 employees

Base question Q3: I will name potential EXTERNAL obstacles to the use of artificial intelligence. Please indicate all that your company has experienced as a challenge or a barrier. Base size: EU27, N=8661. (Base size represents only EU27 Member States, excluding the UK, Iceland and Norway).

5.5 Major obstacles to AI adoption by sector

Sectoral differences with regard to external barriers to AI uptake are rather limited but some interesting variations can be observed when considering the top three barriers most likely to be perceived as a major challenge by enterprises overall: lack of public or external funding, strict standards for data exchange and liability risks linked to damage caused by AI. Lack of public or external funding is most often perceived as a major barrier to AI uptake by organisations active in social work (51%), education (45%), food (43%) and human health (41%). Conversely, sectors such as oil and gas (21%), transport (31%), finance and insurance (31%) and in recreation services (32%) are less likely to perceive lack of funding as a major external obstacle to adopting AI. Enterprises operating in these sectors are more likely to be concerned with the strict standards for data exchange, specifically in the oil and gas (41%) and finance and insurance (40%) sectors, but naturally also those working in human health (40%). In fact, enterprises in the human health sector are consistently in the top three most concerned for all three external barriers, with risks associated with liability for damage caused by AI being rated as a major obstacle by 43% of interviewed enterprises in this sector — the highest proportion across all sectors. Liability for damage caused by AI also stands out as a major obstacle in the transport (39%), accommodation (37%) and other technical and/or scientific (36%) sectors.

Figure 21: External challenges identified as a major obstacle to use of AI in the EU27 – by sector

Sector	I	Lack of public or external funding	Strict standards for data exchange	Liability for damage caused by AI	Sector		Lack of public or external funding	Strict standards for data exchange	Liability for damage caused by AI
Agriculture, forestry and/or		34%	29%	28%	Accommodation		36%	29%	37%
fishing		38%	32%	31%	Recreation activities	يگ	32%	35%	33%
Manufacturing		34%	30%	32%	lΤ		33%	34%	32%
Construction	N	240/	410/	220/	Finance, insurance		31%	40%	32%
Oil and gas	(b) or	21%	41%	23%	Real estate	REAL ESTATE	35%	36%	24%
Waste management		39%	33%	37%	Other technical and/or scientific	8	36%	32%	36%
Water and electricity supply	70	33%	29%	27%	sectors		450/	279/	2/10/
Trade, retail	雷	36%	35%	32%	Education	().	45%	37%	34%
Transport		31%	31%	39%	Human health	Ű	41%	40%	43%
Food	Ď	43%	38%	34%	Social work		51%	32%	27%

Base question Q3: I will name potential EXTERNAL obstacles to the use of artificial intelligence. Please indicate all that your company has experienced as a challenge or a barrier. Base size: EU27, N= 8661. (Base size represents only EU27 Member States, excluding the UK, Iceland and Norway).

5.6 Major obstacles to AI adoption by country

Regional and country-level differences in terms of the experienced external obstacles to AI uptake are in some cases substantial. Notably, half (50%) of enterprises in Southern Europe feel that a lack of public or external funding is a major external challenge or barrier to adopting AI, while in Northern Europe roughly one in four enterprises (27%) consider this a major barrier. Strict standard for data exchange (e.g. data protection laws) is considered a major challenge by 42% of enterprises in the West and 38% in the South region while only 27% perceive it so in the North and East regions. A similar

trend is observed for the need for new laws or regulation, which is perceived more as a major challenge to AI adoption in the South (37%) and West (35%) regions, compared to the North (20%) and East (26%) regions. Lack of trust amongst citizens is perceived as a major barrier by roughly a third of Western (35%) and Southern (34%) European enterprises, compared to only 18% of Northern and a quarter of Eastern (25%) European enterprises. Country differences are generally consistent with these figures.

6 Internal obstacles to the adoption of Artificial Intelligence

Key findings

- Internal barriers are broadly relevant for enterprises with the majority recognising that these barriers to AI are applicable to their business.
- The most prominent internal barrier that businesses face when considering the use of AI is the difficulty to hire new staff with the right skills, which is universal across enterprises of different sizes, most sectors and amongst adopters, non-adopters and those who plan to use AI.
- Sector and size differences are limited, with the ICT sector unsurprisingly least likely to state that many of the internal obstacles are a major barrier to the use of AI.
- In comparison to businesses that have adopted artificial intelligence, those that have not adopted AI, as well as those who plan to adopt AI are more likely to report internal obstacles as a major barrier.
- Difficulties in hiring new staff with the right skills stands out as a universal barrier for all enterprises.

6.1 Introduction

The surveyed enterprises were asked as well about the importance they attach to *internal* obstacles to the use of artificial intelligence. The following list of internal obstacles were covered by the survey:

- The cost of adoption
- Complex algorithms are difficult to understand and trust
- Lack of skills among existing staff
- It is difficult to hire new staff with the right skills
- Lack of internal data
- The cost of adapting operational processes
- Insufficient or incompatible IT infrastructure

Respondents who were aware of at least one technology, meaning that they either use it, plan to use it in the next 2 years or consciously are not using it were asked the degree to which each aspect was a challenge or barrier. Or respondents could indicate that the barrier is not applicable to their enterprise or they did not know.

6.2 Internal obstacles to AI adoption by relevance

Barriers are overwhelmingly relevant for enterprises overall with most barriers being relevant to at least 80% of enterprises identifying the degree to which each obstacle is a relevant barrier for their company. Though there is some variation in which types of barriers are relevant for enterprises. Overwhelmingly, 85% of enterprises responded that difficulties to hire new staff with the right skills is

a relevant barrier for their business. Similarly, 83% find a lack of skills among existing staff to be relevant. On the other hand, complex algorithms are difficult to understand and trust as well as the lack of internal data were less relevant barriers for enterprises, 75% and 76% respectively finding these barriers relevant.

Figure 22: Relevance of internal obstacles to use of AI – overall, adopters, non-adopters and those who plan to use AI

Obstacles by relevance		Overall	Adopters	Non-adopters	Plan to use
Difficult to hire new staff with the right skills	<u> </u>	85%	91%	80%	91%
The cost of adoption	?	83%	89%	79%	90%
The cost of adapting operational processes	3	81%	88%	76%	86%
Lack of skills among existing staff		81%	88%	76%	85%
Complex algorithms are difficult to understand and trust	4	80%	85%	77%	85%
Insufficient or incompatible IT infrastructure	, ₿	76%	82%	72%	83%
Lack of internal data		75 %	82%	70%	81%

Base question Q4: I will now name potential INTERNAL obstacles to the use of artificial intelligence. Please indicate all that you see as a challenge or a barrier for your company.; Base size: EU27, N=8661. (Base size represents only EU27 Member States, excluding the UK, Iceland and Norway).

There are differences between those who have adopted AI, those who have not, and those that have not to date but plan to use AI in the next two years when it comes to the relevance of barriers. The percentage that finds the barriers relevant for their business is higher amongst both adopters, but also non-adopters who plan to use AI. Barriers relating to cost (the cost of adoption and complex algorithms are difficult to understand and trust) being more relevant as barriers for adopters and those who plan to adopt in comparison to non-adopters. 88% of adopters, 86% of those who plan to use compared to 76% of non-adopters find the cost of adoption to be a relevant barrier.

6.3 Major internal obstacles to AI adoption

Looking at enterprises that find the internal barriers relevant to them, the major barrier mentioned by the majority of enterprises **overall** is the difficulty to hire new staff with the rights skills (57%), followed by the cost of adoption (52%). A lack of internal data is only mentioned by 20% of enterprises as being a major barrier.

Figure 23: Internal challenges as a major obstacle to use of AI – overall, adopters, non-adopters and those who plan to use AI

Internal obstacles	Overall	Adopters	Non-adopters	Plan to use	
Difficult to hire new staff with the right skills	PO 9	57%	57 %	57%	61%
The cost of adoption	S	52%	48%	56%	57%
The cost of adapting operational processes	(\$)?? (\$)	49%	44%	53%	55%
Lack of skills among existing staff	?	45%	38%	50%	55%
Complex algorithms are difficult to understand and trust		40%	35%	44%	44%
Insufficient or incompatible IT infrastructure		36%	29%	42%	42%
Lack of internal data	?♥	20%	17%	24%	23%

Base question Q4: I will now name potential INTERNAL obstacles to the use of artificial intelligence. Please indicate all that you see as a challenge or a barrier for your company.; Base size: EU27, N=8661, excluding 'does not apply to my firm'.

How do enterprises experience barriers depending on whether they are adopters, non-adopters or currently non-adopters but plan to adopt AI? A uniform barrier across all enterprises is the difficulty to hire new staff with the right skills with little difference between adopters (57%), non-adopters (57%) and those who plan to adopt AI (61%). According to the latest DESI report on Human Capital (2019)⁴⁴, 53% of enterprises that recruited or tried to recruit ICT specialists reported facing difficulties (an increase from 41% a year earlier). Combined with evidence on the growing number of ICT vacancies, these figures suggest a widening gap between demand and supply of ICT specialists in the EU. Given this context, the figures are hardly surprising since all enterprises face the same job market and therefore find it a universal barrier and is not specific to types of business. Similarly, this barrier did not differ according to company size and there were few sector differences.

However, for the remaining barriers, it is universally the case that a greater percentage of non-adopters find these to be major barriers to the use of AI compared to those who have already adopted the use of AI. This finding is to be expected, given that adopters have the perspective of having overcome any barriers to the use of AI. Furthermore, the percentage of those who are currently non-adopters but plan to use AI in the next two years find these barriers to be a major obstacle is in line with non-adopters (who do not plan to use these technologies).

The barriers that pose a major challenge for non-adopters compared to adopters are the lack of skills among existing staff and insufficient or incompatible IT infrastructure. 55% of non-adopters who plan to use AI in the next 2 years state the lack of skills among existing staff to be a major barrier, compared to 50% of non-adopters and only 38% amongst enterprises that have adopted AI. When it comes to IT infrastructure, 42% of those who plan to use AI (but currently are non-adopters) mention this as a

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 $^{^{44}\,}https://ec.europa.eu/newsroom/dae/document.cfm?doc_id=59976$

major barrier, a similar percentage (41%) of non-adopters (with no plans to use AI) state this to be a major barrier. This compares to 29% of adopters of AI stating this as a major barrier.

6.4 Major internal obstacles to AI adoption by company size

There are very few noteworthy differences between enterprises of different sizes. It is worth stating, however, that only 16% of enterprises with more than 250 employees regard a lack of internal data as being a barrier, which is significantly less in comparison to the average of 20% of enterprises of all sizes. Amongst micro enterprises (5-9 employees), they are more likely to experience complex algorithms being difficult to understand and trust as well as insufficient or incompatible IT infrastructure as a major obstacle to the use of AI compared to enterprises of all sizes (who reported these barriers as a major barrier).

Figure 24: Internal challenges identified as a major obstacle to use of AI – by company size

	四			
<u>Internal obstacles</u>	Micro	Small	Medium	Large
Difficult to hire new staff with the right skills	58%	57%	56%	59%
The cost of adoption	53%	52%	51%	55%
The cost of adapting operational processes	48%	50%	49%	49%
Lack of skills among existing staff	45%	44%	46%	44%
Complex algorithms are difficult to understand and trust	42%	38%	40%	36%
Insufficient or incompatible IT infrastructure	39%	35%	33%	36%
Lack of internal data	21%	21%	20%	16%
5 - 9 employees 10 - 49 employees	50 -	249 employe	es	0 employees

Base question: Q4: I will now name potential INTERNAL obstacles to the use of artificial intelligence. Please indicate all that you see as a challenge or a barrier for your company.; Base size: EU27, N=8661, excluding 'does not apply to my firm'.

6.5 Major internal obstacles to AI adoption by sector

With regard to internal obstacles to AI adoption, there is no clear pattern that a given sector has a tendency to experience a majority of these obstacles as a major challenge. The ICT sector, unsurprisingly, had a lower percentage stating that each obstacle is a major barrier for most barriers compared to enterprises on average with the exceptions of hiring staff with the right skills, lack of internal data and the cost of adapting operational processes.

However, there are some noteworthy differences between the enterprises from different economic sectors. The complexity of algorithms (making them hard to understand), for instance, was especially an issue for the agriculture, forestry and fishing sector, with 49% of enterprises in this sector regarding this as a major challenge or barrier to using AI, and a similar percentage in the food sector (48%) also experiencing this as a major barrier compared to 40% of enterprises from all sectors which experienced this as a major issue. On the other hand, this barrier was a major challenge for only 28% of enterprises in the accommodation sector.

Figure 25: Internal challenges identified as a major obstacle to use of AI – by sector

Sector		Difficult to hire new staff with the right skills	Cost of adoption	Cost of adapting operational processes	Sector		Difficult to hire new staff with the right skills	Cost of adoption	Cost of adapting operational processes
Agriculture, forestry and/or fishing	ha 🗸	60%	51%	44%	7100071111100001011		60%	52%	52%
Manufacturing	17	59%	54%	50%	Recreation activities	<u>ا</u> لد	43%	55%	54%
Construction	1	57%	50%	48%	Finance, insurance		59%	45% 44%	45%
Oil and gas	(d) OIL	69%	64%	49%	Real estate	REAL ESTATE	52% 48%	41%	41%
Waste management		48%	54%	66%	Other technical and/or scientific	REAL ESTATE	59%	53%	50%
Water and electricity supply	17	62%	52%	48%	sectors Education	◆	52%	54%	55%
Trade, retail	雷	56%	53%	48%	Human health	Ų.	55%	60%	54%
Transport		57%	51%	47%	Social work	Ů Å	55%	57%	46%
Food		59%	55%	52%	Jocial Work		33%	3170	40/0

Base question Q4: I will now name potential INTERNAL obstacles to the use of artificial intelligence. Please indicate all that you see as a challenge or a barrier for your company.; Base size: EU27, N8661, excluding 'does not apply to my firm'.

6.6 Major internal obstacles to AI adoption by country

The data also shows some interesting country differences with regard to internal obstacles to AI uptake. With the exception of difficulties to hire new staff with the right skills, a higher percentage of enterprises in Southern Europe find all other barriers to be a major obstacle to their use of AI in comparison to the average. Notably, cost related internal obstacles are most pronounced in Southern Europe. The cost of adapting operational processes is considered a major challenge amongst 59% compared to 42% of enterprises finding this a major challenge in Northern Europe. Similarly, the costs of adoption are a barrier to AI uptake in Southern Europe, where 61% enterprises consider this to be a major challenge or barrier, compared to 46% of enterprises in Northern and 50% in Western Europe that regard costs of adoption as a major barrier.

At the individual country level, differences are larger still, with for instance two thirds (66%) of Spanish enterprises, 64% of the Greek and Bulgarian enterprises and 63% of Slovenian enterprises reporting that the costs of adoption were a major barrier to using AI.

6.7 Skills needs as a specific internal barrier

Key findings

- Staff with sufficient programming skills are particularly sought after, as are staff with big data management skills and/or machine learning or modelling skills.
- Skills needs are broadly similar amongst both adopters and non-adopters, with higher proportions of those who plan to use AI identifying the need for all skills reflecting the fact that they are mostly likely to be in particular need of staff with AI related skills.

When enterprises who identified skills as a barrier were then asked about this lack of skills amongst existing staff or difficulties hiring new staff with the right skills, enterprises identified which skills are most needed.

Enterprises that experienced a lack of AI related skills among their existing staff, were most in need of staff with sufficient programming skills – 52% of these enterprises reported this (see figure below). Enterprises also frequently needed staff with big data management skills and/or machine learning or modelling skills; 43% and 39% respectively.

