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Belgian start-ups in Artificial Intelligence

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Abstract - We attempt to map out as comprehensively as possible the Belgian companies that offer goods or services with an AI component. The 744 Belgian AI start-ups that we identified (founded since 2010) appear, in comparison with non-AI start-ups, to focus primarily on revenue growth, which is often accompanied by a sharp increase in the number of employees. On the other hand, many of the AI start-ups are not yet profitable, especially those with venture capital. AI start-ups without venture capital are overrepresented in the very small group of the most successful Belgian start-ups, which have high turnover, many employees and are very profitable.

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Executive summary

Artificial intelligence (AI) is often seen as a technology that can bring about profound economic and social changes. While there are legitimate concerns about potential risks, recent developments also offer opportunities: AI could accelerate innovation, reverse declining productivity growth and thus contribute to sustainable growth. There is considerable uncertainty about the ultimate impact of AI on economic growth and productivity but high expectations explain why this technology is becoming increasingly central to economic policy and why policymakers consider a critical presence and sufficient dynamism in the AI sector to be crucial for future economic prosperity.

Nevertheless, knowledge about the Belgian AI sector remains fragmentary. There is a lack of information about which companies are active in this field, how successful they are, in which sectors they operate and what their broader impact on the economy is. A better understanding of this sector is necessary in order to evaluate and strengthen AI policy. Our research aims to increase that understanding by mapping Belgian AI producers as comprehensively as possible.

An analysis of a sector or industry usually starts with industry codes, such as the NACE code, which EU countries use to classify the economic activities of companies. For companies active in AI production, there is currently no specific industry code. Most studies of AI companies are therefore based on surveys, data on companies receiving venture capital or companies with patents for AI applications. However, surveys cover only a sample of the business population, and companies with venture capital or patents represent only a small proportion of all AI start-ups, as our study shows. Such an approach therefore provides a very partial overview.

In our study, we therefore started from an existing list of Belgian AI companies, which we supplemented with online information and the results of various web searches in Dutch, French and English. This ultimately yielded 1,027 Belgian companies for which we found a company number in the Crossroads Bank for Enterprises (CBE). We further selected companies that were founded after 2010, to limit ourselves to companies whose core activities are built around recent developments in AI. For our analysis, we only consider companies that offer services or goods based on AI. After verifying that companies are actually active in the field of AI production, and therefore do not just use AI, we are left with 744 Belgian AI start-ups.

Belgian AI start-ups are mainly located in large urban centres, particularly around universities, colleges and research institutions. At the municipal level, Ghent has the largest number of AI companies (108, or approximately 15% of all identified companies). There are 86 based in Antwerp. In Brussels, there are 124 AI start-ups, but they are spread across various municipalities. Leuven (53 AI start-ups) is the only other centre with more than 50 AI start-ups. Hasselt (26), Liège (20), Kontich (16), Louvain-la-Neuve (15) and Charleroi (10) are the only other municipalities with 10 or more AI start-ups.

For the Belgian start-ups in AI that we identified, we tried to determine which AI technologies they use (text mining, speech recognition, speech synthesis, image recognition, machine learning, workflow automation, autonomous robots, text-image generation and hardware) based on available company information (website, media reports). Belgian AI start-ups mainly use AI technologies to automate various workflows or to assist in decision-making, for machine learning for data analysis and for generating written or spoken language (chatbots, translation software). We also tried to find out for which tasks the AI offered can be used (marketing or sales, production or service processes, management, logistics, ICT security, accounting and financial management, research and development). The organisation of business administration or management, marketing or sales, and production or service processes are the main purposes for which Belgian AI start-ups offer applications. Finally, we also examined the sectors in which the customers of Belgian AI start-ups are active. Retail and distribution, health, transport, manufacturing and energy appear to be the most popular sectors.

By using data from the annual accounts of companies, we can compare the business performance of AI start-ups with that of non-AI start-ups. Looking at the main financial ratios, it is striking that the average profitability of Belgian AI start-ups is clearly more negative than that of non-AI start-ups and is also developing less favourably in the period 2010-2023. An increasing proportion of AI start-ups suffer losses and few are managing to make significant profits. In terms of liquidity, however, AI start-ups are performing better than non-AI start-ups. The conclusion regarding solvency is less clear and depends on which indicator is chosen. However, AI start-ups seem to be more dependent on equity financing, such as venture capital, than non-AI start-ups, probably due to the high uncertainty of the activities.

Our analysis also shows that, compared to non-AI start-ups, Belgian AI start-ups mainly aim for rapid growth in turnover, which is often accompanied by a sharp increase in the number of employees. The productivity of AI start-ups is also increasing faster than that of non-AI start-ups. On the other hand, as already evident from the profitability results, many AI start-ups are not yet profitable. In the first few years after their establishment, the losses of AI start-ups often increase, and only from the fifth year onwards is there a slight improvement.

Among the small group of exceptionally successful start-ups (AI start-ups and non-AI start-ups) – companies that simultaneously achieve high turnover, have many employees and are highly profitable – AI start-ups without venture capital are clearly overrepresented. AI start-ups with venture capital, on the other hand, are underrepresented. This can be explained in part by the fact that these start-ups were, on average, established more recently than non-AI start-ups and AI start-ups without venture capital, but perhaps also because they are among the most innovative companies with a higher risk profile, which take longer to become profitable than less innovative companies.

Introduction

In November 2022, the launch of ChatGPT not only led to explosive growth in users worldwide, but also to renewed public interest in artificial intelligence (AI). The chatbot, based on the transformer technology introduced by Google in 2017 (GPT stands for generative pre-trained transformer), uses deep neural networks (deep learning). These networks are particularly suitable for generating language and images, as well as for translation and speech and image recognition.

Some economists are convinced that recent developments in AI are turning it into a general-purpose technology (often also abbreviated to GPT) which, like the steam engine, electricity and the computer before it, will have a major impact on innovation and economic growth and could help to reverse the trend of declining productivity growth. Although it is still too early to tell, there are indications that AI could indeed lead to a technological breakthrough (Damioli *et al* 2024; Baily *et al* 2025; Calvino, Haerle & Liu 2025; Coupé & Wu 2025). The ultimate economic impact will depend on the extent to which companies adopt AI and are able to adapt their business processes to increase their efficiency, the complementarity of AI with the skills of employees, and whether the AI applications offered effectively contribute to productivity growth in general, rather than being limited to useful market niches (Acemoglu 2025; Calvino, Reijerink & Samek 2025; Filippucci *et al* 2025). Brynjolfson, Korinek & Agrawal (2025) discuss the various economic challenges of AI if it were ever to match or even surpass human intelligence in all areas.

Artificial intelligence has a long history. In 1956, during the 'Dartmouth Summer Research Project on Artificial Intelligence', the term 'artificial intelligence' was coined and a research programme was proposed that is still relevant today, covering topics such as natural language processing, neural networks and machine learning. Despite widely differing views on which of the various AI methods had the most potential, there was enormous optimism among all participants about the possibilities of artificial intelligence. The first wave of AI optimism would eventually fade in the early 1970s. New waves followed, following the same pattern of promising research projects and start-ups that could count on government funding – mainly in the United States. Despite some breakthroughs and new insights, each wave ended in disappointment over high expectations that could not be fulfilled. Since the early 2010s, deep neural networks, one of several AI methods, have sparked a new wave of optimism. Most concepts of deep neural networks have been known for a long time. However, what has led to a breakthrough is the availability of large data sets (big data) for training large AI models, and the computing power required for the complex calculations of the models (Mitchell 2019).

Deep neural networks first led to a breakthrough in image recognition and subsequently to large language models (LLMs) and generative AI, with applications such as chatbots, translation programmes, generators of text, images or software code, and numerous other applications. Compared to previous AI waves, where most contributions came from academic research groups, recent breakthroughs are mainly being achieved by large companies that have the resources to make the necessary investments in the development and use of large AI models (foundation models). In addition to the major players, many companies are also being set up worldwide that offer commercial applications based on the large AI models or made possible by adjusting the models to specific tasks. Various parts of the current AI ecosystem are dominated by a limited number of companies. These include the market for specific microprocessors, computer servers (mainly cloud computing) for data storage and calculations, big data required for training neural networks, and the large AI models themselves. Large tech companies such as Amazon, Google and Microsoft are trying to gain a foothold in the large AI models by using their own company data, financial resources and dominance in cloud computing, through participations in Anthropic, DeepMind and OpenAI respectively, but also by strengthening their position in the development of AI microprocessors. The American company NVIDIA, the largest supplier of computer chips for AI, announced a strategic partnership with OpenAI, in which it will invest 100 billion dollars in the construction of AI data centres equipped with NVIDIA computer chips. OpenAI also signed an agreement with the American company AMD, a major competitor of NVIDIA, to supply computing capacity for data centres that will run exclusively on AMD chips.

The increasing concentration throughout the supply chain could potentially slow down the innovative capacity and dynamism of the burgeoning AI sector. For the time being, the market for AI applications is still reasonably dynamic, with numerous start-ups alongside a number of major players. The AI sector is strongly dominated by the United States. However, in early 2025, China's DeepSeek caused a stir with the launch of R1, an open-source language model that, according to the company itself, offers a much cheaper alternative to the large American models. In Europe, there are only a few prominent players. DeepMind, founded in London in 2010 and known for AlphaGo and AlphaFold, was acquired by Google in 2014. French company Mistral, founded in 2023, develops large language models. DeepL, launched in Cologne in 2008, has been offering translation services based on neural networks since 2017. English company Stability AI launched Stable Diffusion in 2022, one of the most popular models for generating images based on a description (text). The Swedish start-up Lovable has experienced rapid growth since its foundation in 2023, thanks to AI applications that enable users to develop software without having to program – an approach known as ‘vibe coding’.

Given the crucial role of the AI sector for innovation and economic growth, it is expected to receive increasing attention in economic policy at regional, national and international level (e.g. EU). However, although it is clear which large companies play a role in the AI ecosystem, there does not currently seem to be a complete overview of Belgian companies active in AI production. The aim of this study is to provide such an overview and analysis of the AI sector in Belgium, focusing specifically on companies established since 2010.

The way in which we identify Belgian start-ups in AI production is discussed in section 1. For the 744 Belgian AI start-ups we identified, we collected additional information about the type of AI technology they use, the purposes for which it is used and the sectors in which their customers operate. In addition, we also tried to find out whether the companies have venture capital, whether they are academic spin-offs and whether they have a patent granted by the European Patent Office (EPO) or the United States Patent and Trademark Office (USPTO). This is discussed in section 2.

The business analysis of the Belgian AI sector is discussed in section 3. In addition to financial ratios such as profitability, liquidity and solvency, we also look at the evolution of turnover, value added, number of employees, operating profit and productivity, comparing AI start-ups with Belgian start-ups that are not active in AI production. We also attempt to determine whether the characteristics of AI start-ups, as discussed in section 2, can partly explain differences in business performance.

1. Identification of Belgian AI start-ups

To obtain an overview of all companies that are active in a particular technological domain in a country, the NACE code is usually considered.[1] This 5-digit code, which all EU countries are required to use when compiling economic statistics and determining industries for national accounts, is used in Belgium by the VAT administration and the National Social Security Office to classify companies according to their economic activities.[2] The NACE codes of Belgian companies are publicly available via the Crossroads Bank for Enterprises (CBE), a database of the FPS Economy in which all basic data on companies and their establishments are collected.

As far as artificial intelligence is concerned, no specific NACE code exists for the direct identification of AI companies.

Weber *et al* (2022), Bessen *et al* (2022) and Altunay & Vetter (2024) used data from Crunchbase, a database containing information about start-ups, particularly venture capital investments, to identify AI start-ups. Bessen *et al* (2022) supplemented this data with two lists of AI start-ups. Dinlersoz, Dogan & Zolas (2024) used the Business Formations Statistics from the U.S. Census Bureau to identify AI start-ups in the United States, for the period 2004-2019, with projections for the years 2020 to 2023. The Business Formations Statistics contain information on applications, for a company registration number, from individuals intending to start a business with employees. Based on a text analysis of the description of planned activities, Dinlersoz, Dogan & Zolas (2024) identify start-ups in AI.

In order to identify which AI companies were created in Belgium – without limiting ourselves to companies that receive venture capital – we opted for a different approach, as shown schematically in Graph 1. We started from existing lists of AI companies, as Bessen *et al* (2022) did to supplement data on start-ups from Crunchbase. Vaeremans (2025) supplemented the list of 'AI start-ups and AI scale-ups in Belgium'. This list was compiled in 2021 by the Observatory for AI and New Digital Technologies, as part of AI4Belgium, a coalition of AI players from government services, the private sector, academia and civil society coordinated by the Federal Public Service Policy & Support (BOSA). We have further supplemented this list based on information available online. There are various lists of 'Belgian AI companies' on the internet, compiled by companies that specialise in 'web scraping', which involves using software to extract information from web pages. In addition to a lot of incorrect and irrelevant data, these lists contain information about Belgian companies with AI activities that were not yet included in the list.