Figure 26: AI skills in demand - overall, adopters, non-adopters and those who plan to use AI

Al skills needed Programming skills	Overall 52%	Adopters 52%	Non-adopters 52%	Plan to use 55%
Big data management skills	43%	43%	43%	48%
Machine learning or modelling skills	39%	40%	38%	45%
Cloud computing skills &	33%	33%	33%	38%
Robotics skills	31%	28%	33%	35%

Base question Q4_3: When it comes to lack of skills among existing staff or difficulties in hiring new staff, which of the following skills do you believe are most needed? Please select maximum three. Base size: EU27, N=7096.

As noted above, the data shows that enterprises that *plan to use* Al are in particular need of staff with Al related skills – 55% of non-adopters who plan to use Al in the next 2 years state the lack of skills amongst **existing staff** to be a major barrier, compared to 50% of non-adopters and only 38% amongst enterprises that have adopted Al. As mentioned earlier, **difficulties to hire staff** with the right skills is

broadly similar amongst adopters (57%) and non-adopters (57%), again with those who *plan to use* also slightly higher in reporting this as a major barrier (61%).

In that sense, it is not surprising that the percentage identifying each of the skills needs is highest amongst the enterprises that plan to adopt AI. This indicates that a broad range of skills are required by non-adopters that plan to adopt AI and it is not a lack of certain skills that explains the difference between adopters and those that plan to adopt. Therefore, there is a distinct pattern that adopters and non-adopters report almost identical percentages of skills needs across the different categories, except for robotics skills, where adopters are less likely to report a need for these skills (28%) in comparison to non-adopters (33%) and those that plan to adopt AI (35%).

Looking at company size, for most skills needs, it is the largest enterprises (250 + employees) that find the skills listed as lacking, with the exception of robotics skills. When it comes to sector differences, programming skills needs are most pronounced in the financial and insurance sector (59%) and manufacturing sector (54%). The manufacturing sector is also likely to report machine learning or modelling skills (43%) and robotics skills (39%). understandably

Figure 27: AI skills needed for AI adoption - by company size

Al skills needed	Micro	Small	Medium	Large
Programming skills	51%	52%	53%	56%
Big data management skills	42%	41%	45%	49%
Machine learning or modelling skills	37%	39%	41%	44%
Cloud computing skills	33%	33%	34%	41%
Robotics skills	27%	33%	32%	34%
5 - 9 employees 10 - 49 employees	50 -	249 employe	ees	employees

Base question Q4_3: When it comes to lack of skills among existing staff or difficulties in hiring new staff, which of the following skills do you believe are most needed? Please select maximum three. Base size: EU27, N=7096.

7 In-depth analysis of the obstacles to AI adoption

7.1 Analysis of the obstacles to adopting specific AI technologies

This section provides an in-depth analysis focusing further on the barrier dimension. The purpose of the present analysis is to identify a set of barriers that could effectively prevent enterprises from implementing the different technologies included in the survey. This type of analysis aims at shedding light on the specificities of each technology in terms of barriers, which can serve to better guide policy makers in their efforts to favour the uptake of AI technologies and their applications. As the analysis is characterised by a level of complexity, this section first introduces the specific methodology used.

7.1.1 Methodology

The analysis looks at the difference of means in the prevalence of barriers between the subpopulations of respondents who already implemented a certain technology (adopters) and those who intend to do so (plan to adopt). The difference in means between these subpopulations should, at least partially, be accounted for by enterprises who previously wanted to implement an AI technology but did not manage to do so or desisted from doing so. In this case, the barriers can be considered to have effectively prevented the implementation. To apply this method, two key assumptions are made. First, the two subpopulations are assumed to be the same, differing only by their timing of adoption. Second, all business leaders are assumed to be aware of the existence of actual barriers.⁴⁵

Technically, the difference in means was computed and its validity was assessed by resampling the dataset 10,000 times under the null hypothesis that there is no difference between the population in these statistics. This hypothesis was rejected if resampled values lied below the computed value more than a certain number of times⁴⁶. A negative difference on a specific barrier means that, on average, businesses planning to adopt a certain technology see a greater challenge in this barrier than enterprises having already implemented it. Therefore, it is assumed that barriers presenting this negative difference would have prevented businesses from adopting the technology. The indicator is based on the variance within the dataset and relies on the fact that businesses face different situations. As such it should be considered with caution given the assumptions made above.

As clear from the results presented below, this indicator usually does not identify the difficulty to hire staff as one of the effective barriers. This is, however linked to the peculiar nature of the job market: all businesses face broadly the same AI workers supply and the difficulties faced when trying to implement an AI solution are essentially the same. If the majority of businesses face difficulties in hiring new staff with the right skills, the fact that those who dropped out also faced these difficulties does not decrease the mean as all the observations are in fact correlated or even equal in this example. Therefore, it should not be expected that this result would be substantially different between those

⁴⁵ Two main caveats must be raised about this approach. The first is that it relies on the assumption that both subpopulations differ only in their state of implementation. Therefore, the existence of confounders cannot be completely ruled out. Further matching in the sample could help in partially alleviating this caveat and can be considered as a potential for improvement in future analyses. The second caveat is that the presence of learning during the implementation cannot be ruled out. Disentangling both effects would require information on the subpopulation which desisted from implementing the technology and flagging this subpopulation should be considered a suggestion for future waves of this survey.

 $^{^{46}}$ Results are reported as "significant" according to these resampling statistics if it is under 5% or 1%.

two subpopulations. As such, the raw value or a measure of variance on the responses to the questions should usually be considered together with this metric.

7.1.2 Results per technology

The table below presents, per technology, the difference of means related to each barrier between the subpopulation having implemented a technology and the one planning to adopt it. The results are reviewed per technology, unveiling the barriers that significantly differ between the two populations and that can thus, at least partially, be considered to have prevented some enterprises from implementing the technology concerned.

The different colours illustrate the importance of the difference and the resulting importance of the barriers. The greater the difference between the two subpopulations of "prospective adopters" and "current adopters" is, the redder the cell will be. Cells that are left white show differences that are not significant and from which no specific conclusion can be drawn.

Table 7 – Barriers to the adoption of AI by technology: difference in means between current and future adopter

	External barriers								Internal barriers						
	Need for new laws	Data standards	Reputation risks	Access to private data	Access to public data	Lack of public/ external funding	Lack of citizens' trust	Liability for damage	Hiring staff with right skills ⁴⁷	Cost of adoption	Lack of skills internally	Lack of internal data	IT infra- structure	Cost of adapting processes	Difficulty to under- stand algorithms
Natural language processing	-0.1065***	-0.0565	-0.027	-0.018	-0.0288	-0.0307	-0.0601	-0.1547***	-0.0435	-0.1287***	-0.1657***	-0.0862**	-0.1534***	-0.1003**	-0.1221***
Computer vision	-0.0262	-0.0836	-0.1055***	-0.0321	-0.0964	-0.0514	-0.0983**	-0.1017**	-0.0191	-0.1541***	-0.2703***	-0.1038***	-0.1058***	-0.1566***	-0.1155***
Anomaly detection	-0.0608	-0.1133***	-0.1171***	-0.1570***	-0.1663***	-0.1238***	-0.0954***	-0.1406***	-0.074	-0.1908***	-0.2116***	-0.2093***	-0.2549***	-0.1109***	-0.1434***
Sentiment analysis	-0.0595	-0.0334	-0.2175***	0.0405	-0.09	-0.1374	-0.1624**	-0.1269	-0.1959***	-0.1159	-0.2597***	-0.2694***	-0.0824	-0.0403	-0.1065
Forecasting	0.007	-0.0496	0.0057	-0.0624	-0.0107	-0.1079***	-0.0295	-0.1499***	-0.0762**	-0.1542***	-0.2364***	-0.0733**	-0.2012***	-0.1225***	-0.112***
Process optimisation	-0.0363	-0.1197***	-0.1464***	-0.0894***	-0.0975***	-0.1457***	-0.0633	-0.1976***	-0.118***	-0.1396***	-0.235***	-0.0782***	-0.1542***	-0.154***	-0.0988***
Recommendation engines	-0.0968**	-0.1497***	-0.0984***	-0.1052***	-0.191***	-0.1553***	-0.2118***	-0.2067***	-0.0849**	-0.1429***	-0.3125***	-0.1367***	-0.2011***	-0.1654***	-0.1997***
Process automation	-0.0137	-0.014	-0.0221	-0.0497	-0.1161***	-0.1018***	-0.0189	-0.0716**	-0.0248	-0.1001***	-0.2046***	-0.0844***	-0.1342***	-0.1072***	-0.1203***
Autonomous machines	-0.2115***	-0.163***	-0.0921**	-0.1586***	-0.1185***	-0.1276***	-0.1781***	-0.1675***	-0.047	-0.2793***	-0.3019***	-0.0655	-0.1122***	-0.1869***	-0.1915***
Creative activities **: resampling p-value < 0	-0.0644	-0.0533	-0.0791	-0.2053***	-0.0746	0.0014	-0.1255**	-0.1117**	-0.007	-0.115**	-0.2556***	-0.1627***	-0.1772***	-0.184***	-0.068

^{**:} resampling p-value < 0.05

^{***:} resampling p-value < 0.01

⁴⁷ A careful read through the methodology section of this analysis is necessary before interpreting this column of the table.

Natural language processing (NLP)

On the external side, two barriers might hinder the actual use of NLP technologies. These are related to the need for new laws and regulations as well as the liability for damages, with the latter showing a greater difference in means than the first.

On the internal side, the main difference comes from the lack of internal skill, followed by the potential liabilities, insufficient or inadequate IT infrastructure, cost of adoption and difficulty to understand algorithms.

Computer vision

The computer vision technology shows three significant differences on the external side, and six out of the seven internal barriers included in the survey are significantly different between current users and future adopters.

The most diverging external challenges are the risks for the reputation, ethical concerns and the potential liability. Those differences, however, pale in comparison to the one on the internal barriers. Ordered by the importance of the differences, internal barriers include the lack of internal skills, the cost of adapting internal processes, the cost of adoption, the difficulty to understand algorithms and finally, inadequate IT infrastructure.

Anomaly detection

Most barriers are significant in terms of difference of means for anomaly detection technologies, except the need for new laws on the external side and the difficulty to hire on the internal challenges' side.

On the external side, access to data, both private and public, shows the higher differences, followed by the liability for damage, the lack of public and external funding, reputation risks, data standards and finally the lack of citizens' trust.

On the internal side, inadequate IT infrastructure again lead the list of significant difference, followed by the lack of internal skills as well as data, the cost of adoption, the difficulty to understand algorithms and, finally, the cost of adapting processes.

Sentiment analysis

Most of barriers considered in the survey do not seem to be a major hindrance to the implementation of sentiment analysis technologies.

On the external side, the risk to the reputation seems to be the most important barrier, followed by the lack of citizens' trust.

Internally, issues related to the lack of internal skills as well as internal data are again significantly different between our two subpopulations. These two barriers can be added to the difficulty to hire staff with the right skills.

Forecasting

On the external side, the difference between the implementers and the ones who intend to do so are the largest in terms of potential liabilities for damage and the lack of citizens' trust.

On the internal side, it is worth noting that all barriers show significant differences. The lack of skills among existing staff and inadequate IT infrastructure show the highest differences, followed by the cost of adopting of the technology and adapting process as well as the difficulty to understand algorithms. The least important differences, but still significant, are related to the lack of data internally and the difficulty to hire people with the right skills.

Process optimisation

Process optimisation technologies show an important set of significant differences between the implementers and the businesses that plan to implement in the next two years. Indeed, only two (external) barriers show non-significant differences between the two subpopulations i.e. the need for new laws and the lack of citizens' trust.

Looking at the significant differences, it can be observed that the highest difference on the external side is related to liability for damages. On the internal side, the highest difference is related to the lack of skills internally. Other differences are of comparable magnitude.

Recommendation engines

All external and internal barriers are relevant to the implementation of recommendation engine technologies, with lack of citizens' trust and liability for damage being the most important on the external side and, once again, the lack of internal skills being the most important on the internal one. It is worth noting that the lack of internal skills in the case of recommendation engines is also characterized by the highest difference compared with the other technologies.

Process automation

For the process automation, the difference of means reveals the need for more public data as well as a better access to external or public funding. The third significant difference concerning the external barriers is related to the liability for damages.

Like in the cases of NLP, computer vision and anomaly detection, all internal difficulties except for the difficulty to hire the right skills are characterized by significant differences between the two subpopulations.

Autonomous machines

Autonomous machines are characterized by significant differences between the two populations for all external barriers. It therefore seems that, like in the case of recommendation engines, external barriers can play a key role on the adoption of such technologies. The most important difference on the external side is related to the need for new laws.

On the internal side, the lack of skills within the existing staff seems again to be a blocking barrier, as well as the cost of adoption. The other barriers characterized by significant differences are related to the difficulty to understand algorithms, the cost of adapting processes and an inadequate IT infrastructure.

Creative activities

Finally, the relevant external barriers to technologies allowing to perform creative activities are the access to private data, the lack of citizens' trust as well as concerns about potential liabilities.

Most of the internal barriers are relevant except for the difficulty to understand algorithms and the difficulty to hire. Once again, it can be observed that the highest difference in means is related to the lack of skills that are available inside the business.

7.2 Analysis of the obstacles to AI adoption per country using cluster techniques

The objective of this cluster analysis is to classify countries under their "barriers profile" using the procedure detailed in section 3.3.1.⁴⁸ In this case, the presence or not of a given barrier was used as a binary variable at the level of the company. If a company met this barrier (or plans on meeting it), even if they declare that it was a minor barrier, it is assumed that the barrier existed.

7.2.1 Principal components

The table below shows the composition of the two first **principal components** of the set. The variance along those two components account for a total of more than 80%⁴⁹ of the total variance of the total data and the results.

Table 8 – Principal component across internal and external barriers to AI adoption.

	Х	Υ
Need of new laws	0.290	0.158
New data standards	0.262	0.349
Reputational risks	0.254	0.351
Liability concerns	0.340	0.217

 $^{^{\}rm 48}$ Please refer to this section before interpreting the results presented here.

⁴⁹ The spread of the variance between the different components can be found in Annex D

Need for private data	0.308	0.139
Need for public data	0.264	0.096
Need for external funds	0.279	-0.285
Ethics concerns	0.293	0.108
High cost of adoption	0.257	-0.345
Results interpretation	0.210	-0.195
Lack of internal skills	0.214	-0.235
Hiring difficulties	0.115	-0.503
Lack of internal data	0.212	0.052
Process adaptation	0.251	-0.295
IT and infrastructure	0.246	-0.078

The first component leads positively on all the barriers with approximately the same intensity^{50,51}. This indicates that this dimension is a measure of **the intensity with which businesses encounter barriers**. A country on the **left of the graph will therefore likely encounter or report less barriers** to its implementation of Al than a country on the right.

The second component nearly perfectly mimics the manual splitting that was implemented during the questionnaire design phase: the positive values are associated with external barriers while the negative values are associated with internal values. This means that enterprises from countries in the bottom of the charts will likely face mostly internal issues such as access to capital and current workforce skill gaps, while enterprises from countries that score higher will likely face more external barriers such as the need for a clearer regulatory framework. The results of the cluster analysis are presented in the figure below.

⁵⁰ This is indeed correlated with the average prevalence of barriers across enterprises in those countries.

⁵¹ With the exception of the difficulty to hire since the variance on this dimension is a priori lower and contains less information.

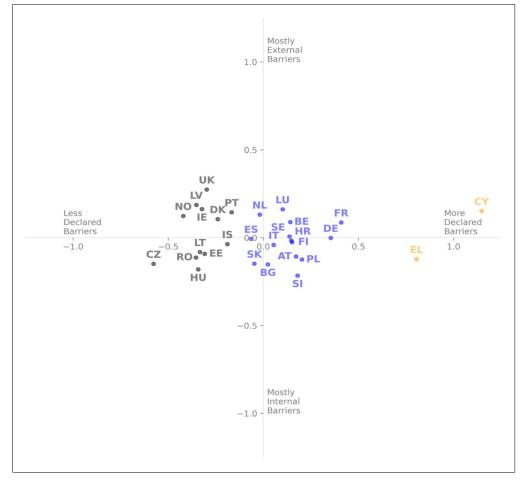


Figure 28: Cluster analysis of obstacles by country

In this case, it seems that three is an adequate number of clusters. Those are the following:

- 1. **Orange**: Cyprus (and in a lesser measure, Greece is the country that scores the highest on the first component, the intensity measure. Apparently, enterprises from that country have, on average more difficulty to implement AI than the others. Both internal and external issues are pointed (although the internal issues seem to be more important).
- 2. **Black**: This cluster contains countries where barriers are on average lower. Along with countries one would suspect (UK, Iceland, Norway, Ireland or Estonia), some other countries are in this cluster such as Czechia (that scores the lowest on the intensity dimension), Romania and Hungary.
- 3. **Blue**: This group is close to average and shows no particular tendency.

It seems that internal issues are more important in countries where the GDP per capita is lower compared to countries with a higher GDP per capita. However, the clustering is understandably mostly done along the first component.

8 Conclusions

At the level of each AI technology, adoption in the EU is still relatively low, with each AI technology at a current adoption rate of 13% or below, but also indicating the diversity in the types of AI technologies adopted by European enterprises.

The picture of adoption at the aggregate level illustrates the relatively high uptake of AI in general; **42% of enterprises have adopted at least one technology**. The intensity of adoption also shows encouraging signs as a quarter (25%) use at least two AI technologies.

In general, Europe is characterised by enterprises that fall into one of two camps, adopters (42%), the vast majority of whom will continue to use AI or use it even more in the next two years, and non-adopters (40%) who do not use AI technologies, nor have plans to do so in the next two years. There is also a third category of enterprises, though smaller than the previous two, as almost one in five (18%) enterprises are currently not using AI technologies but plan to do so in the next two years. Large enterprises are more likely to be adopters compared to smaller businesses, given the potential to benefit most from adoption due to their larger economies of scale and potential return on investment.

Different sectors have different needs when choosing which AI technologies to adopt. While industrial sectors use AI technologies that optimise and automate processes, whereas service sectors adopt a variety of AI technologies to serve their business needs. The homogenous nature of AI technologies used in the industrial sectors compared to the service sectors might mean that AI adoption is already exploited broadly amongst competitors in those industrial sectors. Whilst these are the observable patterns in the kinds of AI that different sectors have adopted, the differences are not very pronounced in the overall adoption of AI technologies when excluding the ICT sector which is unsurprisingly the forerunner in adopting AI. IT and financial sectors are also those which use the biggest range of AI technologies.

When it comes to whether 'adopters' in-source or out-source their AI technologies for use in their business, the **most common sourcing strategies are external**. It is the larger sized enterprises that have found the capacity to have fully customised sourcing of AI solutions as well as the more technical sectors.

Whilst the data indicates that there is a healthy intention to adopt AI technologies in the next two years in terms of the diversity of AI technologies that will be adopted, this assumes enterprises can overcome any obstacles to adoption. The main conclusion from the current research is that whilst external obstacles may be more amenable to interventions, enterprises generally find internal obstacles to be the major challenge. A major barrier facing all enterprises, given that they all face the same labour market, is the lack of AI skills (amongst existing staff and in hiring new staff with the right skills), which certain policies could tackle. Furthermore, the costs involved in implementing AI technologies pose a further challenge. External funding initiatives

could be targeted for enterprises that face more challenges when it comes to adoption, such as micro and small businesses.

These findings illustrate insights from the first EU wide business survey deep diving into the adoption of specific AI technologies, sourcing strategies and the main barriers to adoption. Particularly important to consider are the variations across enterprises of different characteristics. This provides an important baseline for future editions of the survey, which would also benefit from further nuancing enterprises in order to further disaggregate non-adopters, identifying those that have considered or made attempts to adopt AI to arrive at a more in-depth understanding of the obstacles businesses still face.

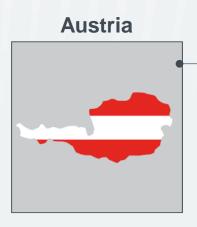
- 9 Annexes
- 9.1 Annex A Country Profiles⁵²

⁵² Malta and Cyprus were excluded from this analysis due to insufficient sample sizes obtained (lower than 50 enterprises in each country).











Al adoption by enterprises

% using at least % using at least one Al technology two Al technologies

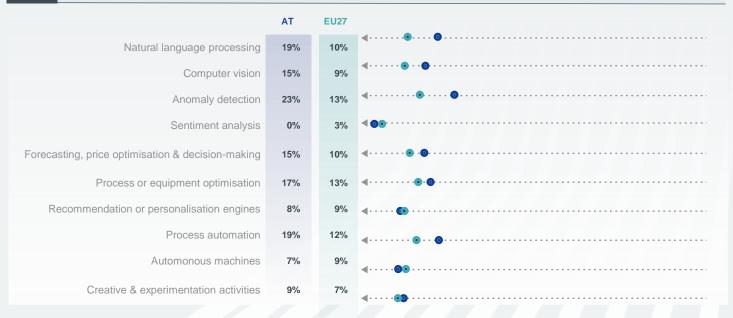
Austria 51% EU27 42% Austria 37% EU27 25% Top 3 in EU

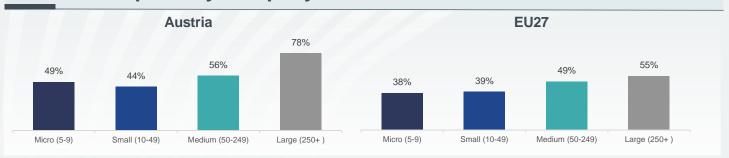
% planning to use Al in the next 2 years

Austria 20% EU27 18% % not using AI at all and not planning to use

Austria 29% EU27 40%

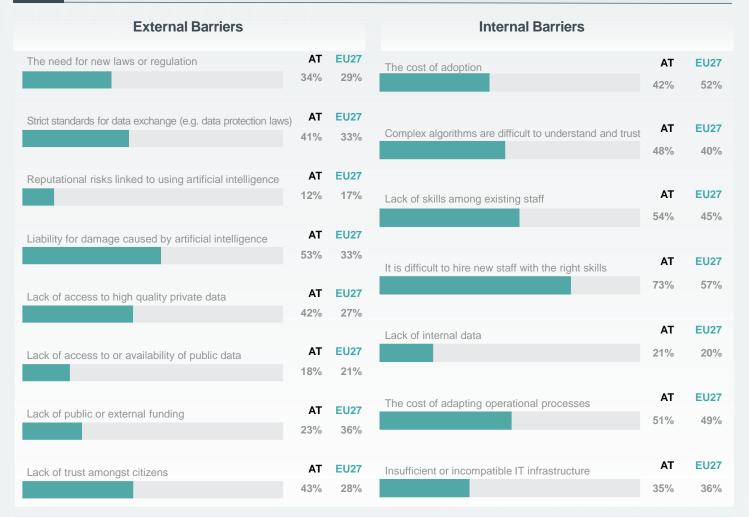






\mathcal{T}^{\otimes}

Barriers to Al adoption













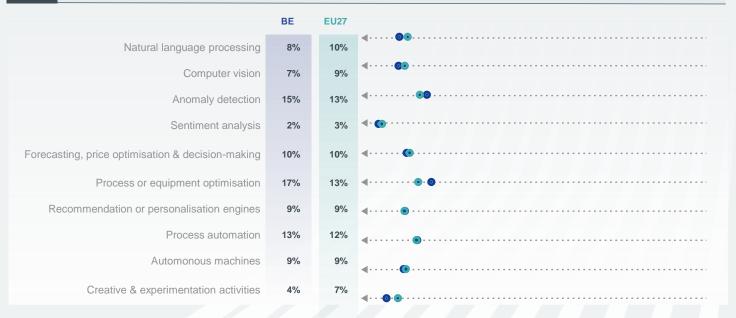


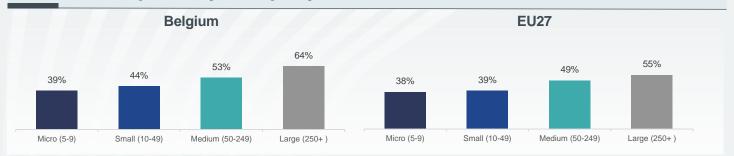


Al adoption by enterprises

% using at one Al tech		% using at least two Al technologies		% planning to use Al in the next 2 years		% not using Al at all and not planning to use	
Belgium	46%	Belgium	24%	Belgium	16%	Belgium	39%
EU27	42%	EU27	25%	EU27	18%	EU27	40%

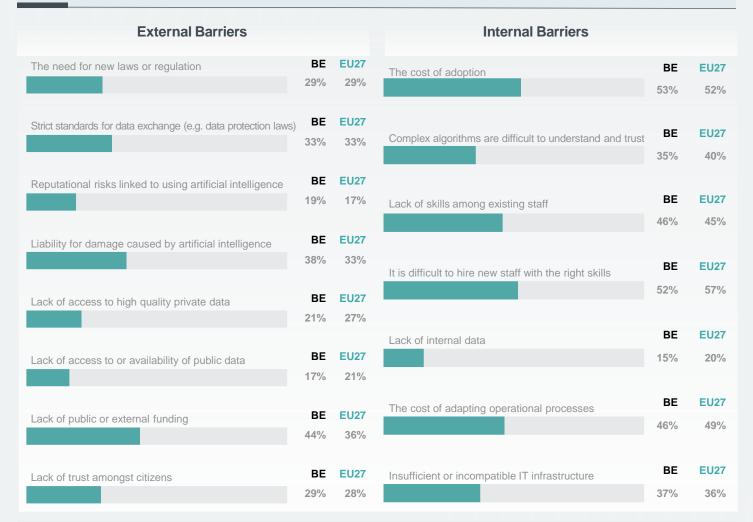






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Barriers to Al adoption





Machine or modell		Cloud co Ski		Big (managem		Prograi ski		Rob Ski	
33% BE	39% EU27	32%	33% EU27	40% BE	43% EU27	47% BE	52 %	26%	31% EU27
			3	ñ	00				8









Al adoption by enterprises

% using at least % using at least one Al technology two Al technologies Bulgaria Bulgaria 54% EU27 EU27 42% 25% Top 3 in EU

% planning to use Al in the next 2 years Bulgaria 31% EU27

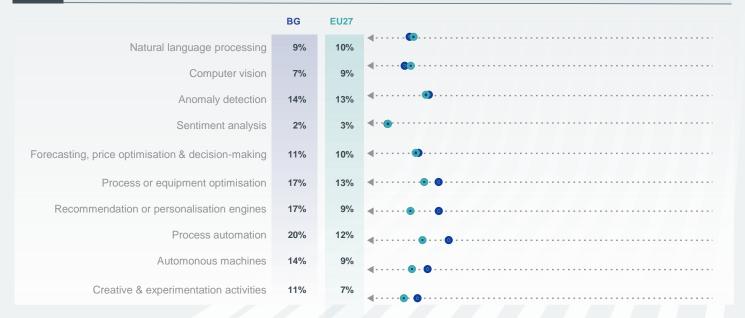
11%

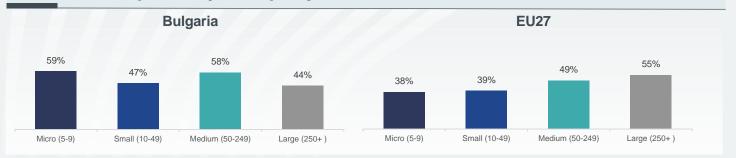
18%

% not using AI at all and not planning to use Bulgaria 36%

40%

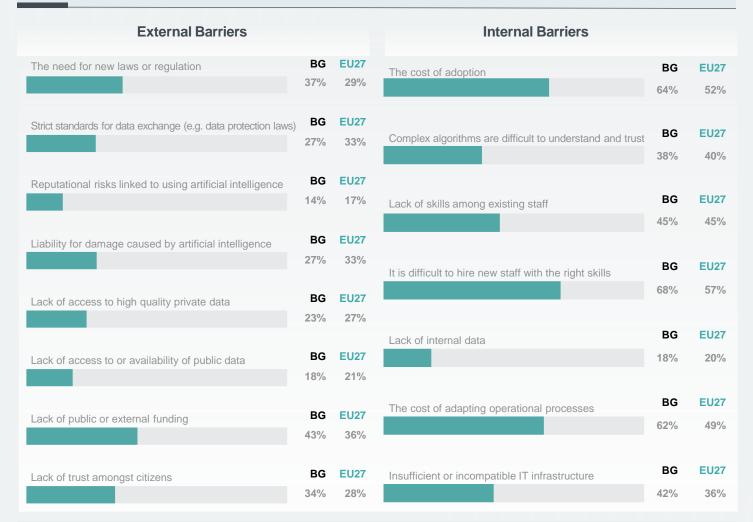
EU27





\mathcal{T}^{\otimes}

Barriers to Al adoption







^{*}Sample: enterprises facing lack of skills as a barrier to Al adoption

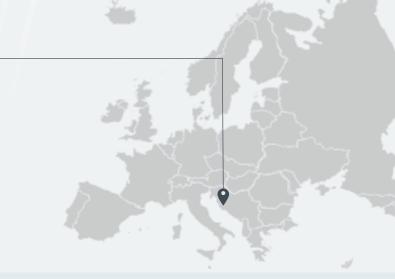


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Croatia







Al adoption by enterprises

% using at least one Al technology

Croatia 36%

EU27 42%

% using at least two Al technologies

21%

EU27 25%

% planning to use Al in the next 2 years

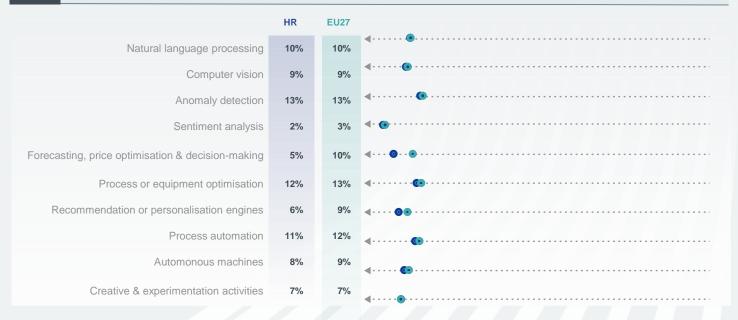
Croatia 23%

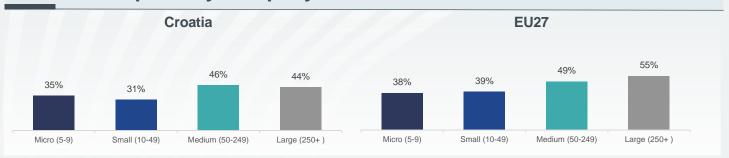
EU27 18% % not using AI at all and not planning to use