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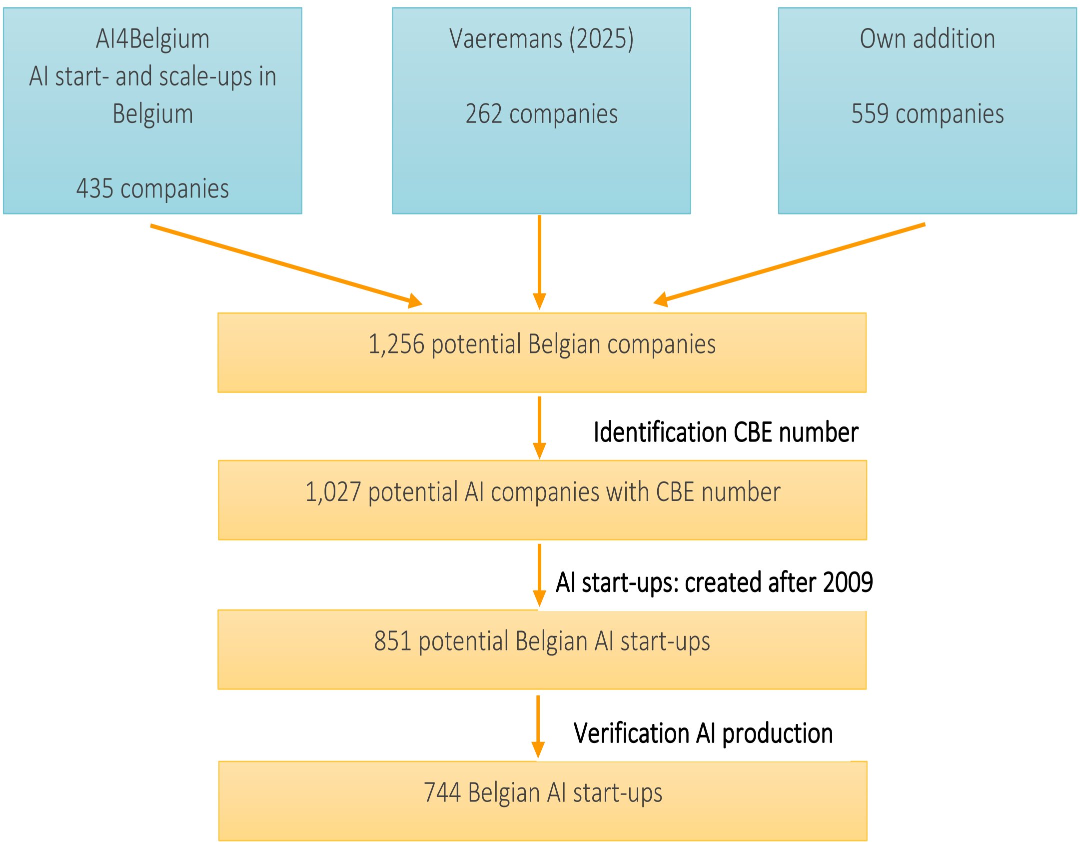
1 NACE stands for Nomenclature générale des Activités économiques dans les Communautés Européennes. The first NACE classification dates from 1970. From 2025 onwards, the fourth revision, NACE 2.1, will be used.

2 When a company registers with the Crossroads Bank for Enterprises (CBE), it must report the activities it will carry out. In the CBE, these activities are then converted into the correct NACE codes, distinguishing between main activities and secondary activities. The activities must also be reported to the VAT administration and the National Social Security Office. The National Social Security Office independently assigns NACE codes when registering a company as an employer. As a result, there may be a difference between the NACE codes according to VAT activities and according to National Social Security Office activities. Almost half (48.5%) of the Belgian AI start-ups that we identified are active in NACE 62010 (Computer programming activities) or NACE 62020 (Computer consultancy activities).

We also carried out various searches for Belgian companies active in Artificial Intelligence, in Dutch, French and English.[3] In addition to references to lists of AI companies, this also yielded information from articles in newspapers or magazines or from websites. This ultimately resulted in a list of 1,256 possible names of Belgian companies that are believed to be active in artificial intelligence.

Graph 1 Identification of Belgian AI start-ups



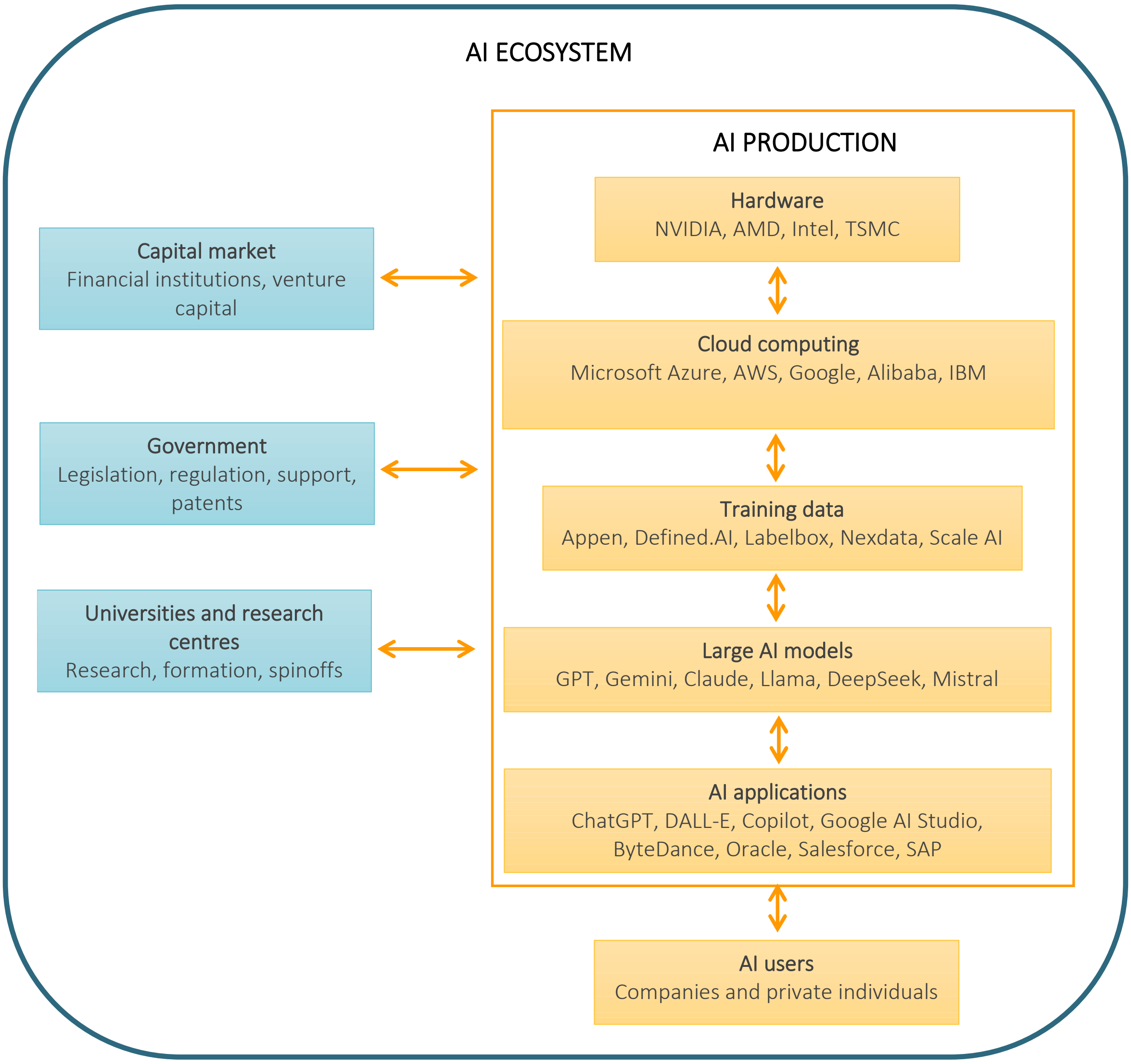
The names on this list were checked to see whether they could be linked to a Belgian company number in the Crossroads Bank for Enterprises (CBE). Some turned out to relate to applications or platforms, for which the name of the company had to be traced, for example on the basis of information on the corresponding website. In several cases, particularly for information based on web scraping, it turned out that there was no artificial intelligence involved or that there was no link whatsoever with a Belgian company. Of the list of 1,256 names, 1,027 CBE numbers could be identified. Natural persons, non-profit organisations, public utility institutions and foreign entities were excluded. For example, universities and colleges that appeared in the list of 1,256 were not included. Although they play a very important role in the artificial intelligence ecosystem, we decided not to include them because the business variables from the annual accounts of universities and colleges only reflect their activities in the field of artificial intelligence to a limited extent.

[3] This list includes the following terms: Dutch - artificiële intelligentie, kunstmatige intelligentie, AI, KI, bedrijven, ondernemingen, start-ups, start-ups, starters, België, Belgische; French - intelligence artificielle, IA, firmes, entreprises, startups; start-ups, jeune pousse, Belgique, belges and English - artificial intelligence, AI, firms, enterprises, companies, startups, start-ups, starters, Belgium, Belgian.

Box 1 The AI ecosystem

The artificial intelligence ecosystem comprises various actors who play a role in the development and diffusion of the technology. For our analysis, we will limit ourselves to AI production. Gambacorta & Shreeti (2025) distinguish five components of the AI supply chain: hardware, cloud computing, training data, large AI models (foundation models) and AI applications (user-facing applications).

Graph 2 The main actors in the Artificial Intelligence ecosystem



Note: the graph is an adapted and expanded version of the representation of the AI supply chain by Gambacorta & Shreeti (2025). The arrows go in two directions because they refer not only to market transactions (supplier-purchasers) but also to knowledge flows that run in both directions. The graph does not show arrows for the various cross-holdings between companies in the value chain, which are gradually turning the global AI ecosystem into an inextricable tangle of mutual and conflicting interests.

Hardware mainly refers to microprocessors, such as graphics processing units (GPUs), which are specifically designed for the calculations involved in training AI models. Cloud computing refers to platforms that offer services, often described as software as a service (SaaS), for data storage or for the computing power needed to train or use AI models. 'Training data' are large files of text, images (photographs, drawings, video) or sound, from public or proprietary sources, which are used to train AI models, often after labour-intensive labelling of the collected data. The foundation models are trained on the basis of large data files, after which they can be used for applications such as chatbots, generating new text or images, predictions, research and development, or coding assistance.

Because we want to focus our analysis on companies whose core activities are built around artificial intelligence (AI natives), we further select, following Weber *et al* (2022), only companies that were founded from 2010 onwards. For all 851 companies founded after 2009, we checked whether there are indications that they are effectively engaged in activities that fall under AI production, as discussed further below. This ultimately brings us to 744 Belgian AI start-ups.

For our analysis, we limit ourselves to AI production, i.e. companies that offer services or goods based on AI technology (see section 2.1 for definitions). Box 1 shows the main actors in the AI ecosystem. We do not consider venture capital providers, universities, colleges, research institutions and the government in our business analysis. For the AI start-ups that we identified, we checked whether they have venture capital (section 2.2), whether they are academic spin-offs (section 2.3) and whether they have been granted patents (section 2.4). Companies that use artificial intelligence but do not offer AI applications themselves are also not included in our analysis.

The first four components of AI production identified by Gambacorta & Shreeti (2025), as shown in Box 1, 'hardware', 'cloud computing', 'training data' and large AI models (foundation models) are dominated by a limited number of large companies. NVIDIA has a market share of approximately 90% for GPUs, and in 2023 Amazon, Microsoft and Google accounted for 74% of the cloud computing market. There are currently more than 300 foundation models, but these are owned by only 14 companies, and OpenAI is said to account for 69% of global revenue from generative AI with GPT-4. High fixed costs and network effects, among other factors, create significant barriers for new players to enter the market, although China's DeepSeek caused a shockwave in early 2025 with its smaller and cheaper R1 model. While AI activities in the areas of hardware and cloud computing are quite profitable, revenues from large AI models are not yet sufficient to offset the high costs of developing and managing these models. The market for AI applications appears to be more open, with many start-ups focusing on commercial applications based on large AI models. Sometimes these are applications that focus on specific sectors, but there are also companies that offer more general applications to automate or predict certain activities or processes. It is possible that market concentration in AI applications will also increase in the long term. ChatGPT already accounts for 60% of all chatbot activity, and OpenAI recently acquired IO, a start-up founded by Jony Ive, the designer of the iPhone, for $6.5 billion, with the aim of developing AI devices in a market that is currently dominated by software applications. Companies such as Microsoft – by offering Copilot in all its products – and Google – by integrating AI assistant Gemini into searches – are also trying to gain a foothold in the AI applications market. Box 1 shows that different companies occupy a dominant position in each component. However, large tech companies are trying to strengthen their position throughout the entire production chain. By using their own company data, financial reserves and dominance in cloud computing, Amazon, Google and Microsoft are trying to gain a foothold in foundation models, through participations in Anthropic, DeepMind and OpenAI respectively, but also in the field of microprocessor development. This trend towards dominance by a small number of companies poses a risk of moderate business dynamics and a brake on innovation. It also increases the gap between socially desirable AI applications and the profit motive of companies (Gambacorta & Shreeti 2025, Korinek & Vipra 2025). According to André, Bétin & Gal (2025), the various segments of the AI value chain are currently more open than expected, with rapid successive innovations, lower prices (adjusted for quality) and sufficient supply, allowing users to weigh up the performance, costs and data protection of AI applications.

Of the Belgian AI start-ups we have identified, the majority are active in AI applications and only a limited number in 'hardware' or 'cloud computing'. To our knowledge, no Belgian company is developing a large AI model itself.

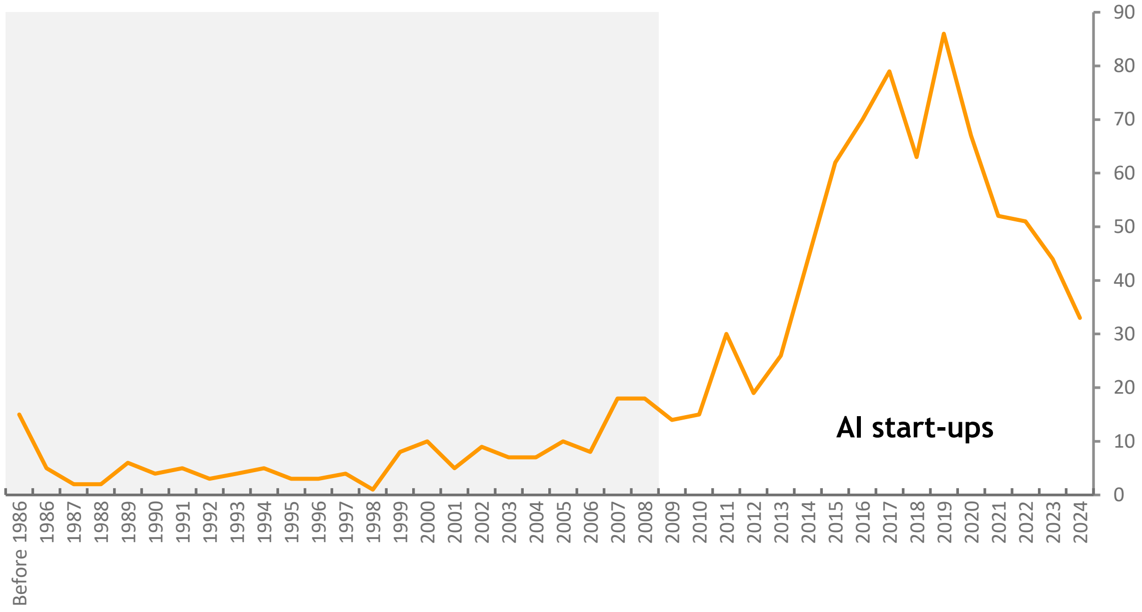
Because we want to define artificial intelligence as narrowly as possible in our analysis, we have decided to consider only companies founded since 2010, as Weber *et al* (2022) did. By limiting ourselves to companies founded since 2010, we are more likely to pick up mainly 'AI native' start-ups, i.e. companies whose core activities are based on artificial intelligence (Weber *et al* 2022, Penzel 2025). In their study on the financing of AI start-ups, Alltunay & Vetter (2024) consider 2012 as the starting year for recent AI developments. This prevents companies such as IBM from being counted as AI start-ups, which is the case in Crunchbase, the database they use for their analysis. IBM Belgium is included in our list of 1,027 identified companies, but since it was founded in 1936, it is not one of the 744 Belgian AI start-ups.

The choice to consider 2010 as the starting year is, given the long history of neural networks that underpin recent AI developments, somewhat arbitrary. Nevertheless, given the following brief overview of a number of recent developments, it seems justified to start from 2010 (Mitchell 2019, pp. 82-91):

– In 2010, the first ImageNet Large Scale Visual Recognition Challenge was organised. ImageNet, developed by Fei-Fei Li, originally contained 3 million labelled images. The Challenge assessed programmes on their ability to correctly categorise images after training on 1.2 million images. The winning team used a sophisticated mathematical algorithm for image recognition (support vector machine) and achieved a score of 72%. The teams that participated with neural network algorithms did not score very high.
– In 2010, DeepMind Technologies was founded in London, which would play an important role in the most recent AI wave, among other things by introducing 'reinforcement learning'. In 2014, this AI start-up was bought by Google for 650 million dollars.
– In the 2012 Imagenet Challenge, the convolutional neural network AlexNet achieved a score of 85%. In the same year, Geoffrey Hinton demonstrated that deep neural networks were superior in speech recognition. His company was acquired by Google. Many large companies hired experts in deep learning, and start-ups in the field could count on support from venture capital funds.
– In 2017, the last Imagenet Challenge took place, with a winning score of 98%. The success of deep neural networks is due to large data sets and fast parallel computing capacity, which has led to applications such as image recognition for smartphones, self-driving cars and medical diagnoses.
– In 2017, there was a new breakthrough in the development of artificial intelligence, with Google's introduction of the 'transformer', which forms the basis of 'generative pretrained transformers (GPTs)', large language models (LLMs) that were quickly developed by other companies such as OpenAI, founded in 2015, which launched ChatGPT in 2022.

Graph 3 shows the number of potential Belgian AI companies according to the year in which they were founded. For the Graph, the 15 companies founded before 1986 are grouped together in the first observation, 'before 1986', because their foundation is spread between 1919 and 1983. The 107 companies that were founded after 2009 but which we did not retain as AI producers after verification are not shown in the Graph. Of the 176 companies that were founded before 2010, and which we therefore do not include in our analysis, we have not verified whether they meet our definition of AI producers.

Graph 3 Belgian AI companies by year of establishment
Number of start-ups



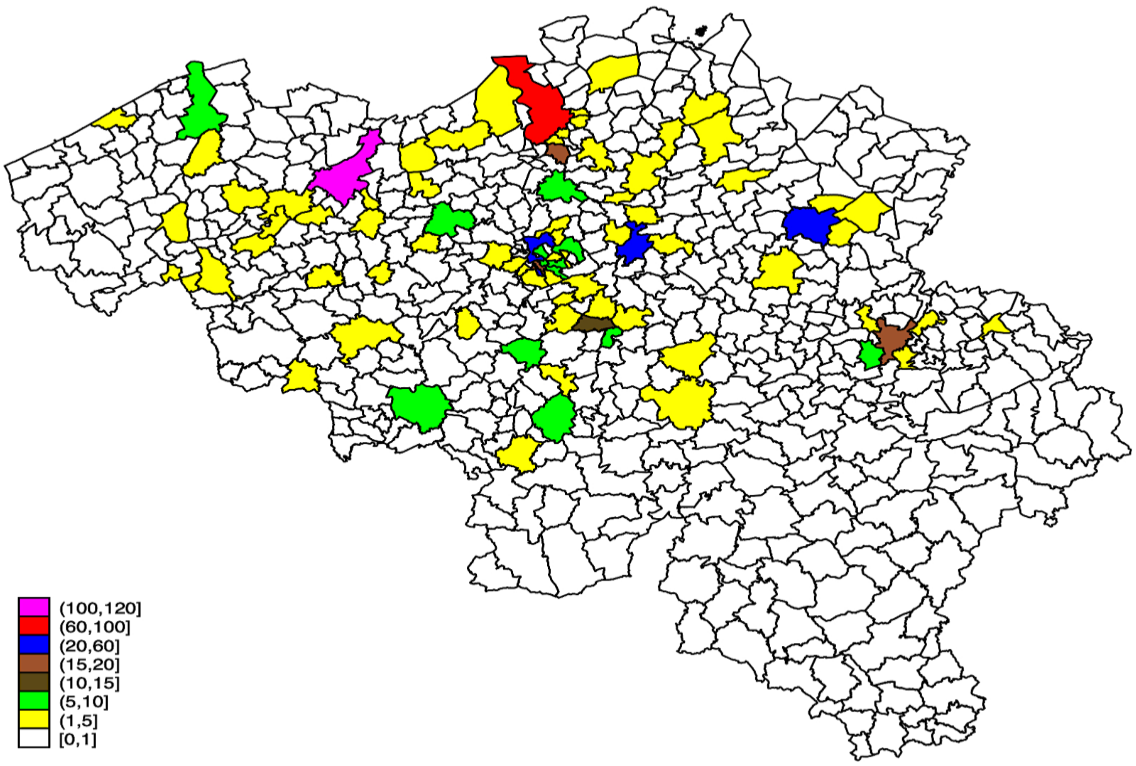
Note: the Graph shows the number of Belgian AI companies identified by us according to year of establishment (registration in the Crossroads Bank for Enterprises).

Graph 3 shows that the number of start-ups remained fairly constant between 1986 and 1998. From 1999 onwards, we see a slight increase, coinciding with the breakthrough of the internet. A surge is apparent after 2010, especially between 2014 and 2020, with a peak of 86 start-ups in 2019. From 2021 onwards, the number of Belgian AI start-ups declined. For the time being, we do not see any strong increase as a result of the launch of ChatGPT in 2022. The identification of AI start-ups for our analysis was completed on 16 April 2025. Consequently, the number of start-ups in 2025 is limited, as only the first months of the year are taken into account. These are therefore not included in Graph 3. The fact that recent start-ups are likely to be more partially included in our database is less important for the business economic analysis, as it is based on information from filed annual accounts, which are not yet available at the time of our study for companies established in 2024 or 2025.

After closing the data collection (16 April 2025) for the analysis discussed in this paper, we identified 17 additional potential Belgian AI companies, mainly based on media reports, of which four were established in 2024, four in 2025 and two before 2010. These companies are not included in the data for Graph 3, nor in our business analysis.

Graph 4 shows the number of AI start-ups since 2010 by municipality, based on information from the Crossroads Bank for Enterprises. It is immediately apparent that AI start-ups are mainly located in large urban centres and, more specifically, around universities, colleges and research institutions.

Graph 4 Location of Belgian AI start-ups (2010-2025) by municipality



At the municipal level, Ghent has the largest number of AI companies (108 or approximately 15% of all identified companies); Antwerp has 86. The concentration of AI companies in Brussels is less noticeable due to their spread across different municipalities, but there are 124 companies in the entire region. Leuven (53) is the only other city with more than 50 AI start-ups. Hasselt (26), Liège (20), Kontich (16)[4], Louvain-la-Neuve (15) and Charleroi (10) are the last locations with 10 or more AI start-ups. The centre of gravity for AI start-ups is therefore in the north of the country, more specifically in Brussels and the provinces of East Flanders, Antwerp and Flemish Brabant.

4 The relatively large presence of AI start-ups in Kontich is due to start-ups linked to the Cronos Group, which is based in Kontich.

2. Characteristics of Belgian AI start-ups

Weber *et al* (2022) distinguish four types of start-ups in AI. For *'AI-charged product/service providers',* ready-made AI models form the core of the reasonably standardised goods or services that they offer. The applications of this type of start-up usually offer a solution for specific tasks such as detecting prohibited items at airports or checking X-rays by dentists. *'AI development* facilitators' focus on facilitating AI developments for customers by offering programmable interfaces or development kits for software, in addition to applications that allow customers to create applications such as chatbots without having to program themselves. The recent development of vibe coding, in which the rapidly growing Swedish start-up Lovable plays an important role, seems to be a good example of this. This type of start-up focuses on a wide range of industries and often tries to generate value through subscriptions rather than one-off payments. The applications offered by *data analytics* providers are based on the integration and analysis of large internal and external data sources. The data is usually analysed using 'conventional' machine learning methods, while the integration often has to be tailored to the customers (mainly companies) first. As an example of this type of AI start-up, Weber *et al* (2022) refer to a start-up that integrates company information with external data to detect and predict anomalies and patterns in customer and profitability data, and a start-up that uses data from sensors and machines to predict the condition of machines. *Deep tech* researchers conduct research and development into niche innovations using the most advanced AI technology, particularly in areas such as robotics, self-driving vehicles and the development of new medicines. This type of start-up is research-driven and does not usually offer standardised or easily adaptable solutions for general use. Some, such as start-ups active in robotics, also develop their own hardware.

The classification of AI start-ups by Weber *et al* (2022) is based on data on 11 dimensions and 39 characteristics from a sample of 100 companies out of a total of 8,076 AI start-ups with venture capital, founded after 2010. The data we collected does not allow us to assign the 744 Belgian AI start-ups to one of the four types.

For the AI start-ups, we do have additional information about the AI technologies they use, the purposes for which those technologies are used and the sectors in which their customers (AI users) operate. We discuss this in section 2.1. In section 2.2, we describe the importance of venture capital and the number of Belgian AI start-ups for which we were able to determine whether they are (or were) supported by venture capital. We also examined whether the AI start-ups are academic spin-offs (section 2.3) and, in section 2.4, whether they hold patents granted by the European Patent Office (EPO) or the United States Patent and Trademark Office (USPTO).

2.1. Technologies, purposes and user sectors

As a guide to the technologies used by AI start-ups and the purposes for which they are used, we follow the definitions used by Eurostat[5] in its survey on the use of ICT and e-commerce in enterprises. For Belgium, this survey is conducted annually by the Belgian Statistical Office (Statbel).

The 2024 survey (Statbel 2024) is based on the following definition of AI: "Artificial Intelligence refers to systems that use technologies such as text mining, computer vision, speech recognition, natural language generation, machine learning and deep learning to collect and/or use data to predict, recommend or decide on the best action to take, with varying levels of autonomy, in order to achieve specific goals."

Artificial Intelligence systems can be entirely software-based, e.g.:

- chatbots and virtual assistants based on natural language processing
- facial recognition systems based on computer vision or speech recognition systems
- automatic translation software
- data analysis based on machine learning, etc.;

or built into equipment, e.g.:

- autonomous robots for warehouse automation or assembly work
- autonomous drones for production monitoring or parcel handling, etc.