Croatia 41%

EU27 40%

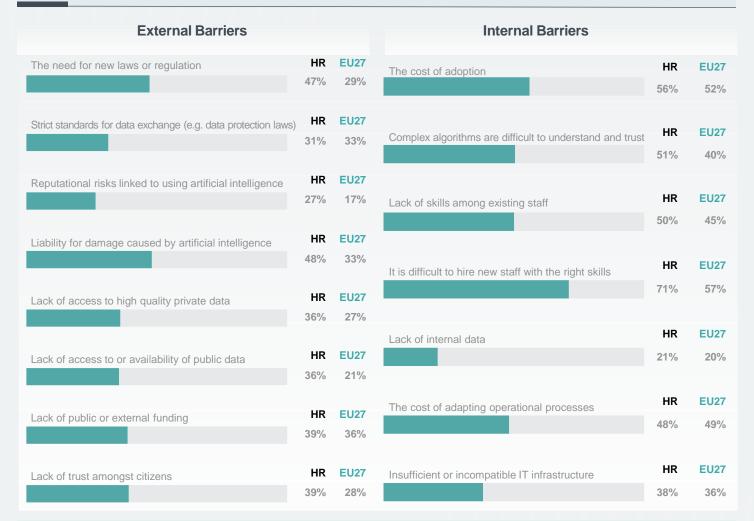






\mathcal{T}^{\otimes}

Barriers to Al adoption







^{*}Sample: enterprises facing lack of skills as a barrier to Al adoption



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Al adoption by enterprises

% using at least one Al technology

Czechia 61% EU27 42%

Top 3 in EU

% using at least two Al technologies

Czechia 40% EU27 25%

Top 3 in EU

% planning to use Al in the next 2 years

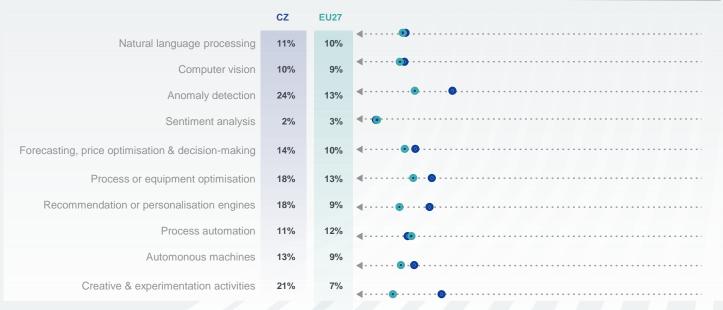
Czechia 1% EU27 18%

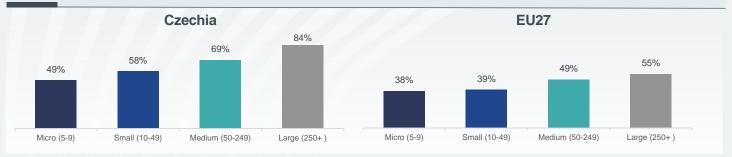
Bottom 3 in EU

% not using AI at all and not planning to use

Czechia 38% EU27 40%

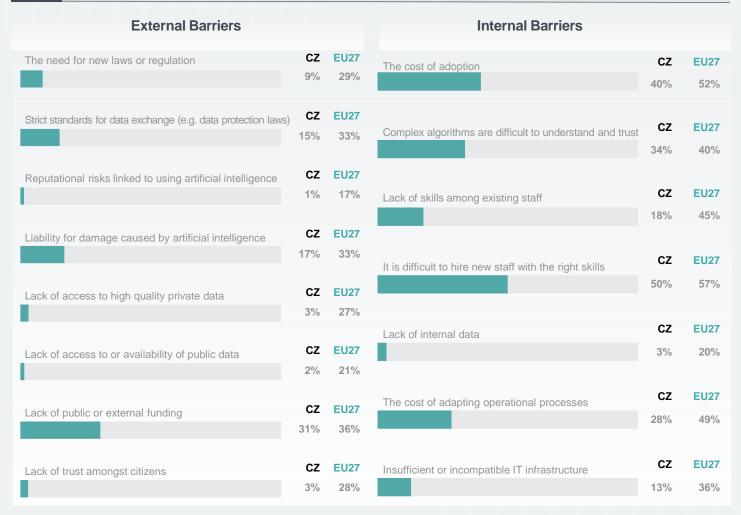






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Barriers to Al adoption



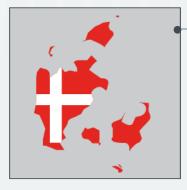




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Denmark





Al adoption by enterprises

% using at least one Al technology

42%

Denmark 40%

EU27

% using at least two Al technologies

Denmark 22%

EU27

25%

% planning to use Al in the next 2 years

Denmark 21%

EU27 18% % not using AI at all and not planning to use

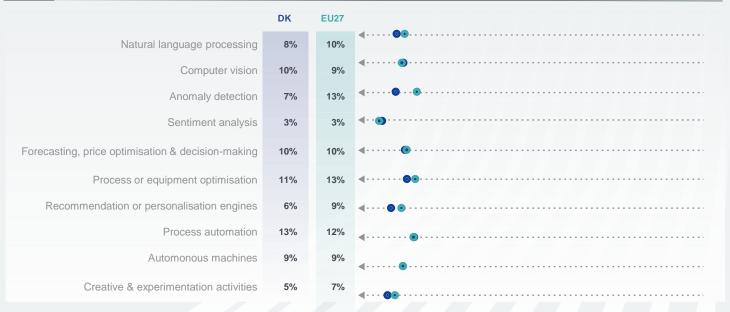
Denmark

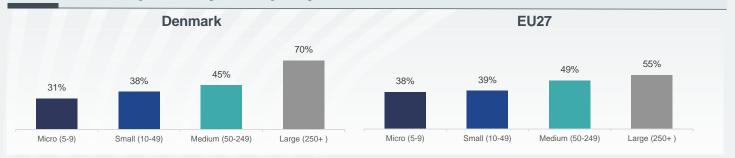
40%

EU27

40%

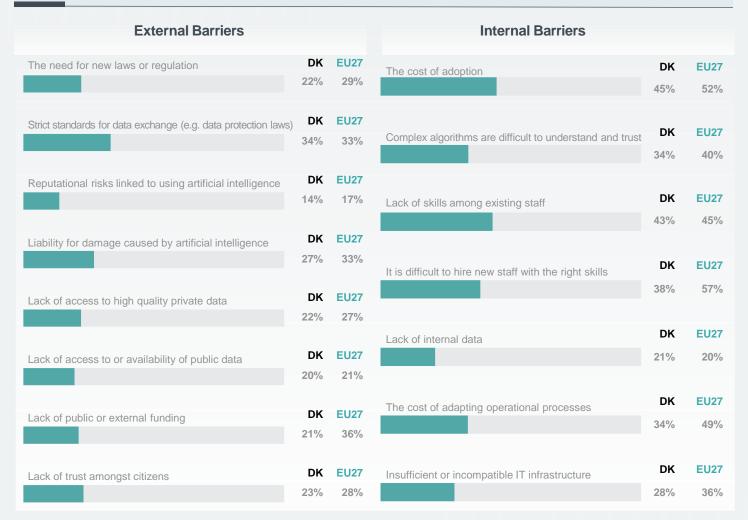






\mathcal{T}^{\otimes}

Barriers to Al adoption







^{*}Sample: enterprises facing lack of skills as a barrier to Al adoption







Estonia





Estonia

EU27

Bottom 3 in EU

Al adoption by enterprises

% using at least % using at least one Al technology two Al technologies

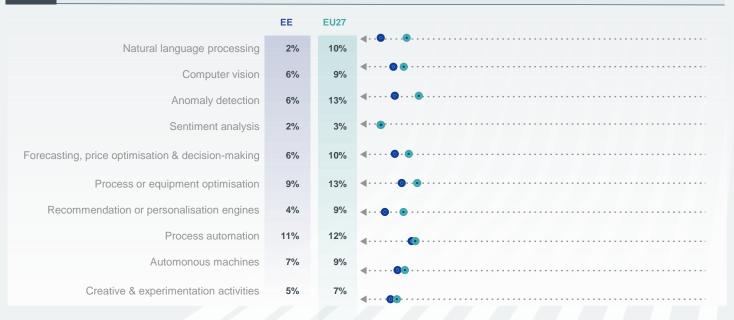
> Estonia 27% 15% EU27 42% 25%

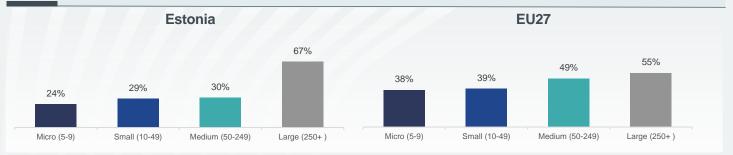
% planning to use Al in the next 2 years

Estonia 20% EU27 18% % not using AI at all and not planning to use

53% EU27 40%

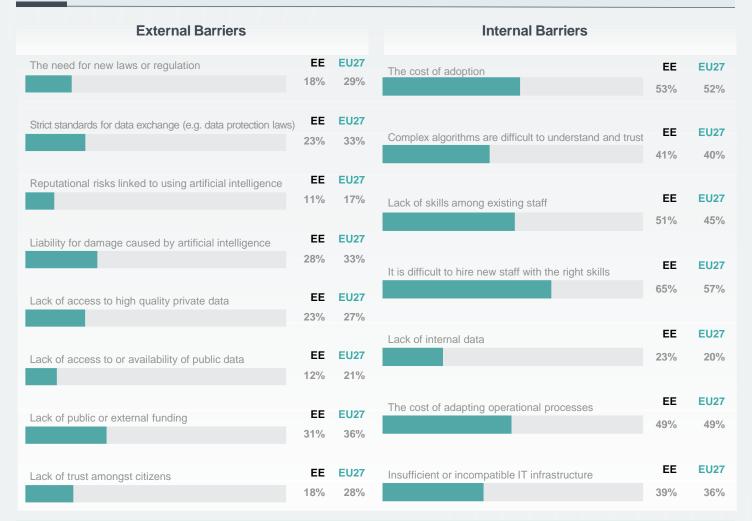






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Barriers to Al adoption







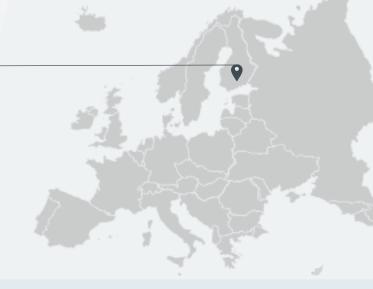


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Finland







Al adoption by enterprises

% using at least one Al technology

Finland 36%

EU27 42%

% using at least two Al technologies

Finland 20%

25%

% planning to use Al in the next 2 years

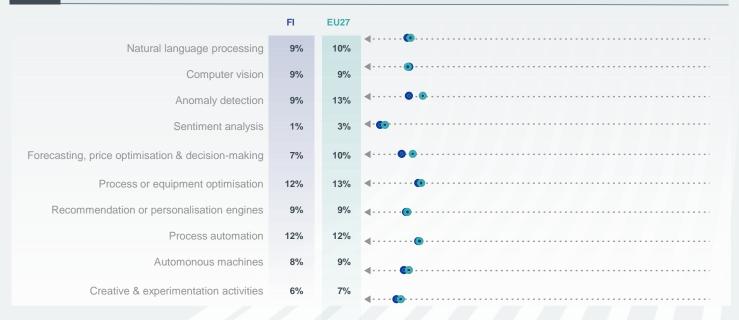
Finland 16% EU27 18% % not using AI at all and not planning to use

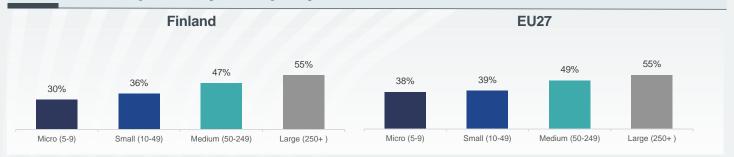
Finland 48% EU27 40%



Adoption per Al technology

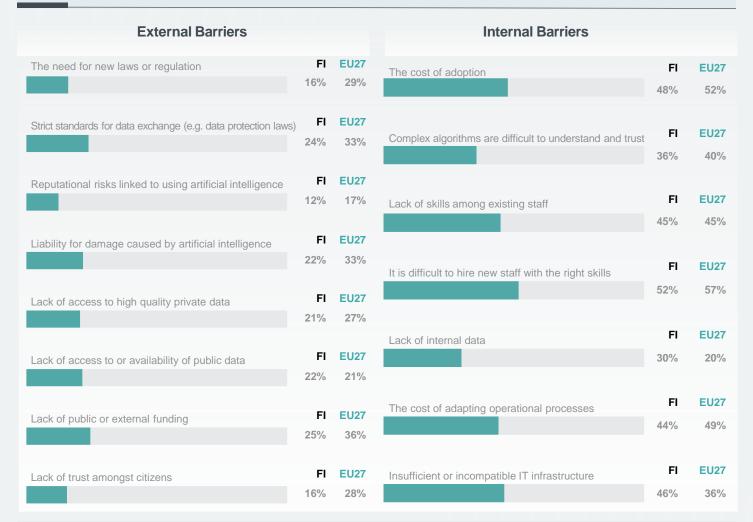
EU27





\mathcal{Z}^{\otimes}

Barriers to Al adoption







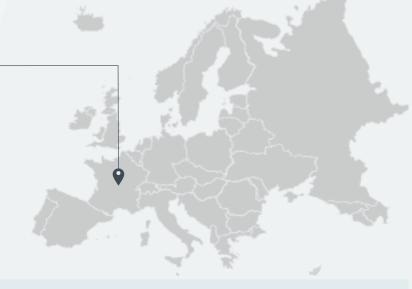






France







Al adoption by enterprises

% using at least one Al technology

France 36% EU27

42%

% using at least two Al technologies

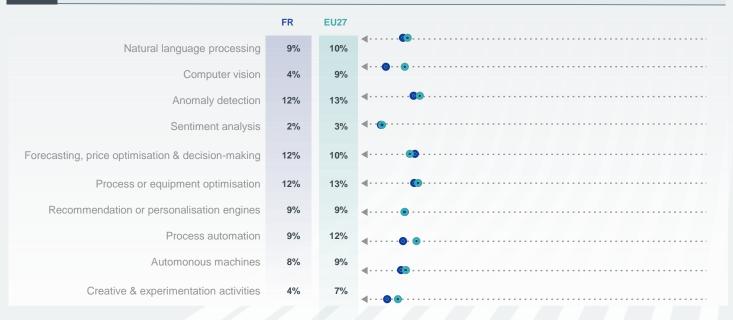
France 19% EU27 25%

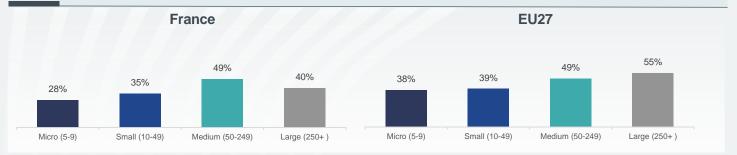
% planning to use Al in the next 2 years

France 22% EU27 18% % not using AI at all and not planning to use

France 42% EU27 40%

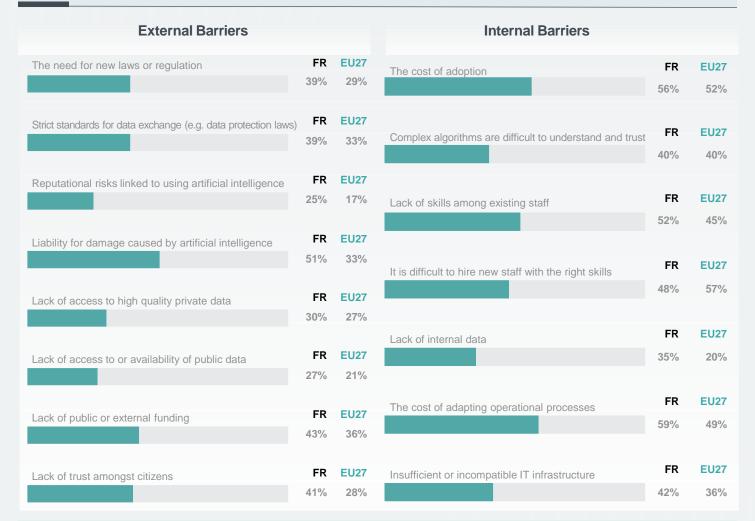






\mathcal{Z}^{\otimes}

Barriers to Al adoption







^{*}Sample: enterprises facing lack of skills as a barrier to Al adoption



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Germany







Al adoption by enterprises

% using at least one Al technology

Germany 44%

EU27 42%

% using at least two Al technologies

Germany 28%

EU27 25%

% planning to use Al in the next 2 years

Germany 14%

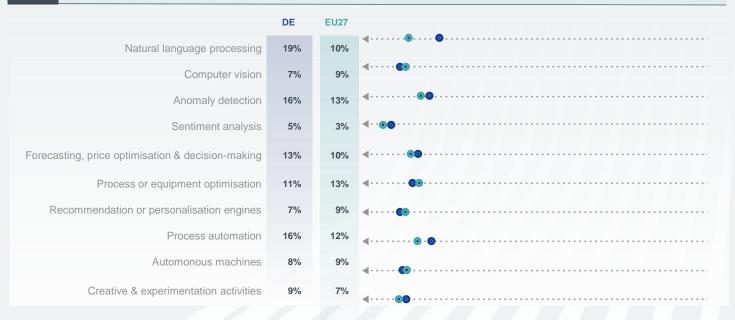
EU27 18% % not using AI at all and not planning to use