The survey considers seven different AI technologies (Statbel 2024):

1) Technologies for analysing written language (**text mining**)
2) Technologies for converting spoken language into a machine-readable format (**speech recognition**)
3) Technologies for generating written or spoken language (natural language generation, **speech synthesis**)
4) Technologies for identifying objects or people based on images (**image recognition**, image processing)
5) **Machine learning** (e.g. deep learning) for data analysis
6) Technologies for **automating various workflows** or assisting in decision-making (artificial intelligence-based software robotic process automation)
7) Technologies that enable the physical movement of machines through autonomous decisions based on observation of the surroundings (**autonomous robots**, self-driving vehicles, autonomous drones).

[5] Eurostat is a directorate-general of the European Union responsible for compiling statistics and striving for comparability between Member States.

To get a full picture of AI production (see Box 1) and to take recent developments into account, we have added two AI technologies to this classification based on descriptions on the companies' websites or reports in the media:

8) **Text-image generation**. In addition to generating written or spoken language, with chatbots and translation programmes as the main applications, GPT models are also used to generate new images based on text or visual input, or to obtain descriptions of images based on images. Image generation is a relatively recent application and is therefore probably not yet included in Eurostat's definition. However, a significant number of AI start-ups already appear to be offering applications in the field of image generation, often based on major players such as DALL-E (from OpenAI), Stable Diffusion (from the British company Stability AI) and the American company Midjourney.

9) **Hardware.** Some companies specialise in offering hardware specifically for AI applications. This includes access to computer servers, whether or not via cloud applications, but also specially designed chips, in which graphics processing units (GPUs) are particularly important and in which the American company NVIDIA has acquired a dominant market position. The number of Belgian start-ups focusing on hardware for AI seems limited, but because of their important role in the ecosystem, we have nevertheless added this category.

A much-discussed recent development – with a long history – is AI agents and collaboration between AI agents (multi-agents). These are AI applications with a certain degree of autonomy to make decisions. Some see this as a potential breakthrough for increasing the productivity of businesses and organisations through far-reaching automation. When AI agents are mentioned by Belgian start-ups, we have assigned this to technologies for automating various workflows or assisting in decision-making[6] .

Eurostat also considers seven purposes for which AI can be used by companies (Statbel 2024):

1) For **marketing or sales,** e.g.
   - natural language processing-based chatbots for customer support
   - autonomous robots for order processing
   - customer profiling, price optimisation, personalised marketing offers, market analysis based on machine learning, etc.

2) For **production or service processes,** e.g.
   - preventive maintenance or process optimisation based on machine learning
   - tools for classifying products or detecting defects in products based on computer vision
   - autonomous drones for production monitoring, security or inspection tasks
   - assembly work by autonomous robots, etc.

[6] Mitchell *et al* (2025) provide an overview and discussion of the advantages and disadvantages of AI agents.

3) For the organisation of business administration or **management,** e.g.
   - business virtual assistants based on machine learning and/or natural language processing, e.g. for drafting documents
   - data analysis or strategic decision-making based on machine learning, e.g. risk assessment based on machine learning
   - planning or business forecasting based on machine learning
   - personnel management based on machine learning or natural language processing, e.g. pre-selection of candidates, employee profiling or performance analysis, etc.

4) For **logistics,** e.g.
   - autonomous robots for pick-and-pack solutions in warehouses for parcel shipping, tracking, distribution or sorting
   - route optimisation based on machine learning, etc.

5) For **ICT security**, e.g.
   - facial recognition based on computer vision for the authentication of ICT users
   - detection and prevention of cyber-attacks based on machine learning, etc.

6) For **accounting**, controlling or financial management e.g.
   - machine learning to analyse data that assists in financial decision-making
   - invoice processing based on machine learning
   - machine learning or natural language processing for accounting documents, etc.

7) For **research and development** (R&D) or innovation activities (excluding AI research), e.g.
   - data analysis for conducting research, solving research problems, developing a new or significantly improved product/service based on machine learning, etc.

Based on information available on the companies' websites or information in newspapers, magazines or other online sources, we tried to find out which AI technologies all 744 Belgian AI start-ups used and for what purposes.

Table 1 shows the number of Belgian AI start-ups that use the nine different AI technologies for the AI production or for the products that they offer. With the information available to us, it is not always possible to distinguish between AI technology used by AI start-ups in the production of the goods or services that they offer and AI technology provided by AI start-ups to their customers. AI is clearly most commonly used for services that help companies automate their business administration processes and for data analysis. Despite its relatively recent development, there are already 49 companies offering text-image generation applications. The number of Belgian start-ups specialising in artificial intelligence hardware is very limited. Belgian AI start-ups use an average of 2.1 different AI technologies.

Table 1 AI technologies used by Belgian AI start-ups
Number of start-ups using the technology mentioned

1.	Automating various workflows or assisting in decision-making	486
2.	Machine learning for data analysis	461
3.	Speech synthesis, generating written or spoken language (chatbots, translation software)	252
4.	Image recognition, image processing	172
5.	Autonomous robots, self-driving vehicles, autonomous drones	61
6.	Text mining	57
7.	Text-image generation	49
8.	Speech recognition	42
9.	Hardware (servers, cloud services, computer chip design or development)	9

Note: the table shows, for each category of AI technology as defined in the text, the number of Belgian AI start-ups that use it for the services (or goods) they offer. An AI start-up may use different technologies.

Results from the Belgian survey 'ICT and e-commerce in enterprises' from 2023 (Statbel 2024) show that the use of AI technologies by Belgian enterprises is comparable to the results in Table 1, except for written language analysis (text mining). According to the survey, this is the most widely used technology by both small enterprises and enterprises with 250 or more employees, but it only ranks sixth in Table 1. Although our data only relate to companies active in AI production, and not to all Belgian companies that use AI as in the survey, it is possible that we underestimate the importance of text mining by AI producers because they do not provide specific information on this technology. The fact that Belgian companies mainly use AI to generate language, to automate workflows or decision support, or for machine learning for data analysis is consistent with the results in Table 1.

Table 2 shows that Belgian AI start-ups mainly use their AI technologies to provide goods or services for the organisation of business administration or management, marketing or sales, and production or service processes. On average, they have 1.6 different purposes.

Table 2 AI purposes of Belgian AI start-ups
Number of start-ups with stated purpose

1.	The organisation of business administration or management	371
2.	Marketing or sales	256
3.	Production or service processes	245
4.	Logistics	148
5.	Research and development or innovation activities	120
6.	Accounting, financial management control	55
7.	IT security	22

Note: the table shows, for each category of purpose of the AI technology used, as defined in the text, the number of Belgian AI start-ups for which the purpose could be identified. There may be different purposes for the same AI start-up.

Table 3 shows, for each AI technology, the percentage of AI start-ups that use the given technology for a given purpose. The technologies and purposes are ranked in descending order, as shown in Table 1 and Table 2 respectively.

Table 3 Combination of artificial intelligence technologies and purposes by Belgian AI start-ups
Percentage of companies using technology for a given purpose

	Management	Marketing	Production/service	Logistics	Research and development	Accounting	IT security
Automation	66	35	31	21	13	10	3
Machine learning	52	34	34	20	20	8	4
Speech synthesis, generating written or spoken language (chatbots, translation software)	68	54	27	11	8	10	3
Image recognition	33	28	53	28	19	2	2
Robotics	23	8	72	52	15	0	2
Written language analysis	81	39	14	11	2	18	4
Image generation	39	61	47	14	12	2	0
Speech recognition	48	45	38	19	21	2	0
Hardware	22	0	67	11	33	0	0

Note: the table shows, for each AI technology, the percentage of AI start-ups that use that technology for which purpose. A technology can be used for different purposes, so the percentages do not add up to 100 per row (technology).

Of the companies that provide AI-based goods or services to automate various workflows or to assist in decision-making, 66% apply this technology for the organisation of business administration or management, 35% for marketing or sales, and 31% for production or service processes. Some technologies are slightly more specifically targeted at certain purposes, such as robotics, which is used by 72% of companies for production or service processes, and written language analysis (text mining), which is used by 81% of companies for the organisation of business administration or management.

We also attempted to identify the customers of AI start-ups, for example based on customer testimonials or project discussions on the website of the AI start-ups or in media reports, and to assign them to sectors. We consider 38 different sectors (see Table 4). The identification of the sectors in which AI start-ups operate, based on publicly available information, is likely to provide only a partial picture of their activities. For some companies, it is more difficult to identify who their customers are. For example, AI start-ups that specialise in ICT security are understandably reluctant to discuss their customers.

Table 4 shows the sectors in which AI start-ups are active, based on information about their customers or specific applications. On average, they appear to offer their AI applications in 3.5 sectors. Since only part of the information about the customers of Belgian AI start-ups is publicly available, the distribution per sector must be based on partial information. Retail and distribution, health, transport, manufacturing and energy are the sectors in which Belgian AI start-ups are most active. In addition, there also appear to be a relatively large number of applications for the public sector and non-profit organisations, the financial sector, private individuals (leisure), the IT sector and the pharmaceutical sector. Baily *et al* (2025) find that in the United States, AI is used relatively frequently in sectors such as health, energy, finance and IT.

Table 4 Sectors in which the customers of Belgian AI start-ups are active
Number of AI start-ups that have at least one customer in the sector

1	Retail and distribution	216
2	Health	200
3	Transport	183
4	Manufacturing industry (except where specifically mentioned)	178
5	Energy	143
6	Government + non-profit	138
7	Financial sector	129
8	Leisure (culture, sports, events, etc.)	116
9	Information technology	114
10	Pharmaceutical	111
11	Food	99
12	Education/training	80
13	Media	77
14	HR	77
15	Construction	77
16	Telecommunications	68
17	Security	60
18	Real estate	53
19	Environment	52
20	Advertising/marketing	42
21	Chemistry	40
22	Agriculture	39
23	Consultancy	36
24	Accounting	34
25	Legal	34
26	Hospitality	33
27	Waste processing	26
28	Tourism	25
29	Electronics	23
30	Augmented Reality/Virtual Reality (AR/VR)	23
31	Engineers/consultancy firms	21
32	Gaming	21
33	Personal services (cleaning, temporary work, etc.)	18
34	Beauty care, cosmetics	15
35	Mining	14
36	Aerospace	10
37	Translation	9
38	3D printing	5

Note: the table shows the number of Belgian AI start-ups offering their services or goods in the sector. For example, there are 216 AI start-ups that have at least one customer in retail and distribution.

2.2. Venture capital

The availability of venture capital[7] is often seen as an important factor in the success and growth of start-ups. However, venture capital financing of many successful start-ups may be the result of a selection mechanism, whereby venture capital providers select start-ups with the greatest investment potential. Bertoni, Colombo & Grilli (2011) studied 538 Italian start-ups in high-tech sectors, 58 of which received venture capital. Their study shows that venture capital has a positive impact on the growth of companies, mainly in terms of the number of employees. For their sample of Italian start-ups, there were no indications of a selection mechanism.

Pantea & Tkacik (2024) provide a recent overview of 34 studies for 17 European countries over the period 2000-2023, including 14 studies that also consider Belgium. Venture capital appears to have a positive impact on employee and turnover growth as well as on investment by companies, as it reduces the credit constraints of start-ups. Studies on the impact on productivity and innovation provide more mixed results.

Alltunay & Vetter (2024) examine the financing of AI start-ups. Start-ups often encounter difficulties in obtaining credit from financial institutions because they are not yet profitable and do not have sufficient assets to serve as collateral for a loan. They are therefore more reliant on equity financing from specialised investors, such as business angels or venture capitalists. In addition to their financial contribution, these investors can also contribute to the success of start-ups through their experience, network or complementary expertise. Based on data on start-ups and venture capital from Crunchbase, the study maps a network of 10,779 AI start-ups and 17,111 investors. In contrast to previous studies with mixed results on the impact of venture capital provided by large companies (corporate venture capital) on the success of start-ups, the results of the study for AI start-ups point to strongly positive effects. The results for the impact of other venture capital providers on AI start-ups are less clear. Berger *et al* (2025), on the other hand, based on an analysis of company data for 60 countries, find evidence that participation by corporate venture capital has a negative impact on the innovation of the acquired start-ups, measured by the number of patents granted after the participation or acquisition. An analysis by Huang *et al* (2023) shows that participation by large tech companies in IT start-ups has a negative impact on the amounts that the latter raise in subsequent financing rounds and also reduces the likelihood of a successful exit (initial public offering or acquisition). According to the authors, large tech companies use patents to try to establish a dominant position in new technologies in order to exclude potential new investors in subsequent financing rounds.

To assess the impact of venture capital, we tried to find out whether the 744 Belgian AI start-ups that we identified benefit from venture capital. For this, we relied on online information and media reports. We also used information from imec.istart, which since 2011 has been providing *seed capital* to start-up technology companies in the early stages of their development, for amounts ranging from €100,000

[7] Venture capital is capital made available to start-ups by, for example, venture capital funds or investment funds. Venture capital providers invest in start-ups with strong growth potential, but which are subject to considerable uncertainty, with the aim of eventually selling their risky stake at a high return, for example through an acquisition by a large company or an initial public offering.

to €250,000. Launched in 2024, the imec-istart future fund provides capital for promising start-ups in digital technology to continue to grow, known as Series A financing.[8]

According to the State of Belgian Tech Report 2024 (Syndicate One, Bain & Company, & Sofina 2024), the ecosystem of capital providers and support institutions around technology companies in Belgium has recently been strengthened, although it is still less mature than in the United States and other European countries. Compared to other countries, financing for start-ups in Belgium is currently still more focused on the initial development phase of start-ups and less on the later growth phase. With nearly €500 million in venture capital invested in start-ups in the first half of 2024, Belgium reached a record amount and experienced a stronger post-COVID recovery than Europe as a whole. AI companies accounted for 70% of venture capital provided in Belgium. However, the recent increase in funding for AI start-ups is largely due to a limited number of large funding rounds, such as those of the Ghent-based companies TechWolf and Robovision.[9] The report also mentions that Belgium currently has only four unicorns. These are young companies with a valuation of 1 billion dollars or more. The four Belgian unicorns - team.blue, Collibra, Odoo and Deliverect - are on our list of 1,027 identified AI companies and, except for Odoo, which was founded in 2002, are also among our AI start-ups. Founded in 2017, Ghent-based Lighthouse Intelligence became the fifth Belgian company to achieve unicorn status at the end of 2024 and is also one of our 744 AI start-ups.[10]

For 156 of the 744 Belgian AI start-ups, we have information that they have been able to count on venture capital, without being able to distinguish between the stage of financing or the type of investor.

Graph 5 shows the evolution of venture capital investments in AI between 2012 and 2024, based on data from the OECD, both in millions of dollars (left graph) and in the number of investments (right graph). We compare the evolution for Belgium with the global evolution, that for the United States and for the EU 27 as a whole. In the right-hand side graph, in addition to the OECD data for Belgium, we also show the number of Belgian AI start-ups that we identified, for which we have been able to ascertain that they have received venture capital.

The evolution of the total amount of venture capital investment in AI in Belgium is very similar to the global evolution, with an increase until 2021 and a decline in the following years.[11] In 2024, there is a temporary resurgence - probably as a result of the breakthrough of ChatGPT in 2023 – that is more pronounced in Belgium than in the world, the United States or the EU 27. Looking at the number of investment files, it appears that in Belgium, unlike the rest of the world, these will continue to rise after 2021, peaking at 23 in both 2022 and 2024. Belgium's share of global venture capital investment in AI is fairly low but has risen sharply, from 0.04% in 2012 to 0.13% in 2024 in terms of Belgium's share of the

[8] Various phases are distinguished in the financing of start-ups. Alltunay & Vetter (2024) distinguish between the seed, start-up, expansion and buy-out phases. For financing after the seed phase, a further distinction is made between Series A, B and C.

[9] TechWolf, founded in 2018, is included in our list of 744 Belgian AI start-ups. Robovision, founded in 2008, is included in our list of 1,027 identified Belgian companies, but because it was founded before 2010, it is not one of our 744 AI start-ups. But Robovision Integrated Solutions, founded in Ghent in 2011, is in that list.

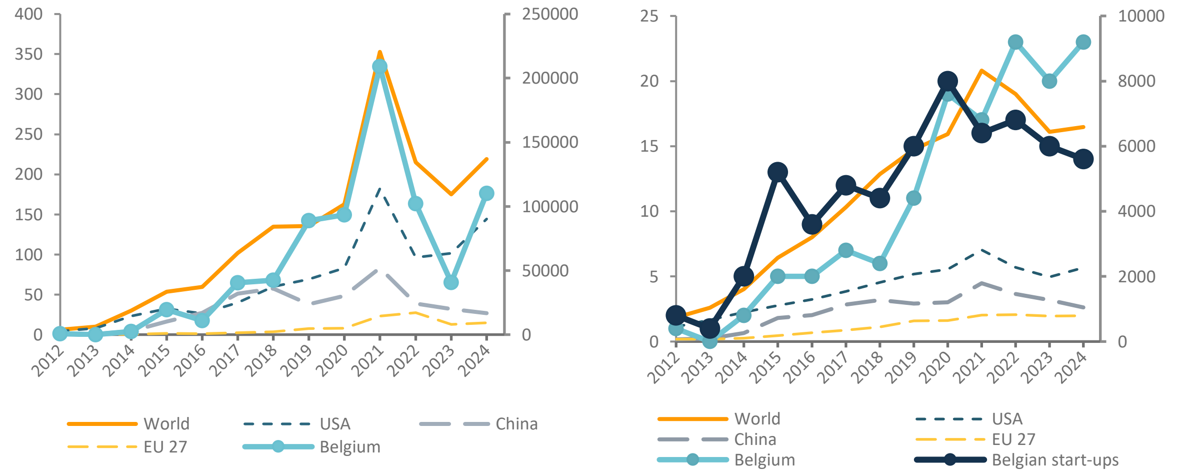
[10] Funk (2024) offers a critical analysis of the performance of unicorns and, more generally, of the role of venture capital providers in successive hypes and speculative bubbles surrounding new technologies.

[11] Depending on the source, there are sometimes significant differences in both the number of cases and the total amount of venture capital investments.

total amount, and from 0.15% in 2012 to 0.35% in 2024 for Belgium's share of the global number of investments.

Graph 5 Venture capital investment in AI (2012-2024)

In millions of dollars (left Graph) and number of investment files (right Graph)



Source: OECD.AI (2025), visualisations by JSI based on data from Preqin, consulted on 30/4/2025, www.oecd.ai. The right-hand side graph also shows the number of Belgian AI start-ups identified by us for which we have been able to determine, based on various sources, that they have received venture capital and were established in the given year.

Note: the observations for Belgium are plotted against the left-hand side axis in both graphs, and against the right-hand side axis for the world, the US and EU 27.

The evolution of the number of Belgian venture capital investments is also very similar to the number of Belgian AI start-ups with venture capital that we have identified (right-hand side of Graph 5) until 2021.[12] Whereas the number of AI start-ups with venture capital identified by us in each year up to 2020 is higher than the number of Belgian investments in the OECD data, the opposite appears to be true for the years 2022, 2023 and 2024. It is possible that our data for the more recent years is missing a number of AI start-ups, but it is also possible that it relates to investments concerning new financing rounds for companies that were established earlier, such as the aforementioned large financing round in 2024 for TechWolf and Robovision. The OECD data does not provide details on the individual files that would allow for further investigation. The top five largest Belgian AI start-ups with venture capital that the OECD does publish show that they are involved in various venture capital investments, with seven for Collibra Belgium, four for TechWolf, two for Aerospacelab and Nobi and one for I-care.

2.3. Spin-offs

Commercial applications of new technologies are often based on knowledge and ideas developed at universities and colleges. Graph 4 reveals that AI start-ups in Belgium are mainly located near universities and colleges.

When scientists affiliated with a university establish a company to commercially develop their research results, this is referred to as a university or academic spin-off. Studies yield varying results on the success

12 The right-hand side of Graph 4 shows the number of Belgian AI start-ups with venture capital according to year of establishment, not according to the year in which venture capital was received, about which we have insufficient information. Start-ups can receive venture capital in different years, whether or not in different phases of start-up financing.

of spin-offs and their contribution to innovation, which depends on the policy framework and government support, but also on the knowledge, experience, ambition and motivation of the founders (Bahuleyan *et al* 2024, Civera *et al* 2024). Based on data on 988 AI start-ups, Chattopadhyay, Honoré & Won (2025) conclude that start-ups with at least one academic researcher as a founder have knowledge that is applicable in more market segments than AI start-ups without founders from academia. The publications and patents of spin-offs appear to be more generally applicable. Unlike other technology domains, such as biotech and lasers, AI companies require less capital to tap into different markets. This allows academic entrepreneurs with domain-specific expertise in AI to gain a strong market position without significant additional investment. An OECD analysis combining data from Crunchbase and Dealroom on 81,318 start-ups, including 8,065 with founders from academia, shows that academic start-ups receive relatively more grants and other forms of financial and non-financial government support than non-academic start-ups, but seem to have more difficulty attracting capital. Over the period 2000-2022, the share of academic spin-offs in the total number of start-ups created remained fairly constant at around 10%. On average, academic start-ups appear to have more patents than their non-academic counterparts. Academic spin-offs are relatively better represented in sectors such as healthcare (mainly biotech), energy, manufacturing and information technology. The share of academic spin-offs in the total number of start-ups is higher in Belgium, which is ranked eight, than the OECD average (Berger, Dechezleprêtre & Kirpichev Cherezov 2025).

Based on our information on the 744 Belgian AI start-ups, we have been able to establish that 38 are spin-offs from a Belgian university or college. The business data discussed in section 3 largely confirm the conclusions of the OECD analysis. The ratio of equity to debt capital of Belgian spin-off AI start-ups is on average 1.4 times higher, and capital subsidies 1.2 times higher, than for AI start-ups that are not spin-offs. Looking at the sectors in which the customers of Belgian AI start-ups operate (see Table 4), spin-off AI start-ups are better represented than AI start-ups that are not academic spin-offs in the pharmaceutical sector, the health sector and the manufacturing industry. In contrast, they are less well represented in energy and ICT.

2.4. Patents

To protect inventors against the use of the knowledge that they have generated, by others without compensation, governments grant inventors patents that confer a temporary exclusive right to the industrial application of a new product, research result or working method. In some high-tech fields, particularly in the pharmaceutical sector and biotechnology, companies use patents to shield themselves from competition in order to recoup their investments in research and development. However, patents can also be misused and hinder rather than promote innovation. There is still much debate about the ultimate contribution of patents to innovation and productivity (de Rassenfosse 2024). In the past, patents were less important for ICT companies because of the shorter life cycle of ICT products, but also because it is more difficult to obtain a patent for software. Software code is protected by copyright, but that protection does not extend to the underlying technical concept. Although the European Patent Convention does not consider software to be an invention and therefore, unlike in the United States, it is not eligible for patent protection, it is possible in Europe to obtain a patent for so-called 'computer-implemented' inventions[13] if the invention offers an innovative and non-obvious solution to a 'technical problem'. The rules of the European Patent Office have been further refined in response to developments in the field of AI. For example, the use of a neural network in a heart monitoring device to recognise irregular heartbeats can be considered a technical contribution that is eligible for a patent, as is the classification of digital images based on characteristics such as the edges or pixel properties of the images, or the separation of sources in speech signals and speech recognition, for example for converting speech to text.

Recent data from Aranda *et al* (2025) show that the number of identified AI-related patents rose sharply after 2010, mainly from 2015 to 2020, when the average annual growth rate was 30%. Although the number of AI-related patents reached a record level of 17,000 in 2023 (the last year for which data is available in the analysis), there has been a clear slowdown in growth since 2020 (averaging 2% per year). The sharp increase until 2020 was mainly noticeable in areas such as generative AI and large language models (LLM), while applications for industrial processes, which make up the majority of AI-related patents, grew much more slowly. The analysis shows that in 2023, Belgium was one of the countries with the lowest specialisation in AI-related patents.

Based on information from the USPTO, we were able to identify 21 Belgian AI start-ups with at least one patent granted by the USPTO. We took all patents into account, not just those in the AI CPC codes determined by Aranda *et al* (2025). There are 45 Belgian AI start-ups with at least one patent granted by the European Patent Office (EPO). Ten AI start-ups have both at least one USPTO patent and at least one EPO patent. Thus, 56, or 7.5%, of the Belgian AI start-ups we identified have at least one USPTO patent or at least one EPO patent. Of the Belgian AI start-ups with venture capital, 15, or 9.8%, have at least one patent. Of the Belgian academic AI spin-offs (as defined in section 2.3) 5, or 13.2%, have at least one patent. The latter confirms the finding by Berger, Dechezleprêtre & Kirpichev Cherezov (2025) that academic spin-offs have more patents on average than non-academic start-ups.

[13] Inventions relating to computers, computer networks or other programmable devices, where at least one feature is realised by means of a programme.

3. Business analysis of Belgian AI start-ups

In this section, we discuss the results of a business economic analysis of the 744 Belgian AI start-ups we identified. In addition to traditional financial ratios such as profitability, liquidity and solvency, we also look at turnover, value added, number of employees, operating profit and productivity. Data from companies' annual accounts form the basis of our analysis. Most Belgian companies are required to file annual accounts with the National Bank of Belgium. The data is collected by the Central Balance Sheet Office. Annual accounts consist of a balance sheet, a profit and loss account and notes. The balance sheet provides an overview of a company's assets, such as plant, machinery and equipment, and its liabilities, broken down into equity and debts. The balance sheet provides an overview of the financial position at the end of a financial year, determined by financing and past results (including the financial year just ended). The profit and loss account provides an overview of the operating and financial results for the financial year ended and shows, among other things, the profit or loss for the financial year. For companies with capital, there are three models of annual accounts: the full format, the abridged format and a micro format. Which format to follow depends on thresholds for average staff numbers, turnover and balance sheet total. According to data from the Central Balance Sheet Office, in 2024 the annual accounts of 12% of companies with capital were filed according to the full format, 39% according to the abridged format and 49% according to the micro format. Since turnover and the purchase of goods, materials and services only have to be reported under the full format, information on these important variables is missing for 88% of companies so that we need to use other sources. We use data for all non-financial companies[14] for the period 2010-2023 (2023 was the most recent financial year for which complete data was available).