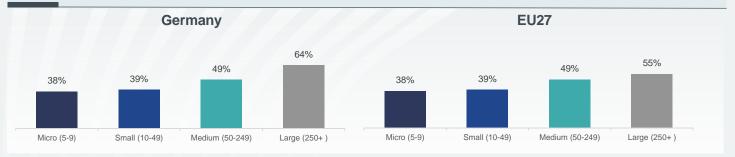
Germany

42%

EU27 40%

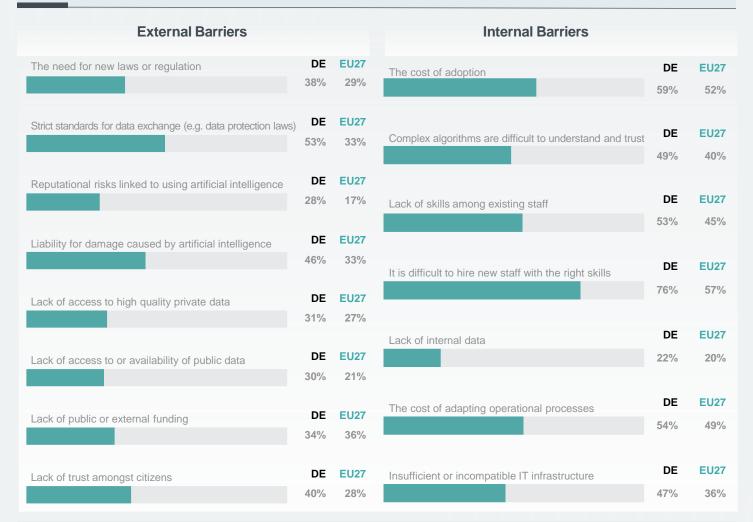






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Barriers to Al adoption













Greece







Al adoption by enterprises

%	using at least	
one	Al technology	

Greece 43% EU27 42%

% using at least two Al technologies

Greece 34% EU27 25%

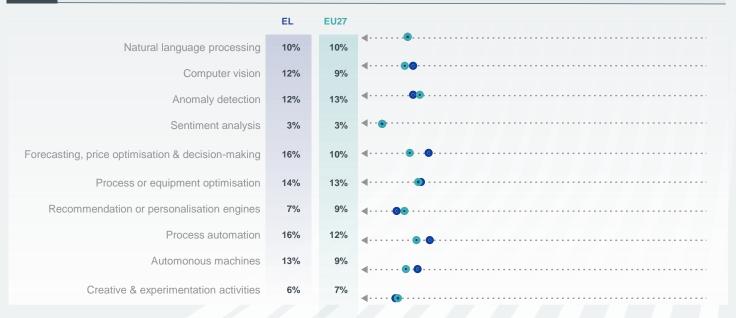
Top 3 in EU

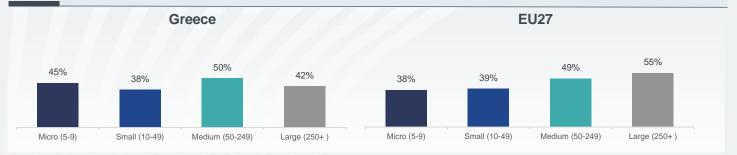
% planning to use Al in the next 2 years

Greece 19% EU27 18% % not using AI at all and not planning to use

Greece 37% EU27 40%







\mathcal{T}^{\otimes}

Barriers to Al adoption









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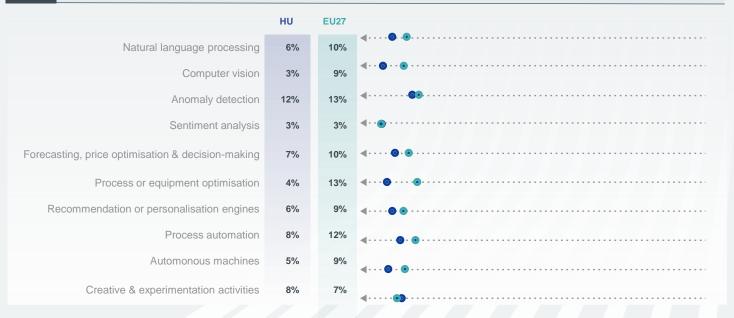


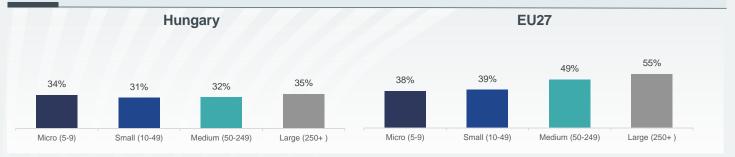


Al adoption by enterprises

% using at least % using at least % planning to use % not using AI at all and one Al technology two Al technologies Al in the next 2 years not planning to use Hungary Hungary Hungary Hungary 33% 17% 25% 42% EU27 EU27 EU27 EU27 42% 25% 18% 40%

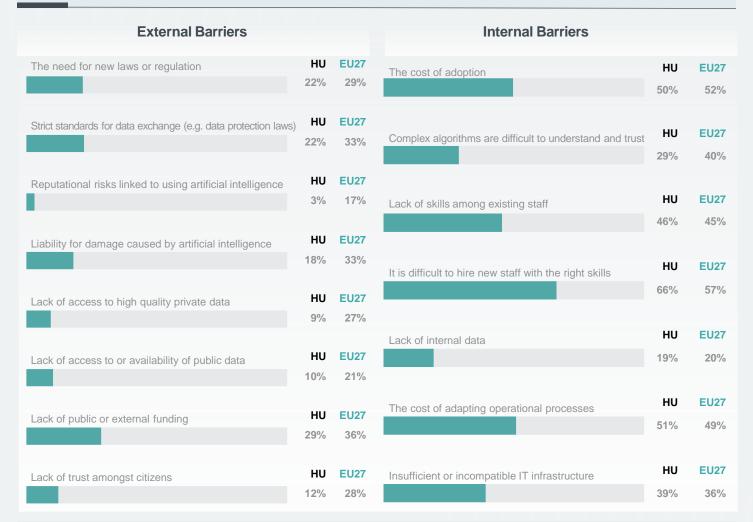






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Barriers to Al adoption













Ireland







Al adoption by enterprises

% using at least
one Al technology

Ireland 35% EU27 42%

% using at least two Al technologies

Ireland 14% EU27 25%

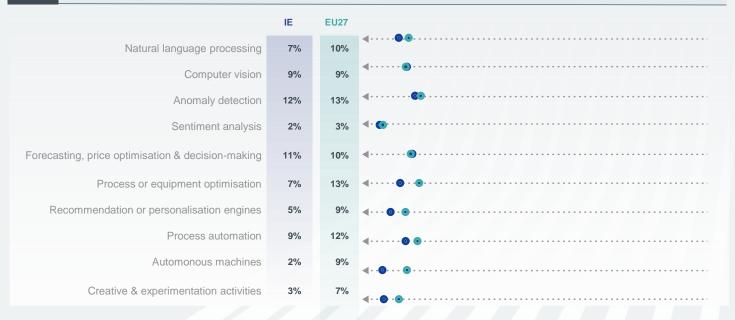
Bottom 3 in EU

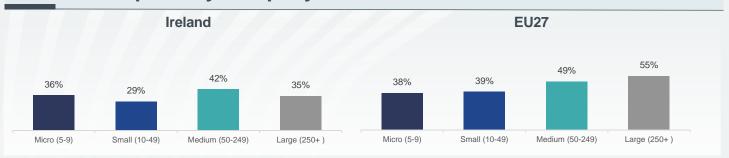
% planning to use Al in the next 2 years

Ireland 13% EU27 18% % not using AI at all and not planning to use

Ireland 52% EU27 40%

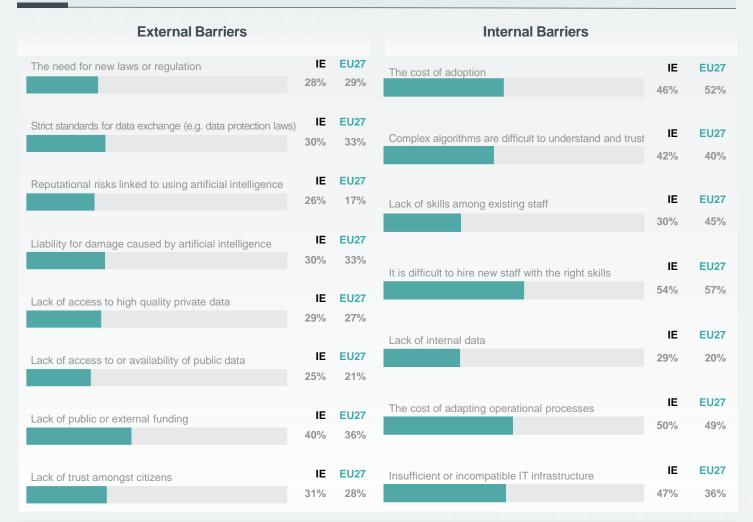






\mathcal{T}^{\otimes}

Barriers to Al adoption







^{*}Sample: enterprises facing lack of skills as a barrier to Al adoption



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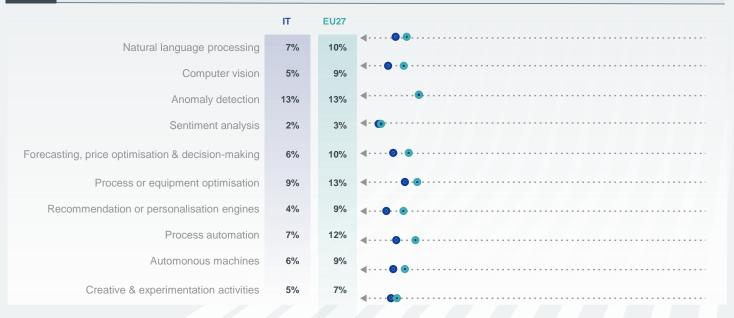


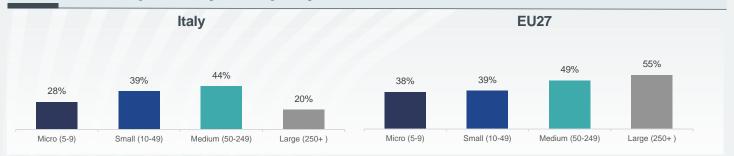


Al adoption by enterprises



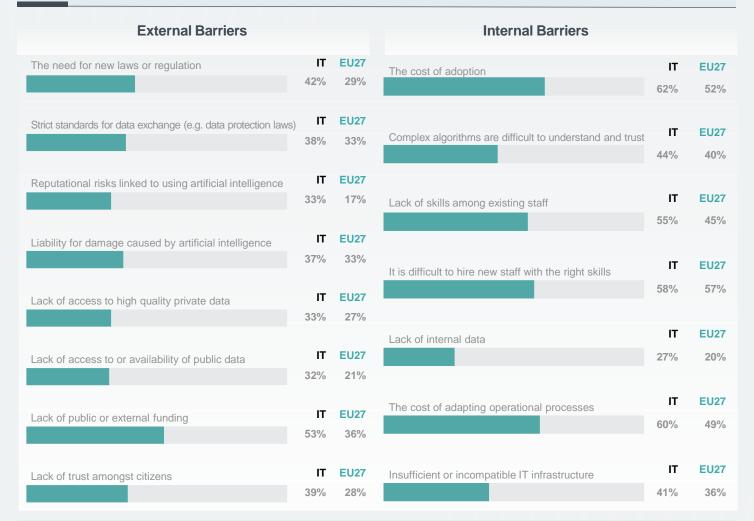






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Barriers to Al adoption







^{*}Sample: enterprises facing lack of skills as a barrier to AI adoption













Al adoption by enterprises

% using a one AI tech		% using two Al tecl	j at least nnologies
Latvia	40%	Latvia	21%

42%

Latvia	21%
EU27	25%

% planning to use Al in the next 2 years

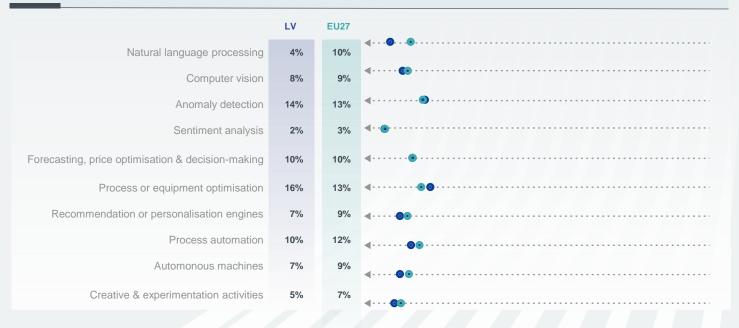
Latvia	21%
EU27	18%

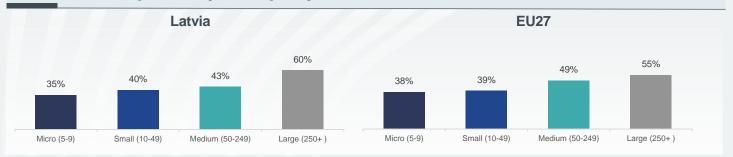
% not using AI at all and not planning to use

Latvia	39%
EU27	40%



EU27





€ M

Barriers to Al adoption





Machine loor modelli			Big data management skills		Programming skills		Robotic Skills		
48%	39%	23%	33%	44%	43%	49%	52%	31%	31%
LV	EU27	LV	EU27	LV	EU27	LV	EU27	LV	EU27
		SILE.							