To assess the performance of AI start-ups, we consider a reference group of non-AI start-ups. These are companies that were also established from 2010 onwards but for which we have not found any information that they offer goods or services in the field of artificial intelligence. Of the 744 Belgian AI start-ups, 692 have at least one annual available. Companies established in 2024 or 2025 cannot be included in the analysis because, by definition, the annual account for 2023, the most recent year with complete annual accounts data, are missing. Of the 692 AI start-ups with at least one annual account, 128 have zero employees. Only people employed as manual workers or clerical staff are considered employees. People who work on a self-employed basis for a company are therefore not counted as employees. In addition, the use of a management company is on the rise in Belgium. This means, for example, that a company director can act as an intermediary through management company A to provide services to another company, company B, set up by the company director. The costs of the services provided by company A will then be reported in the income statement of company B, but if the company director is the only person working for company B, the latter will officially have no employees. A company established by several people in the industry ‘Computer programming activities’ (NACE 62010), where the founders offer their services to the established company through a management company (industry NACE 70200 - Activities of management consultancies and other management advisory services) and are the only ones working for the established company, will not have any employees. These legal arrangements imply that the number of employees reported in the annual accounts underestimates the

[14] This corresponds to institutional sector S11 in the national accounts, which therefore does not include the self-employed (S14).

actual employment in many companies. However, there is no information available to verify how many people, regardless of their status, actually work for the company in NACE 62010.

The lack of accurate information on the number of people working for a company complicate meaningful business analysis. It is actually not possible to consider these companies in terms of productivity. We will therefore not include companies with officially 0 employees in our analysis. In 2023, 18.5% of AI start-ups with turnover had 0 employees. Together, they represented only 1.8% of the total turnover of all AI start-ups in the same year, so the exclusion of these companies is likely to have a limited impact. When AI start-ups with turnover but without employees subsequently do have employees, they are included from the first year in which they have one or more employees. There are 564 AI start-ups with at least one employee in at least one year during the period 2010-2023. It is this group that we will consider further and compare with a reference group of non-AI start-ups: Belgian non-AI companies that were established from 2010 onwards and have at least one employee. The reference group consists of 156,576 non-AI start-ups. Because most company data are characterised by significant measurement errors, we consider the bottom 0.5% and top 0.5% of our observations to be extreme values, which we do not include in the analysis. All monetary variables were converted into constant prices (reference year 2005), using deflators at NACE 2-digit level from the OECD's STAN database.

Of the 1,027 potential Belgian AI companies we identified, 851 (83%) were established after 2009 (see Graph 1 in section 1) and 687 (67%) after 2014. A large proportion of the companies are therefore start-ups or young enterprises. This points to the important role that new enterprises play in the introduction of new technologies, as Schumpeter (1934) already emphasised. Hvide & Meling (2025) tested Schumpeter's hypothesis of ‘creative destruction’ on the roll-out of broadband internet in Norway between 2000 and 2010. They found little impact on established companies, but the introduction of broadband internet was accompanied by a 25% increase in the number of start-ups. One possible explanation offered by the authors is the 'replacement effect', which refers to the reluctance of established companies to invest in new and potentially disruptive technologies, and the complementary assets and training of personnel, because this would cannibalise the profits they generate with existing technologies. In addition to a Schumpeterian view of entrepreneurs as those who introduce new goods, services or organisational forms, driven by the prospect of monopoly profits that can be realised through innovation, there is also a line of thought dating back to Knight (1921) in which entrepreneurship is regarded as the allocation of resources and the organisation of activities under uncertainty.[15] Estrin *et al* (2024) combine both views in a growth model involving the creation of new enterprises. Applying this to 331 new ICT enterprises, they find evidence that start-ups must weigh the speed at which they become profitable (speed-to-breakeven) against the level of profit when they become profitable (revenue-at-breakeven). Due to greater uncertainty, the most innovative companies have a lower 'speed-to-breakeven' and/or 'revenue-at-breakeven'.

The high level of uncertainty inherent in starting a business is reflected in the low survival rate of start-ups. In a meta-analysis, Song *et al.* (2008) found eight robust success factors for new tech companies across all the studies they examined: integration into the supply chain, market size, age of the company, size of the founding team, financial resources, marketing experience of the founders, experience of the

15 Townsend *et al* (2025) investigate whether AI can reduce the uncertainty for entrepreneurs defined by Knight, in line with the view of Agrawal, Gans & Goldfarb (2022) that recent AI developments are leading to greater predictability.

founders with the relevant market, and patent protection. In an update of the study by Song *et al* (2008), based on research published after 2008, van Zantvoort (2020) confirmed the importance of experience in the relevant market for the success of tech start-ups, but unlike the previous study, he found that previous experience with start-ups is also important. In addition to Song *et al* (2008), van Zantvoort (2020) found that the contribution of venture capital and employees with an academic background also contributes to the success of new tech companies.

Despite extensive research into the success and failure factors of start-ups, most of the variance in the performance of start-ups remains unexplained. These factors vary across the development phase of start-ups and the technology domain in which they operate. For AI start-ups, with an ecosystem that is still in full development, it is not clear how meaningful results for start-ups in other sectors are. This is particularly true for the market for AI applications, in which virtually all Belgian AI start-ups are active. AI technology itself appears to have an impact on the activities of start-ups. By building their organisation and products entirely around artificial intelligence, 'AI-native' start-ups appear to be able to launch products and generate revenue faster than start-ups in other technologies. The automation potential of AI allows them to scale up with smaller teams than was previously the case. As a result, successful AI start-ups may create fewer jobs. The trend towards 'lean start-ups' implies that the growth in the number of employees, often used by policymakers as a measure of the success of start-ups, may be less relevant for the AI sector than it was for earlier developments in the field of digital platforms or 'cloud computing'. Many AI start-ups are also experiencing problems attracting talented employees due to competition from the major AI hubs in San Francisco, Paris (Mistral) and Stockholm (Lovable) (O'Brien & Cati 2025, Penzel 2025, Tang *et al* 2025). However, Brynjolfsson, Chandar & Chen (2025) find that the use of generative AI has a significant negative impact on the employment of young people (aged 22 to 25) in the United States, mainly in professions where AI is widely used, such as software developers.

According to Heikkilä & Bradshaw (2025), companies that develop products based on large language models generate enormous revenues from a rapidly growing number of users. These include companies that create applications that assist in writing software code or can increase business productivity by adding value to the work of experts. There seems to be a consensus that most value will be created with AI applications and less with the large AI models (foundation models) on which the applications are based. These companies appear to generate high revenues much faster than non-AI companies, partly because they can quickly switch to cheaper or better AI models when they become available. However, more and more questions are raised about the high valuations of AI companies. For example, it is unclear how sustainable the growth in revenue is. Some investors fear that even the best of today's AI applications are simply a *wrapper* around an AI model and that successful applications could quickly be outcompeted by similar products from large companies with a broader customer base. Companies that develop AI applications are also heavily dependent on developments and the cost of using large AI models. Andrew Lee, founder and CEO of Shortwave, an American AI start-up that focuses on applications for more efficient use of email, admits that his company would probably have gone bankrupt if a new cache function in Claude Sonnet (a foundation model from Anthropic, founded in 2021) had not reduced the cost of building developments by 90%. Although companies that develop AI applications prefer open source models, there is pressure from customers to offer applications based on paid models, such as OpenAI's GPT models, because they are generally considered to be more cutting edge. Due to the high cost of use, this reduces the profit potential. The proliferation of new AI models also makes it difficult for start-ups to keep abreast of the capabilities of the various models (Lee 2025).

However, rapid developments in the AI sector also offer opportunities, as evidenced by the testimony of the two founders of an AI start-up we identified, Antwerp-based BlackBear Labs, founded in 2023. By experimenting with ChatGPT, they developed four applications in six months, including a chatbot and MemoryGPT, which remembers information about previous chat sessions, for which they would they claim to have reached 6,000 users in a week time, without any marketing effort. Experimenting with AI is said to be faster and cheaper than ever, and user feedback can be processed immediately. Some of BlackBear Labs' tools are said to have been built in a matter of hours. The founders do add that speed is needed to stay ahead of competitors but that they cannot keep launching new AI tools indefinitely. They believe that now is the time to further develop existing tools, seeing particular growth opportunities in combining new AI products with products tailored to specific companies (Bloovi 2025).

Despite the very high valuations of some AI companies and the significant revenues generated by some start-ups, questions arise about the possibility of achieving sustainable profits from 'foundation models' or AI applications (Matthews 2025, Polevikov 2025). Many companies in the upper echelons of AI production (see Box 1), such as manufacturers of AI-specific hardware or providers of cloud computing services, are quite profitable, but the revenue generated by companies that develop foundation models does not currently offset the rapidly rising costs of training and operating the models. Of the thousands of start-ups that have been established worldwide since 2010, to offer applications based on large AI models, it is also unclear how many are profitable and can remain so. As for the possibilities of making predictions with current generative AI, especially when it comes to human behaviour, claims made by companies about its effectiveness are difficult to verify (Narayanan & Kapoor 2024, Polevikov 2025).

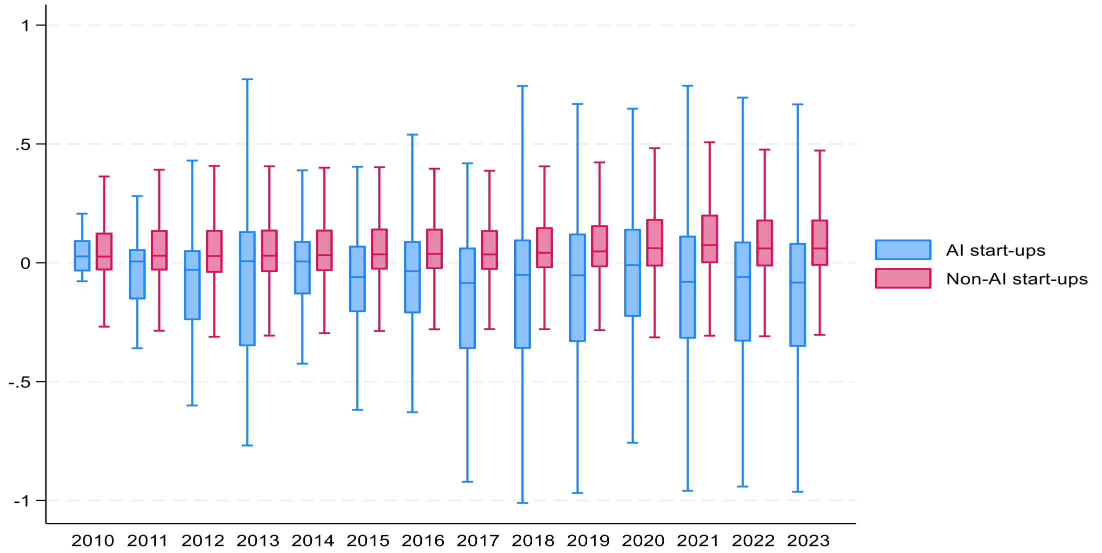
3.1. Profitability, liquidity and solvency

A company's financial situation is usually analysed on the basis of ratios such as profitability, liquidity and solvency. Profitability allows us to assess whether the difference between a company's revenues and costs is sufficient in comparison with the invested capital. Liquidity compares cash inflows and cash outflows and reflects the extent to which a company can cover its expenses with its income. Solvency provides an indication of a company's debt ratio. The three ratios are interrelated and are usually considered together to obtain a complete overview of a company's financial health.

Ooghe & Van Wymeersch (1991) discuss various alternatives for the three financial ratios, depending on which variables from the balance sheet or income statement are considered. Since the majority of AI start-ups file annual accounts according to the abridged format or the micro format, we limit ourselves to ratios for which no data are needed that are only required in the full format. We only consider the ratios that, in the study by Benoot & Vanhessche (2012) on the characteristics of failing companies in Belgium, most clearly distinguished between active companies and companies that exited.

Graph 6 shows the difference in net return on assets before tax, calculated as the profit (or loss) for the financial year before tax in relation to total assets, for AI start-ups and non-AI start-ups in the period 2010-2023. The distribution of profitability is shown using a box plot. The median (horizontal line in the box) of the net profitability of AI start-ups is lower than that of non-AI start-ups in all years.

Graph 6 **Net profitability of AI start-ups and non-AI start-ups**

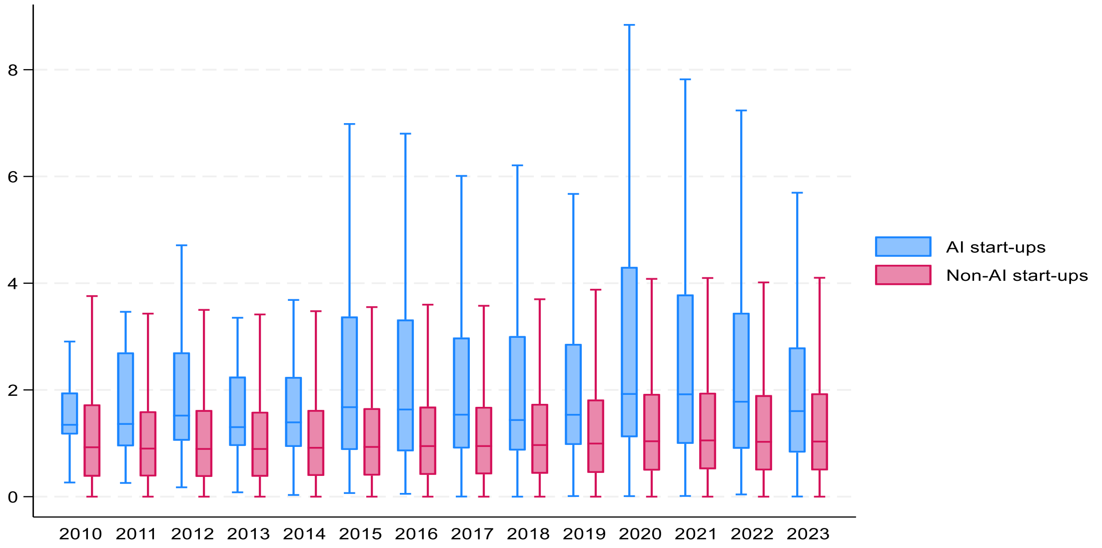


Note: the graph (box plot) shows the evolution of the distribution of net profitability of assets before tax, for AI start-ups and non-AI start-ups. A box plot shows the spread of profitability based on the median (horizontal line), the first quartile (bottom) and the third quartile (top) of the distribution. The upper and lower lines are determined on the basis of the interquartile range. Outliers are not included in the box plot.

This also applies to the average profitability, which is negative for AI start-ups and positive for non-AI start-ups, but close to 0 (not shown in the graph). For AI start-ups, the median profitability is also negative in most years, in contrast to non-AI start-ups (for which the median is always positive). The difference in the median between AI start-ups and non-AI start-ups is increasing over time. The spread around the median is much larger for AI start-ups than for non-AI start-ups. The profitability of AI start-ups is therefore diverging further and further from that of non-AI start-ups. The portion of the 'box' below the median, representing AI start-ups, is gradually becoming larger than the portion above the median. This means that a larger proportion of AI start-ups are incurring increasing losses. On the other hand, there are also a number of AI start-ups with higher profitability than the most profitable non-AI start-ups. Despite the wide spread, the difference between the average negative profitability of AI start-ups and the average slightly positive profitability of non-AI start-ups is statistically significant. This also applies to the difference in net return on equity before tax and net return on equity after tax (not reported).

Graph 7 shows liquidity in the narrow sense (acid test ratio), which reflects the ratio of receivables due in less than one year, cash investments and cash equivalents to debts due in one year or less. The liquidity position of AI start-ups appears to be systematically better than that of non-AI start-ups, and the difference is also gradually increasing. Not only is the median higher, but the portion above the median and the upward tail are also larger for AI start-ups. The positive difference in liquidity between AI start-ups and non-AI start-ups is statistically significant. The difference in average liquidity in the broad sense (current ratio) and the net cash ratio of AI start-ups compared to non-AI start-ups is also positive and statistically significant (not reported).

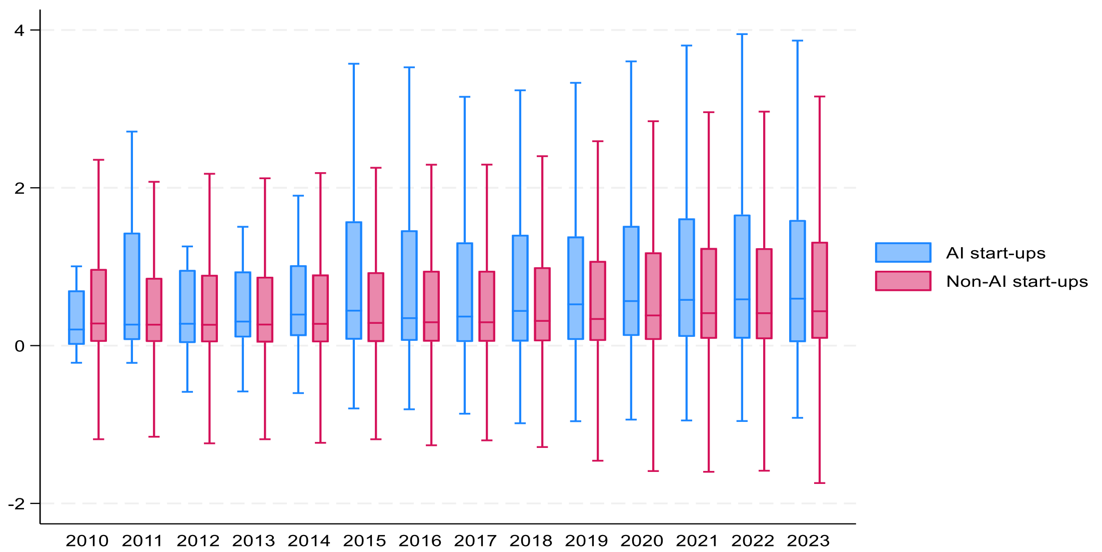
Graph 7 Liquidity (in the narrow sense) of AI start-ups and non-AI start-ups



Note: the Graph shows, using a box plot, the evolution of the distribution of liquidity in the narrow sense (acid test ratio) for AI start-ups and non-AI start-ups. . A box plot shows the spread of profitability based on the median (horizontal line), the first quartile (bottom) and the third quartile (top) of the distribution. The upper and lower lines are determined on the basis of the interquartile range. Outliers are not included in the box plot.

Graph 8 compares the evolution of the financial independence of AI start-ups with that of non-AI start-ups.

Graph 8 Financial independence of AI start-ups and non-AI start-ups



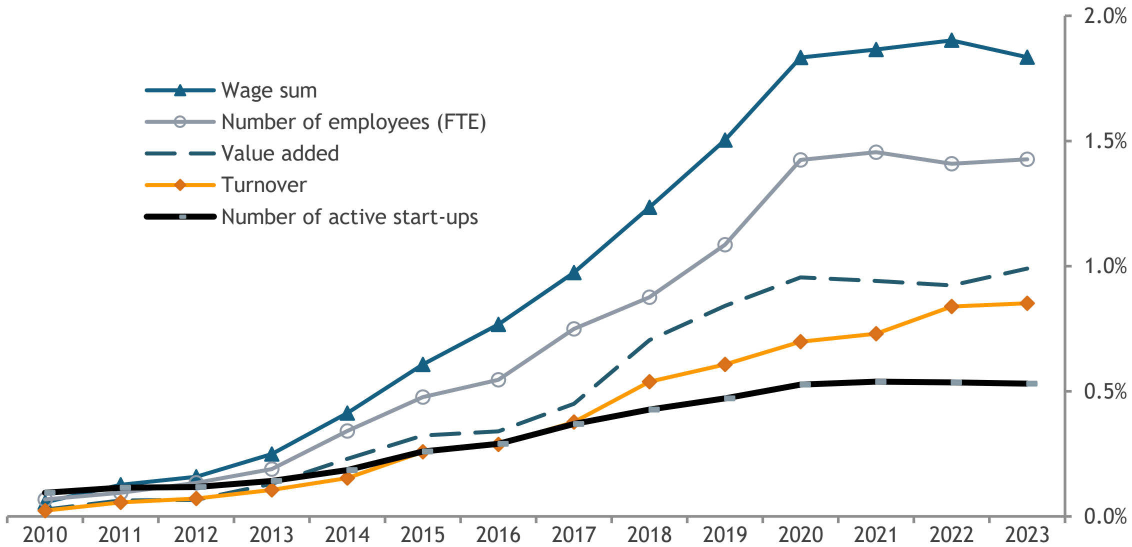
Note: the Graph uses a box plot to show the evolution of the distribution of financial independence for AI start-ups and non-AI start-ups. . A box plot shows the spread of profitability based on the median (horizontal line), the first quartile (bottom) and the third quartile (top) of the distribution. The upper and lower lines are determined based on the interquartile range. Outliers are not included in the box plot.

This solvency measure reflects the ratio of equity to debt. In most years, the financial independence of AI start-ups is greater than that of non-AI start-ups. Due to the greater uncertainty of the AI sector, AI start-ups appear to be more reliant on equity financing, such as venture capital. AI start-ups have more equity and less debt per employee (FTE) than non-AI start-ups. AI start-ups also appear to rely less on short-term debt financing, which partly explains their better liquidity position, as short-term debts are included in the denominator of liquidity in the narrow sense (Graph 7). The difference in average financial independence between AI start-ups and non-AI start-ups is slightly positive but not statistically significant. The difference in the self-financing ratio (another solvency measure), on the other hand, is negative and statistically significant. This ratio includes retained earnings or losses in the numerator and, as shown in Graph 6, the profitability of AI start-ups is lower than that of non-AI start-ups.

3.2. Turnover, value added and employees

The financial ratios discussed in the previous section provide an indication of the financial health of companies. To determine the importance of start-ups for the national economy, their contribution to turnover, value added or job creation is usually considered. Since the number of AI start-ups is relatively limited compared to the total number of start-ups, their direct contribution will also remain fairly limited. However, we can determine how their contribution evolves in relation to their share of the total number of start-ups. The solid black line in Graph 9 shows that although the share of active AI start-ups in the total number of active start-ups (AI and non-AI) is gradually increasing in the period 2010-2023, it only amounted to 0.53% in 2023. The graph also shows the evolution of the share of AI start-ups in total turnover, value added, the wage bill and the number of employees of all start-ups. In 2023, the share of AI start-ups in these four economic variables surpassed their share in the number of all active start-ups greater. For example, the share in turnover in 2023 of 0.85% was 1.6 times greater than the share in the number of active start-ups.

Graph 9 Share of AI start-ups in the total turnover, value added, number of employees and wage bill of all start-ups



Note: the Graph shows the evolution of the share of AI start-ups in the total turnover, value added, number of employees and wage bill of all start-ups. The solid black line shows, as a reference, the evolution of the share of active AI start-ups in the total number of active start-ups (AI and non-AI).

For the three other variables, the share of AI start-ups is greater than the share in total turnover, and the share of AI start-ups in the total number of start-ups even exceeded this share earlier on (in 2013 or 2014). In 2023, the share of AI start-ups in value added, in the number of employees and in the wage bill was 1.9, 2.7 and 3.5 times greater than their share in the total number of start-ups, i.e. twice as high or more.

To determine whether the differences in the evolution of turnover, value added and the number of employees between AI start-ups and non-AI start-ups are statistically significant, we use a first difference estimation, which is one of the three methods applied by McElheran *et al.* (2025) to estimate the impact of AI use on the productivity of companies in the United States (period 2017-2021).[16] The other two methods, 'selection-on-variables' and an instrumental variables (IV) estimation, are not applicable to our data. An estimate in first differences has the advantage of taking into account unobserved factors that vary little over time and can have a significant effect on the variable to be explained. The disadvantage of the method is the loss of information and the ignoring of a selection problem. The results should therefore be interpreted with caution and in any case, cannot be considered as evidence of causal effects. The main variable in the estimation is a dummy variable that is equal to 1 for AI starters and equal to 0 for non-AI starters. Following Lee *et al* (2022) and McElheran *et al* (2025), we include several control variables, such as the number of employees, tangible and intangible fixed assets[17] and dummies for the industry to which companies belong (NACE 3-digit level). To control for the impact of the year in which the company was started, dummies are also included for each cohort of start-ups (companies founded in the same year). The coefficient of the AI dummy provides an indication of the direction and significance of the difference in the explanatory variable (turnover, value added, number of employees, wage bill) between AI start-ups and non-AI start-ups, controlling for the variables that may also explain variation in the dependent variable. Due to the large number of control variables and the limited certainty about their relevance, we opted for a lasso estimation. Lasso (least absolute shrinkage and selection operator) can be used for predictions, model selection and inference. We use lasso to estimate the coefficients and the associated standard errors of the variables we are interested in. In addition, lasso allows us to include a large number of control variables, for which we are not so much interested in their marginal effect but rather whether they are relevant to the model specification. Control variables that are not relevant are dropped from the estimation. Compared to an ordinary least squares (OLS) estimate, lasso includes a penalty for including additional variables, which increase explained variance but complicate the model specification. The parameter λ determines the 'penalty' for additional variables. This can be determined by the estimator itself or through optimisation. We use lasso procedures in Stata, in which λ is always determined through optimisation. More details about Lasso can be found in Drukker (2019) and in the Stata manual.

In Stata, there are three alternative lasso procedures: 'double selection', 'partialing out' and 'cross-fit partialing out'. Because we want to include a relatively large number of potential control variables in relation to the limited number of observations for AI starters, we prefer 'cross-fit partialing out' (Stata procedure xporegress). This procedure, in which the observations are divided into 10 equal-sized subpopulations, takes longer than the other two but takes greater account of the parsimony requirement (not including too many unnecessary control variables). In this procedure, the parameter λ is optimised using the 'plugin' method.

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16 Lee *et al* (2022) also use a first difference estimate to determine the impact of AI adoption by South Korean companies on their turnover.

17 AI start-ups have significantly less tangible fixed assets, and more intangible fixed assets per employee, than non-AI start-ups.

Table 5 shows the results of cross-fit partialing out estimates of growth in turnover, value added, the number of full-time equivalent (FTE) employees and the wage bill. We used variables in logs for the first differences estimation. Due to the large number of observations, we consider the average over the period 2010-2023. The table shows that AI start-ups have experienced stronger growth for the four variables considered than non-AI start-ups and that the difference is statistically significant, regardless of the growth measure that we consider. The estimates indicate growth that is 7% to 13% higher for AI start-ups than for non-AI start-ups. Our results are in line with those of Dinlersoz, Dogan & Zolas (2024), who find that AI start-ups in the United States experience higher growth in turnover and average wages than non-AI start-ups.