^{*}Sample: enterprises facing lack of skills as a barrier to Al adoption



GAME CHANGERS losos



Lithuania







Al adoption by enterprises

% using at least one AI technology

Lithuania **54%**EU27 **42%**

Top 3 in EU

% using at least two AI technologies

Lithuania **34%**EU27 **25%**

% planning to use Al in the next 2 years

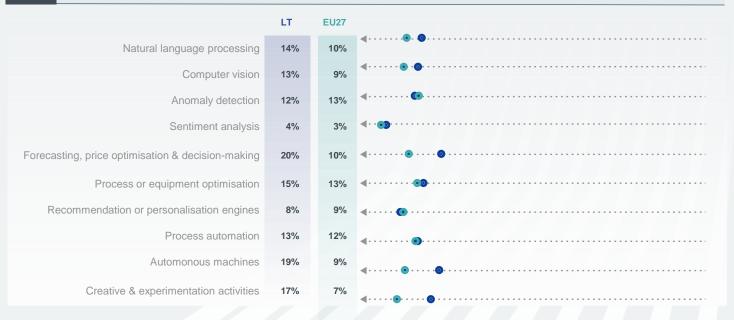
Lithuania **8%**EU27 **18%**

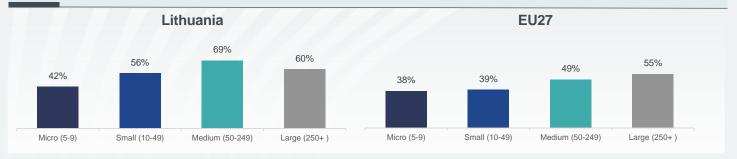
Bottom 3 in EU

% not using Al at all and not planning to use

Lithuania **38%**EU27 **40%**







\mathcal{T}^{\otimes}

Barriers to Al adoption





Machine or modell							Programming skills		Robotic Skills	
31% LT	39% EU27	31% LT	33% EU27	40% LT	43% EU27	46% LT	52%	18% LT	31% EU27	
			Tro .	ñ					FR)	

^{*}Sample: enterprises facing lack of skills as a barrier to Al adoption



GAME CHANGERS losos



Luxembourg







Al adoption by enterprises

% using at least one Al technology

Luxembourg 51% EU27

42%

% using at least two Al technologies

Luxembourg 32%

EU27

25%

% planning to use Al in the next 2 years

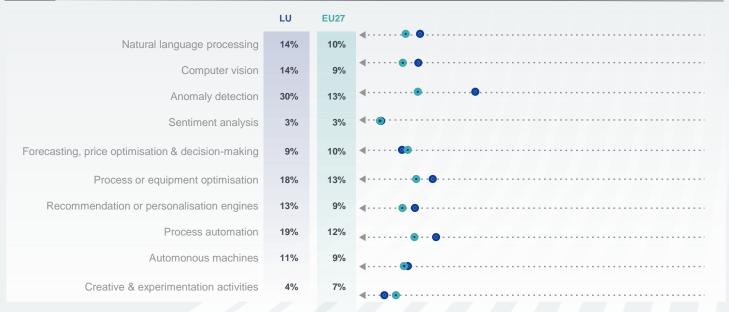
Luxembourg 12%

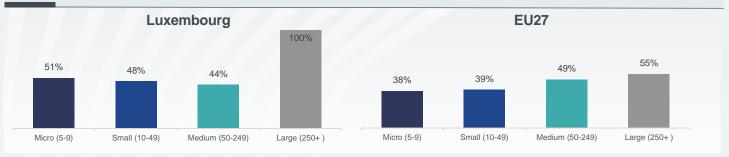
EU27 18% % not using AI at all and not planning to use

Luxembourg 37%

EU27 40%







\mathcal{T}^{\otimes}

Barriers to Al adoption







^{*}Sample: enterprises facing lack of skills as a barrier to Al adoption

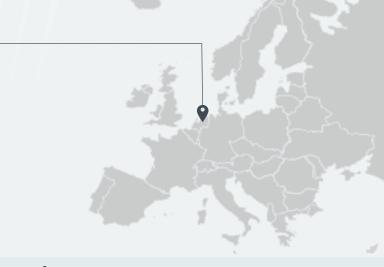


GAME CHANGERS losos



Netherlands







Al adoption by enterprises

% using at least one Al technology

Netherlands 40%

EU27

42%

% using at least two Al technologies

Netherlands 24%

25%

EU27

% planning to use Al in the next 2 years

Netherlands 27%

EU27

18%

Top 3 in EU

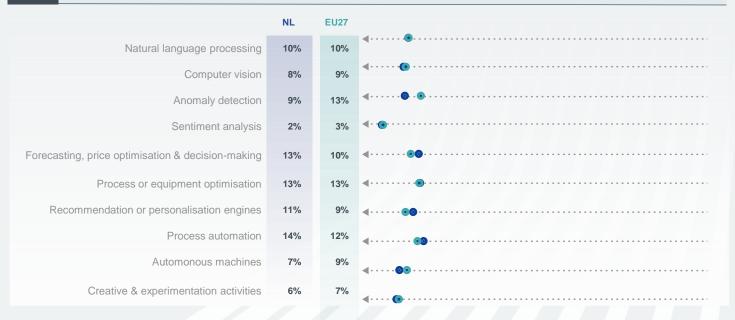
% not using AI at all and not planning to use

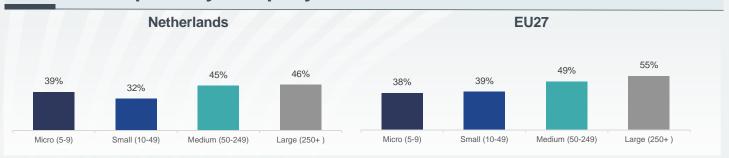
Netherlands

32%

EU27 40%

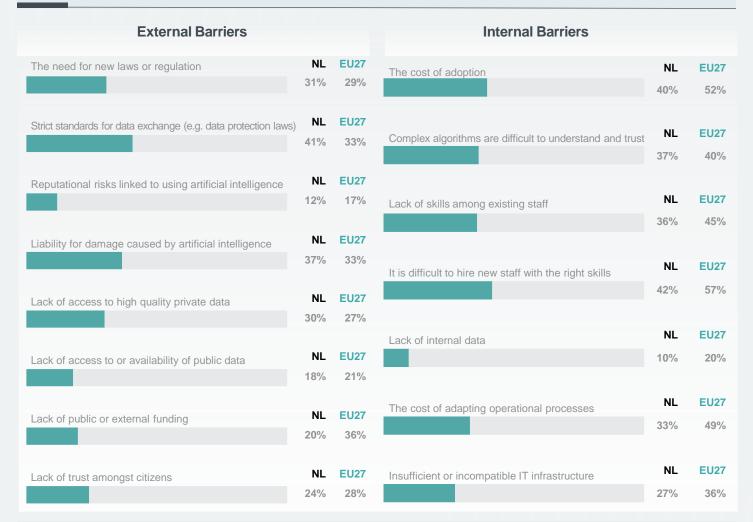






\mathcal{T}^{\otimes}

Barriers to Al adoption







^{*}Sample: enterprises facing lack of skills as a barrier to Al adoption



GAME CHANGERS Ipsos











Al adoption by enterprises

% using at least one Al technology

Poland 34% EU27

42%

% using at least two Al technologies

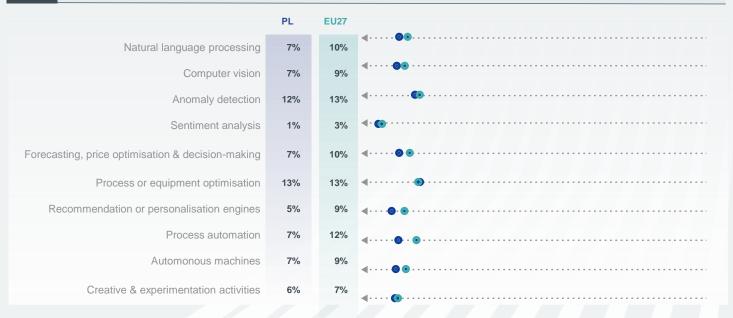
Poland 18% EU27 25%

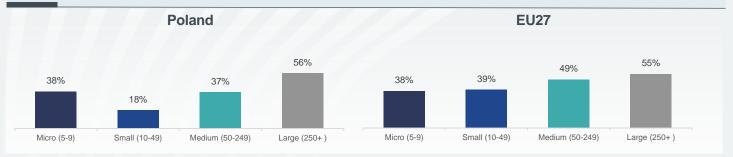
% planning to use Al in the next 2 years

Poland 22% EU27 18% % not using AI at all and not planning to use

Poland 44% EU27 40%

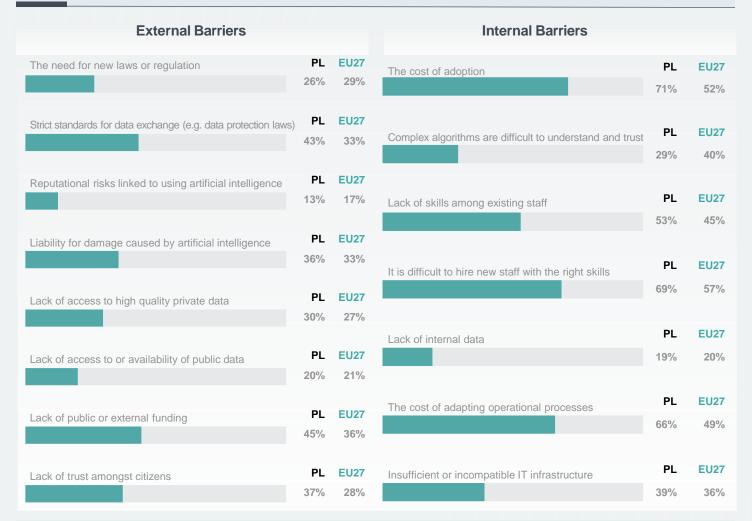






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Barriers to Al adoption









GAME CHANGERS Ipsos



Portugal



% using at least



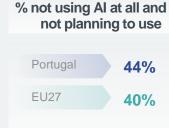
Al adoption by enterprises

% using at least

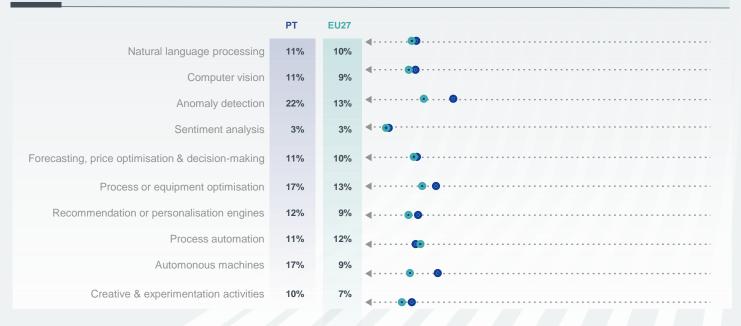
one Al techn		two Al technologie				
Portugal	48%	Portugal	31%			
EU27	42%	EU27	25%			

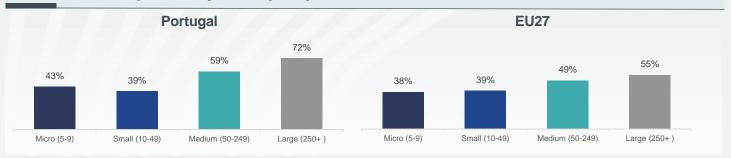


% planning to use



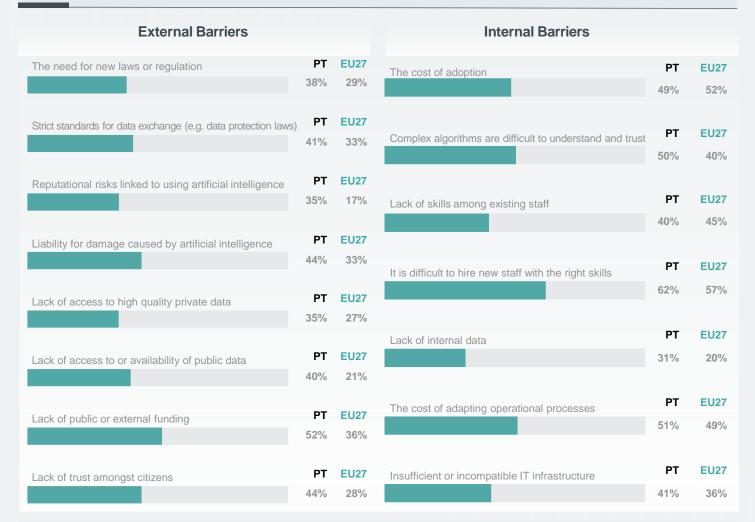






\mathcal{T}^{\otimes}

Barriers to Al adoption







^{*}Sample: enterprises facing lack of skills as a barrier to Al adoption

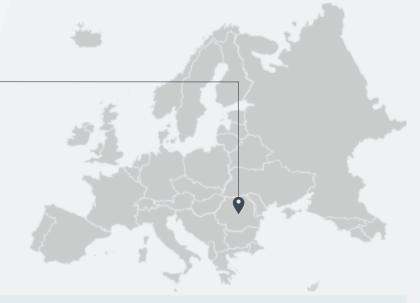


GAME CHANGERS losos



Romania







Al adoption by enterprises

% using at least one Al technology

Romania 48% EU27

42%

% using at least two Al technologies

Romania 31%

25%

% planning to use Al in the next 2 years

Romania 26% EU27 18%

Top 3 in EU

% not using AI at all and not planning to use

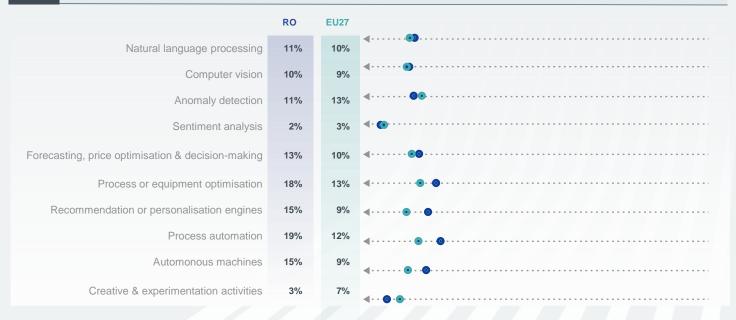
Romania 26%

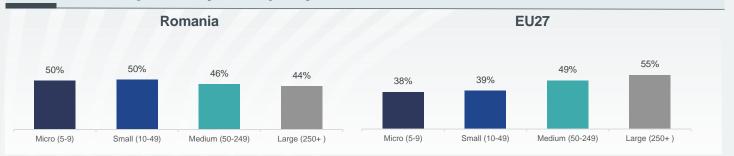
EU27 40%



Adoption per Al technology

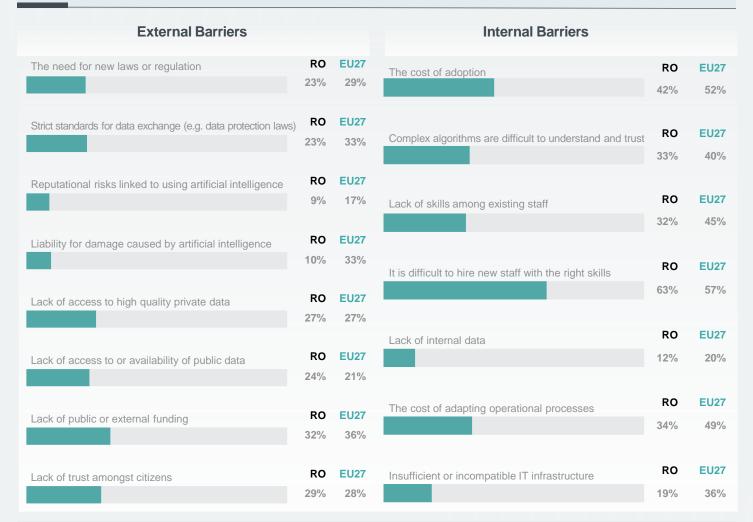
EU27







Barriers to Al adoption







^{*}Sample: enterprises facing lack of skills as a barrier to Al adoption







Slovakia







Al adoption by enterprises

% using at least one Al technology

Slovakia 29% EU27 42%

Bottom 3 in EU

% using at least two Al technologies

Slovakia 15% EU27 25%

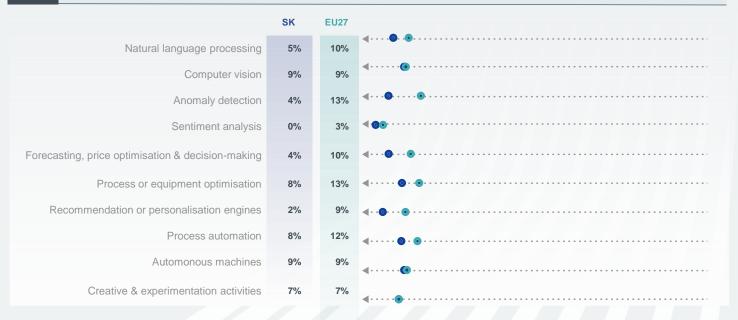
% planning to use Al in the next 2 years

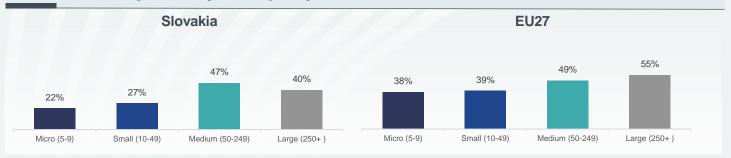
Slovakia 16% EU27 18% % not using AI at all and not planning to use

Slovakia 55%

EU27 40%

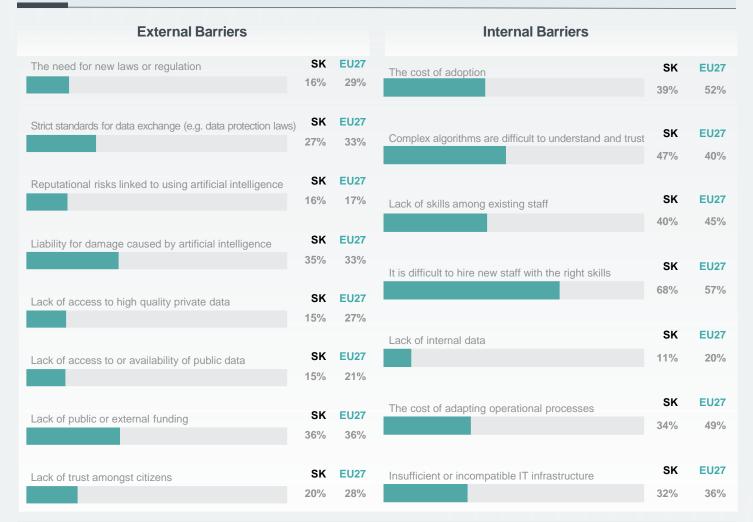






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Barriers to Al adoption







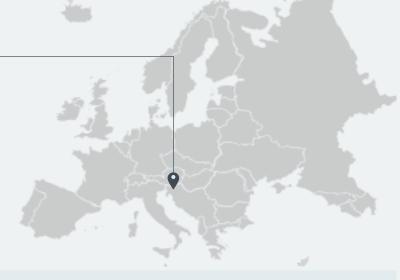


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Slovenia







Al adoption by enterprises

% using at least one Al technology

Slovenia 46%

EU27 42%

% using at least two Al technologies

Slovenia 33%

EU27 25%

% planning to use Al in the next 2 years

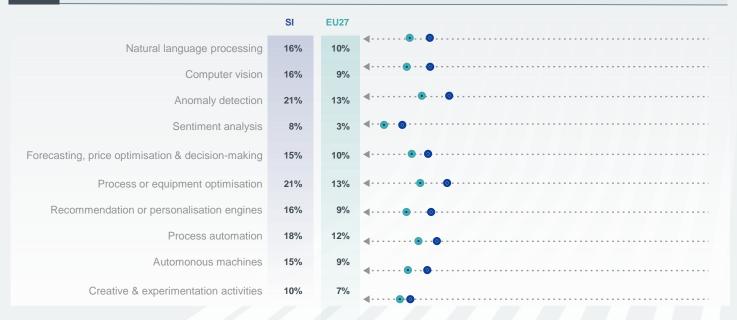
Slovenia 21%

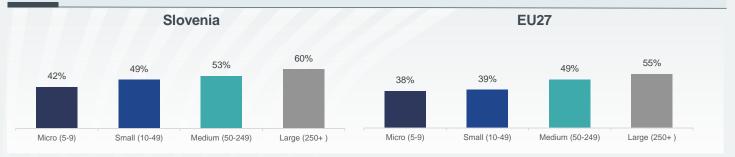
EU27 18% % not using AI at all and not planning to use

Slovenia 32%

EU27 40%

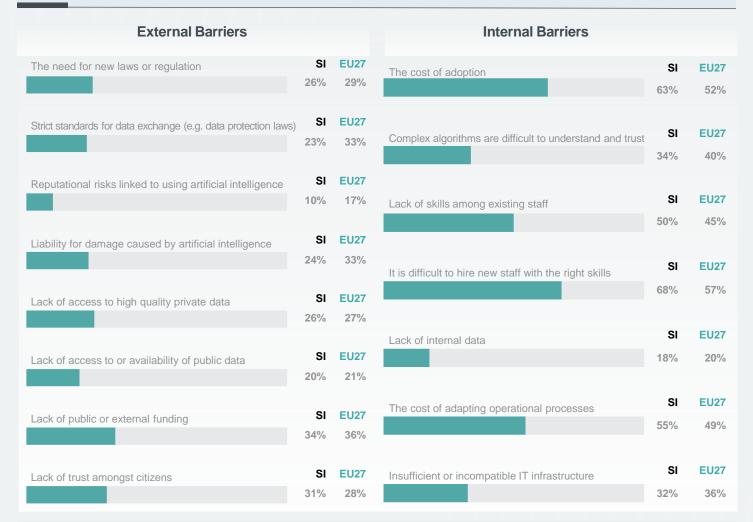






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Barriers to Al adoption









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Spain







Spain 40% EU27

% using at least

one Al technology

42%

% using at least two Al technologies

Spain 22%

EU27 25%

% planning to use Al in the next 2 years

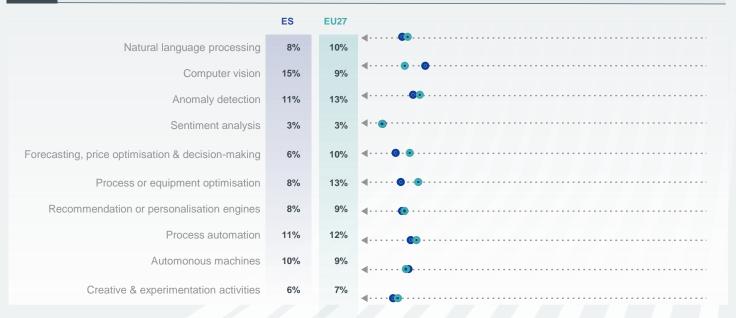
Spain 10% EU27

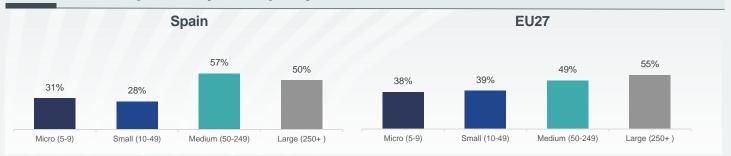
18%

% not using AI at all and not planning to use

Spain 51% EU27 40%

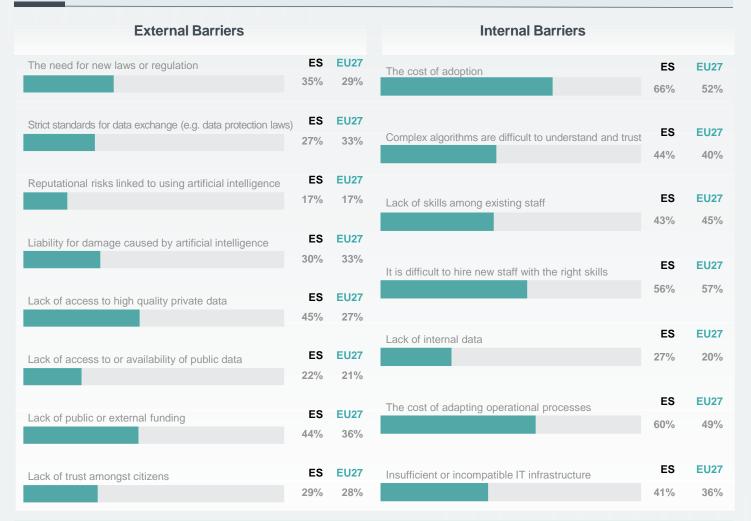






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Barriers to Al adoption













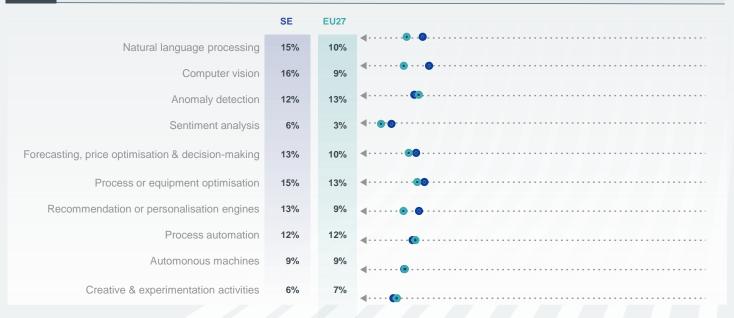


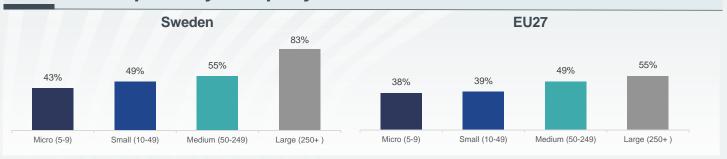


Al adoption by enterprises

% using at least one AI technology		% using at least two Al technologies		% plannir Al in the nex		% not using AI at all and not planning to use		
Sweden	50%	Sweden	30%	Sweden	18%	Sweden	32%	
EU27	42%	EU27	25%	EU27	18%	EU27	40%	

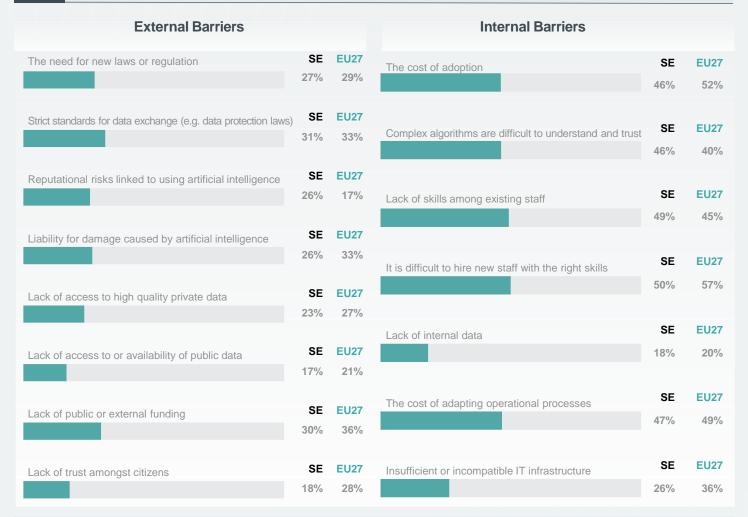






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Barriers to Al adoption





^{*}Sample: enterprises facing lack of skills as a barrier to Al adoption



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the UK





Al adoption by enterprises

% using at least one Al technology

the UK 34% EU27

42%

% using at least two Al technologies

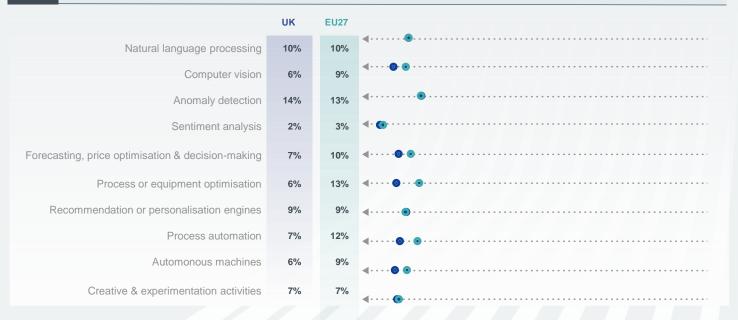
the UK 16% EU27 25%

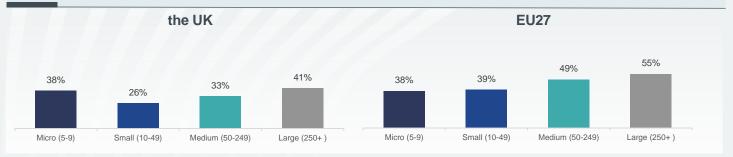
% planning to use Al in the next 2 years

the UK 20% EU27 18% % not using AI at all and not planning to use

the UK 46% EU27 40%

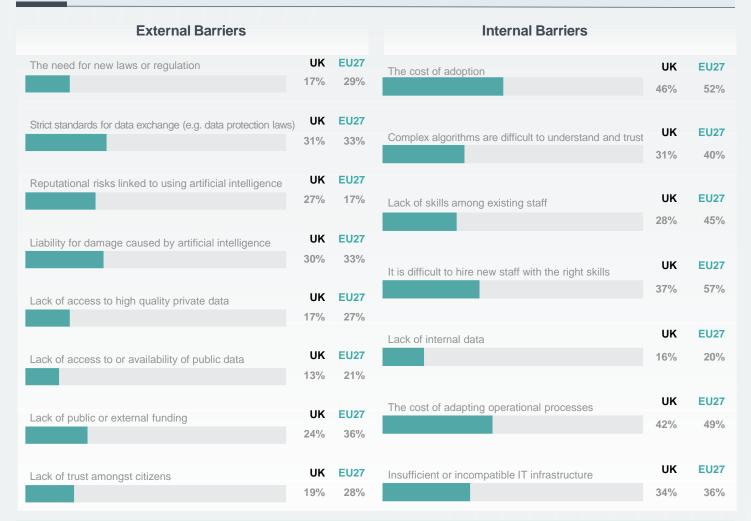






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Barriers to Al adoption





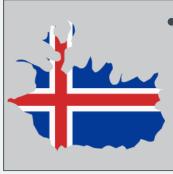
Machine learning Cloud comp or modelling skills Skills			uting Big data management skills			Programming skills		Robotic Skills	
40%	39%	39%	33%	42%	43%	50%	52%	18%	31%
UK	EU27	UK	EU27	UK	EU27	UK	EU27	UK	EU27
		्रा	Tree)	and the same of th		</th <th></th> <th></th> <th></th>			



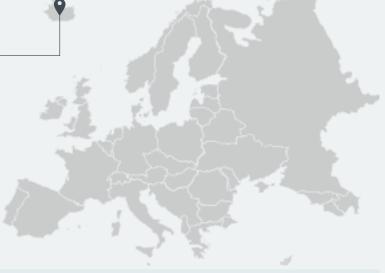




Iceland









Al adoption by enterprises

% using at least one Al technology

Iceland 37%

EU27 42%

% using at least two Al technologies

Iceland 19% EU27

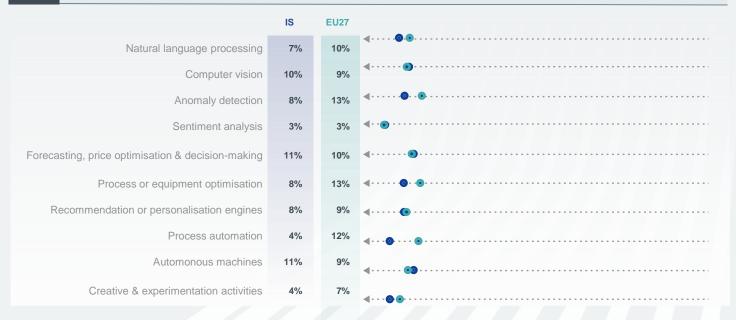
25%

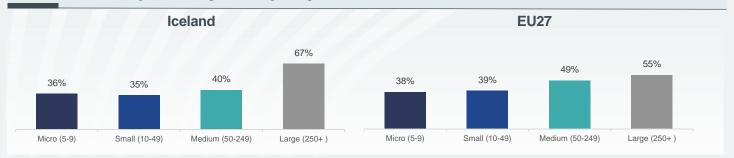
% planning to use Al in the next 2 years

Iceland 17% EU27 18% % not using AI at all and not planning to use

Iceland 46% EU27 40%

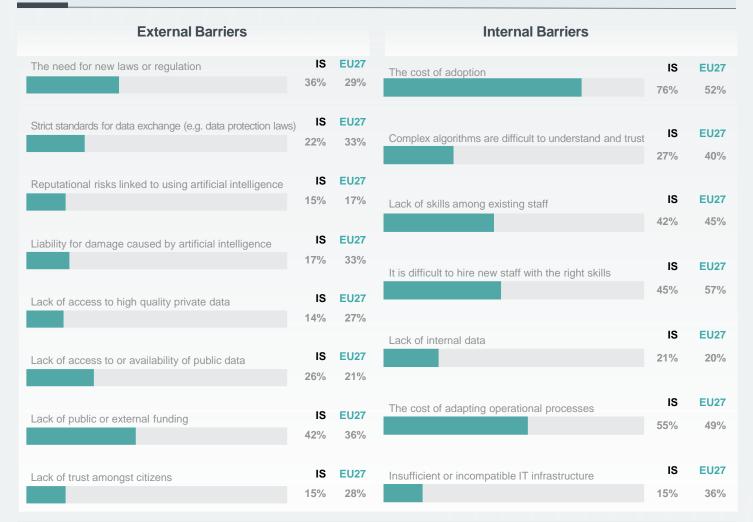






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Barriers to Al adoption









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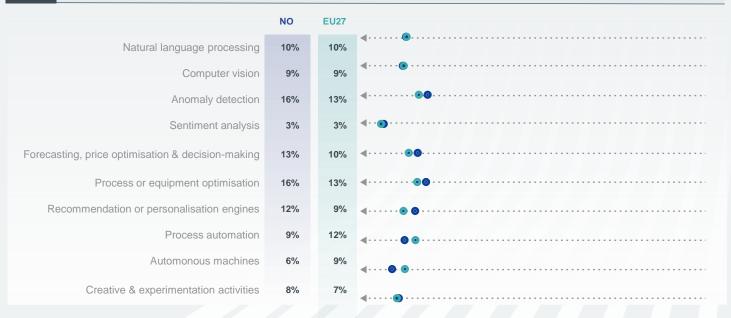


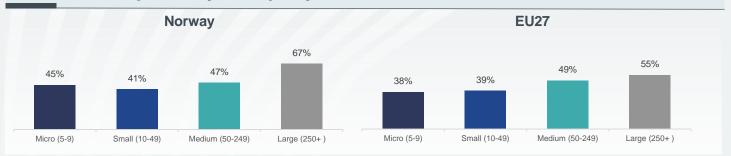


Al adoption by enterprises

% using at least % using at least % planning to use % not using AI at all and one Al technology two Al technologies Al in the next 2 years not planning to use Norway Norway Norway Norway 46% 27% 16% 38% EU27 EU27 EU27 EU27 42% 25% 18% 40%







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Barriers to Al adoption





Machine learning Cloud computing or modelling skills Skills		Big data		Programming		Robotic			
		management skills		skills		Skills			
31%	39%	32%	33%	33%	43%	38%	52%	16%	31%
NO	EU27	NO	EU27	NO	EU27	NO		NO	EU27
			3		0	(4)			P8)

9.2 Annex B – Final Questionnaire

I. INTRODUCTION AND SCREENER

Base: all respondents

Intro1. Good [morning/afternoon/evening]. My name is [name] and I'm calling on behalf of lpsos, a research company.

We are conducting a survey across Europe on behalf of the European Commission, to gain better insight into the adoption of artificial intelligence technology in firms. We are looking for someone who knows about the use of technology in your firm. [Interviewer instruction: IF NEEDED CLARIFY "We are looking for someone who knows how technology is used in your business."]

Base: all respondents

SCR1. [S]

Would you be willing to answer a few questions about this topic? The survey will take only 8 minutes of your time and the results will be used to inform future policy developments in Europe on this topic.

- 1. Yes, I will participate
- 2. Yes, but another time [Interviewer instruction: MAKE APPOINTMENT]
- 3. I am not familiar with the use of technology but can provide you the details of a colleague who is [O] [Interviewer instruction: NOTE DOWN CONTACT AND MAKE APPOINTMENT]
- 4. I am not willing to participate or provide you with additional information

SCRIPTER: IF SCR1=4: SCREENOUT

Scripter: show Intro2 and SCR2 on the same page

Base: IF SCR1=3 = REFERRAL

Intro2.

Good [morning/afternoon/evening]. My name is [name] and I'm calling on behalf of Ipsos, a research company.

We are conducting a survey across Europe on behalf of the European Commission, to gain better insight into the adoption of artificial intelligence technology in firms. We are looking for someone who is familiar with technology in your firm. A colleague of yours provided us with your contact details. [Interviewer instruction: IF NEEDED CLARIFY "We are looking for someone who is technology-oriented and/or knows how technology is used in your business."]

Base: IF SCR1=3 = REFERRAL

SCR2. [S]

Would you be willing to answer a few questions about this topic? The survey will take only 8 minutes of your time and the results will be used to inform future policy developments in Europe on this topic.

- 1. Yes, I will participate
- 2. Yes, but another time [Interviewer instruction: MAKE APPOINTMENT]
- 3. I am not familiar with the use of technology but can provide you the details of a colleague who is [O] [Interviewer instruction: NOTE DOWN CONTACT AND END SURVEY]
- 4. I am not willing to participate or provide you with additional information

SCRIPTER: IF SCR2=3 or 4: SCREENOUT

Base: all respondents

Intro3. [S]

Participation is voluntary, and you can change your mind at any time. The survey will be carried out under all the confidentiality and data protection rules. All data we gather will be completely anonymised.

Are you happy to proceed with the interview?

- 1. Yes
- 2. No.

Interviewer instruction: READ IF NEEDED: If you would like to read the Privacy Notice beforehand, you can access it online at

https://survey.ipsos.be/privacynoticeArtificalIntelligence.pdf

SCRIPTER: IF Intro3=2: SCREENOUT

Base: all respondents

SCR3. [S]

How many people does your company employ in total, including yourself?

Interviewer instruction: READ IF NECESSARY: Please include freelancers working regularly for your company. Full-time and part-time employees should each count as one employee.

- 0. 1-4
- 1. Between 5-9 employees
- 2. Between 10-49 employees
- 3. Between 50-249 employees
- 4. More 250 employees

SCRIPTER: IF SCR3=0: SCREENOUT

Base: all respondents

SCR4. [S]

What would you say is the main sector in which your company operates?

- 1. Agriculture, forestry and/or fishing
- 2. Manufacturing
- 3. Construction
- 4. Oil and gas
- 5. Waste management
- 6. Water & electricity supply
- 7. Trade, retail
- 8. Transport
- 9. Food
- 10. Accommodation
- 11. Recreation activities
- 12. IT
- 13. Finance, insurance
- 14. Real estate,
- 15. Other technical and/or scientific sectors
- 16. Education
- 17. Human health
- 18. Social work
- 99. Other [Interviewer: Do not read]

Scripter: if SCR4=99: SCREENOUT

II. MAIN QUESTIONNAIRE

Base: all respondents

Q0. [S]

In general, would you say that you know what artificial intelligence is?

- 1. Yes, I do.
- 2. I am not sure.
- 3. No, I don't.

Interviewer instruction: If respondent answers "Yes" but seems unsure or asks further what is meant by AI or if they answer "Not sure" or "No, I don't", read the following:

"Artificial Intelligence is not easy to define but let me try: It is technology that tries to automate one or more (human) cognitive functions or processes. It provides predictions, recommendations or decisions to achieve specific objectives. It does so by continuously learning about its environment or results from its actions. This survey will ask about the adoption of such technology in your company by providing clear examples of its applications. You do not need to be familiar with artificial intelligence to answer the questions."

Base: all respondents

Q1. [SGRID]

I will now name technological applications that are directly dependent on artificial intelligence. To the best of your knowledge, what is the current state of adoption in your firm for each of these applications?

Interviewer instruction: Read answer options once before reading the questions items. Make sure the respondent understands them and only repeat them if asked.

Rows (randomize items):

- 1. Speech recognition, machine translation or chatbots, also known as natural language processing. *Please exclude grammar or spell checkers*.
- 2. Visual diagnostics, face or image recognition, also known as computer vision
- 3. Fraud detection or risk analysis, also known as anomaly detection
- 4. Analysis of emotions or behaviours, also known as sentiment analysis
- 5. Forecasting, price optimisation and decision-making using machine learning algorithms. *Please exclude the use of classical statistical techniques*.

- 6. Process or equipment optimisation using artificial intelligence. *Please exclude optimisation via Programmable Logic Controllers*.
- 7. Recommendation & personalisation engines using artificial intelligence to produce customised recommendations, via matching algorithms or information retrieval. *Please exclude classical CRM systems or automated email campaigns*. [Interviewer instruction: If asked, CRM refers to customer relationship management systems]
- 8. Process automation using artificial intelligence, including warehouse automation or robotics process automation (RPA).
- 9. Autonomous machines, such as smart and autonomous robots or vehicles
- 10. Creative and experimentation activities, such as virtual prototyping, data generation, artificial music or painting

Columns:

- 0. I am not aware of it
- 1. We do not use it or have plans to use it
- 2. We currently use it
- 3. We have plans to start using it in the next 2 years
- 99. Don't know [Interviewer: Do not read]

SCRIPTER: IF Q1=0 or 99 on all items: SCREENOUT

Base: if any row in Q1=2

Q2. [M] (randomize)

Artificial intelligence software or systems can be acquired via different sources. Which of the following have been used by your firm? Please confirm all that apply.

- 1. We developed it fully in-house
- 2. We modified commercial software or systems
- 3. We modified open-source software or systems
- 4. We purchased software or systems ready to use
- 5. We hired external providers to develop it
- 6. None of the above [S] (fixed)
- 99 Don't know [Interviewer: Do not read] [S] (fixed)

Q3_1. [SGRID]

I will name potential **EXTERNAL** obstacles to the use of artificial intelligence.

Please indicate all that your company has experienced as a challenge or a barrier.

Rows (randomize items):

- 1. The need for new laws or regulation
- 2. Strict standards for data exchange (e.g. data protection laws)
- 3. Reputational risks linked to using artificial intelligence
- 4. Liability for damage caused by artificial intelligence
- 5. Lack of access to high quality private data
- 6. Lack of access to or availability of public data
- 7. Lack of public or external funding
- 8. Lack of trust amongst citizens

Columns:

- 1. Not a challenge or barrier
- 2. A minor challenge or barrier
- 3. A major challenge or barrier
- 4. Does not apply to my firm
- 99. Don't know [Interviewer: Do not read]

Base: if all rows in Q1≠ 2 AND ANY ROW IN Q1 = 1 OR 3

Q3_2. [SGRID]

I will name potential <u>EXTERNAL</u> obstacles to the use of artificial intelligence. Please indicate all that you see as a challenge or a barrier for your company.

Rows (randomize items):

- 1. The need for new laws or regulation
- 2. Strict standards for data exchange (e.g. data protection laws)
- 3. Reputational risks linked to using artificial intelligence
- 4. Liability for damage caused by artificial intelligence
- 5. Lack of access to high quality private data

- 6. Lack of access to or availability of public data
- 7. Lack of public or external funding
- 8. Lack of trust amongst citizens

Columns:

- 1. Not a challenge or barrier
- 2. A minor challenge or barrier
- 3. A major challenge or barrier
- 4. Does not apply to my firm
- 99 Don't know [Interviewer: Do not read]

Base: if any row in Q1=2

Q4.1. [SGRID]

I will name potential <u>INTERNAL</u> obstacles to the use of artificial intelligence. Please indicate all that your company has experienced as a challenge or a barrier.

Rows (randomize items):

- 1. The cost of adoption
- 2. Complex algorithms are difficult to understand and trust
- 3. Lack of skills among existing staff
- 4. It is difficult to hire new staff with the right skills
- 5. Lack of internal data
- 6. The cost of adapting operational processes
- 7. Insufficient or incompatible IT infrastructure

Columns:

- 1. Not a challenge or barrier
- 2. A minor challenge or barrier
- 3. A major challenge or barrier
- 4. Does not apply to my firm
- 99. Don't know [Interviewer: Do not read]

Q4.2. [SGRID]

I will now name potential <u>INTERNAL</u> obstacles to the use of artificial intelligence. Please indicate all that you see as a challenge or a barrier for your company.

Rows (randomize items):

- 1. The cost of adoption
- 2. Complex algorithms are difficult to understand and trust
- 3. Lack of skills among existing staff
- 4. It is difficult to hire new staff with the right skills
- 5. Lack of internal data
- 6. The cost of adapting operational processes
- 7. Insufficient or incompatible IT infrastructure

Columns:

- 1. Not a challenge or barrier
- 2. A minor challenge or barrier
- 3. A major challenge or barrier
- 4. Does not apply to my firm
- 99. Don't know [Interviewer: Do not read]

Base: IF ANY ROW IN Q1 ≠ 0 AND (Q4.1 3 OR Q4.1 4=2-3 OR Q4.2 3 OR Q4.2 4=2-3)

Q4.3. [M] max 3 answers] (randomize)

When it comes to lack of skills among existing staff or difficulties in hiring new staff, which of the following skills do you believe are most needed? Please select maximum three.

- 1. Machine learning or modelling skills
- 2. Cloud computing skills
- 3. Big data management skills
- 4. Programming skills
- 5. Robotics skills
- 6. None of the above [S] (fixed)

Base: if any row in Q1=2

Q5. [S]

Finally, when it comes to using artificial intelligence in the next 2 years, which applies best to your company?

- 1. We have plans to use it less.
- 2. We have plans to use it about the same.
- 3. We have plans to use it more.
- 99. I don't know.

Base: if any row in Q1=2 OR 3

Q6. [S]

Do you agree to share your company name (not your personal details) with the European Commission for participation in follow-up research on this topic?

- 1. Yes
- 2. No

Base: all respondents

End page

Thank you very much for your participation.

You can consult, correct, or delete the information you give at any time. At any moment, you can stop the processing of your information, have your information transferred to you, and withdraw your consent.

Interviewer instruction: if the respondent has questions, refer them to the privacy notice https://survey.ipsos.be/privacynoticeArtificalIntelligence.pdf

This explains the purposes for processing their personal data as well as their rights under data protection regulations to access their personal data, withdraw consent, object to processing of their personal data and other required information.

9.3 Annex C – List of sectors' codes

Code	Sector				
А	Agriculture, forestry and/or fishing				
В	Oil and gas				
С	Manufacturing				
D	Electricity & Water supply				
E	Waste management				
F	Construction				
G	Trade, retail				
Н	Transport				
I	Accommodation, food				
J	ICT				
К	Finance, insurance				
L	Real estate				
М	Other technical and/or scientific sectors				
Р	Education				
Q	Human health, social work				
R	Recreation activities				

9.4 Annex D – Pareto-charts of the variance contained in each component

Figure C1: Spread of variance in the factorization (PCA) of the sectors in function of technologies

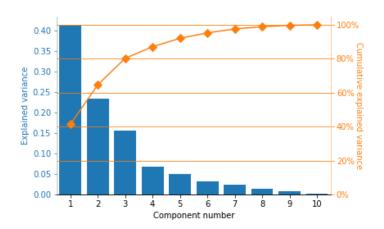
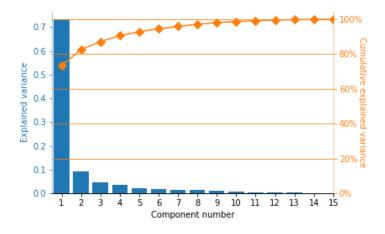


Figure C2: Spread of variance in the factorization (PCA) of the countries in function of the barriers



European Commission

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