Table 5 The difference in growth in turnover, value added, number of employees and wage bill between AI start-ups and non-AI start-ups

	Turnover	Value added	Number of employees	Wage bill
Difference between AI start-ups and non-AI start-ups	0.13***	0.07**	0.09***	0.13***
Number of observations	167,936	167,882	172,156	169,480
Number of control variables	251	251	251	251
Number of selected control variables	206	215	213	214
Wald chi2(14)	25.56	5.72	22.22	46.56
Prob > chi2	0.00	0.02	0.00	0.00

Note: the table shows the coefficient of a dummy equal to 1 for AI start-ups and equal to 0 for non-AI start-ups in a first difference estimation (average 2010-2023), with turnover, value added, number of full-time equivalent (FTE) employees and wage bill respectively. The estimates include various potential control variables such as age, number of employees, tangible and intangible fixed assets, and industry dummies (NACE 3-digit level). Apart from the age of companies and dummy variables, all variables in the estimates are included in logarithms. The estimates were performed in Stata using a 'cross-fit partialing out' lasso estimate (xporegress procedure). In this procedure, an optimal selection is made of the number of specified control variables that are ultimately selected. The chi-square Wald test, tests the hypothesis that all coefficients together are equal to 0 (they have no explanatory value). A value for Prob > chi2 less than or equal to 0.05 indicates that this hypothesis is rejected at a level of statistical significance of 5%. The coefficients of the difference between AI starters and non-AI starters indicate whether the coefficient differs from 0, for statistical significance of 10% (*), 5% (**) or 1% (***).

To identify what might explain the difference in the growth of AI start-ups, we have considered additional information about AI start-ups for estimation, in particular the AI technologies used, the AI purposes and the sectors in which the customers of the AI start-ups operate, as discussed in section 2.1. Since only AI start-ups are considered for these estimates, there are significantly fewer observations.

Table 6 shows the results of cross-fit partialing estimation for growth in turnover, value added, number of full-time equivalent (FTE) employees and wage bill, with the variables relating to AI technologies and purposes included as relevant variables. In addition, the number of sectors in which the customers of AI start-ups are active has also been included as a relevant variable in order to examine the difference between companies that focus on one or a limited number of sectors and companies that offer applications in multiple sectors. In terms of turnover and value added, the AI technologies used do not appear to explain differences in growth.

Table 6 The difference in growth in turnover, value added, number of employees and wage bill between AI start-ups (AI technologies and AI purposes)

	Turnover	Value added	Number of employees	Wage bill
AI technology:				
Text mining	0.03	-0.08	-0.21*	-0.28**
Speech recognition	0.07	-0.16	0.01	0.03
Generation of written/spoken language	0.03	-0.06	-0.07	-0.05
Image recognition, image processing	0.03	-0.01	0.07	0.06
Machine learning for data analysis	0.04	0.05	-0.07	-0.06
Automating various workflows	0.13	0.07	0.02	0.06
Autonomous robots, self-driving vehicles, etc.	0.20	0.06	0.01	0.02
Text-image generation	0.01	-0.03	-0.19*	-0.09
Hardware	-0.03	-0.09	0.12	0.23*
AI purpose:				
Marketing or sales	-0.15	-0.01	0.0	0.07
Production or service processes	-0.08	0.07	-0.05	-0.07
Business administration/management	-0.08	0.06	0.03	0.04
Logistics	-0.23**	0.13	-0.13	-0.02
ICT security	-0.24*	-0.18	0	0.05
Accounting, financial management control	-0.20	0.13	-0.08	-0.09
Research and development	-0.07	0.14	-0.06	0.04
Control variables:				
Number of sectors of use	-0.43***	0.09	-0.47***	-0.34
Number of patents USPTO	0.05	-0.36	-0.09	-0.06
Number of patents EPO	0.00	0.09	0.06**	0.03
Venture capital	0.17*	0.17*	0.13*	0.16***
Academic spin-off	-0.05	-0.10	-0.05	-0.05
Number of observations	1,503	1,014	1,578	1,525
Number of control variables	114	114	114	114
Number of selected control variables	96	89	98	99
Wald chi2(14)	22.15	20.57	29.82	37.37
Prob > chi2	0.39	0.49	0.10	0.02

Note: the table shows the coefficients of dummies that indicate whether the AI starter uses a particular AI technology or for a particular purpose, in an estimate in first differences of turnover, value added, the number of employees in full-time equivalents (FTE) and the wage bill, respectively. See the text and note in Table 5 for more information about the estimation procedure. The coefficients for the difference between AI start-ups and non-AI start-ups indicate whether the coefficient differs from 0, for statistical significance of 10% (*), 5% (**) or 1% (***).

AI start-ups focusing on logistics and ICT security have lower turnover growth than other AI start-ups, and AI start-ups with users in many different sectors also experience less turnover growth than start-ups focusing on a limited number of sectors. AI start-ups with venture capital have stronger growth in turnover and value added than AI start-ups without venture capital. However, for both turnover and value added, the Wald test indicates that all the variables included together would have no explanatory value, which means that we must interpret the results of these estimates with some caution.

For the estimates of the growth in the number of employees and the wage bill, the null hypothesis of the Wald test is rejected, albeit only at a significance level of 10% for the number of employees.

AI start-ups that use text mining and text-image generation have a statistically significant lower growth in the number of employees (FTE). The negative coefficient for text mining is also statistically significant for wage bill growth. Companies that also develop hardware have a statistically significant faster growth in their wage bill than other AI start-ups. As with revenue growth, AI start-ups with users in many different sectors have statistically significant lower growth in the number of employees. The venture capital coefficient is also positive and statistically significant for the growth in the number of employees and the wage bill. The results in Table 6 for the venture capital variable are clearly in line with studies showing that companies with venture capital are more focused on growth than companies without venture capital (Bertoni, Colombo & Grilli 2011, Pantea & Tkacik 2024).

We also attempted to do estimations using the sectors of the AI start-ups' customers as relevant variables, but the lasso estimates encountered a convergence problem, probably due to the large number of sectors. The sectors are included as control variables in the estimate for Table 6.

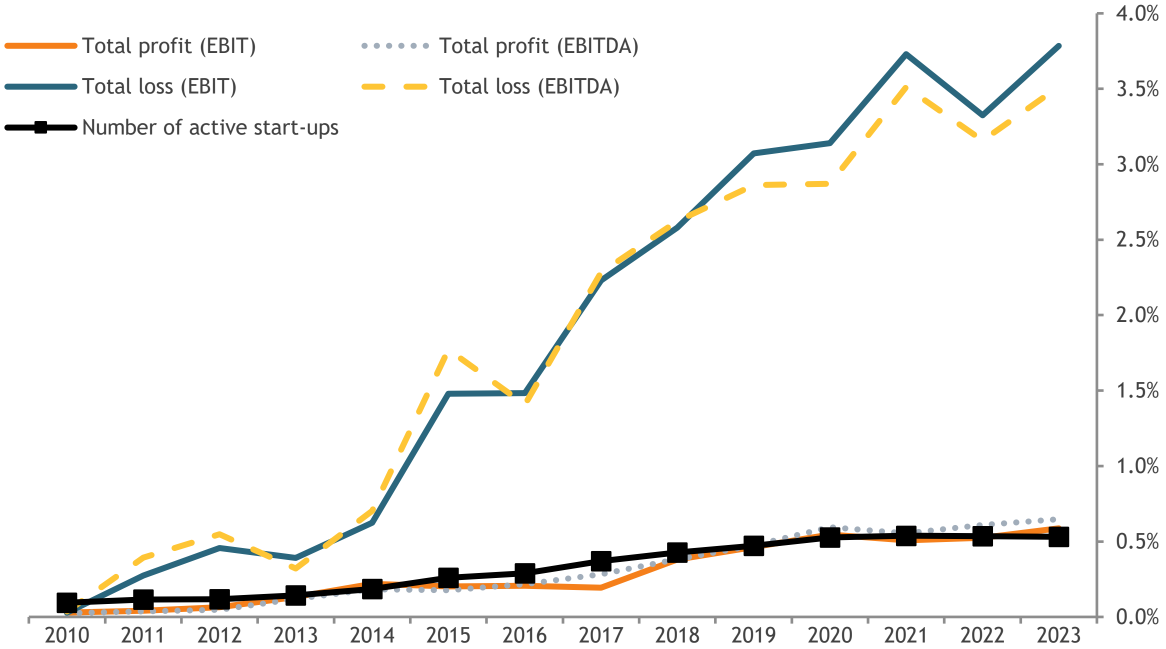
3.3. Operating result

The value added of a company is calculated as turnover minus the cost of purchased goods and services. The value added created by a company is used to pay the wages of employees, and what remains after payment of a number of other costs is the profit or loss of the company, the operating result. Graph 8 shows that the share of AI start-ups in the value added of all start-ups is greater than the share of AI start-ups in the total number of start-ups. The share of AI start-ups in the total wage bill of all start-ups is even greater than the share of AI start-ups in the total value added of all start-ups. This seems to indicate that the operating result of AI start-ups is negative. Section 3.1 already pointed to the lower profitability of AI start-ups compared to non-AI start-ups. In this section, we will discuss the evolution of the operating result in more detail, as this is clearly a variable for which, unlike turnover, value added and the number of employees, AI start-ups are currently performing less well than non-AI start-ups.

An article in De Tijd (23 June 2025) reports that the Ghent-based AI unicorn Team.blue saw its turnover and gross operating profit increase in 2024, but that its net loss and debts rose. The founder of Team.blue, Jonas Dhaenens, argues that the increase in net loss is not really a problem, as the net loss is purely an accounting agreement and that if the company were to operate according to the International Financial Reporting Standards (IFRS) instead of the Generally Accepted Accounting Principles (GAAP) rules applicable in Belgium, the operating result would be better. According to IFRS, the current value of the assets must be assessed and a certain percentage of the assets must not be depreciated every year. We do not express our opinion on the different views of the accounting rules but in our analysis we use both the net operating result, or the profit or loss before interest and taxes (Earnings before interest and taxes – EBIT) and the gross operating result or profit or loss before interest, taxes, depreciation and amortisation (Earnings before interest, taxes, depreciation and amortisation – EBITDA).

Graph 10 shows the evolution of the share of AI start-ups in the total operating result of all start-ups. Because the result can be both positive and negative, we divide the operating result into profit and loss. The Graph shows the shares for both EBIT and EBITDA.

Graph 10 Share of AI start-ups in the operating result of all start-ups (EBIT and EBITDA)

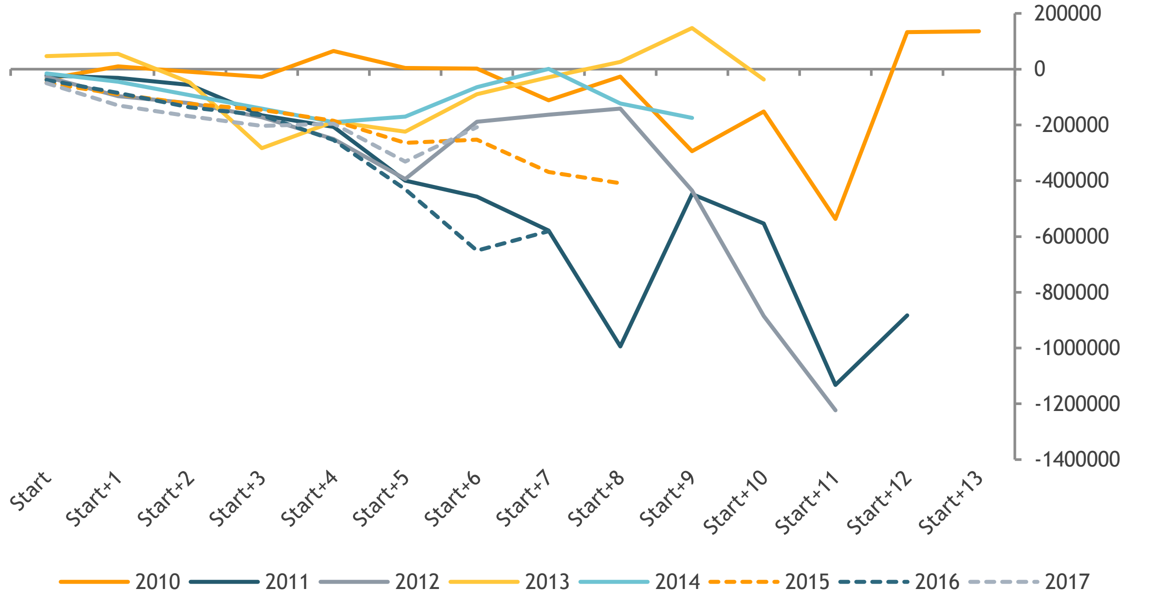


Note: the graph shows the evolution of the share of AI start-ups in the total profit and total loss of all start-ups, both for operating profit before interest and taxes (EBIT) and operating profit before interest, taxes, depreciation and amortisation (EBITDA).

Despite the substantial difference between EBIT and EBITDA, there is little difference in the evolution of the shares of AI start-ups. The evolution of the share of AI start-ups in total profit largely follows the evolution of the share of AI start-ups in the total number of start-ups. However, AI start-ups account for a disproportionate share of the total loss of all start-ups. This share is also increasing almost continuously. A comparison of (unshown) box plots of EBIT and EBITDA between AI start-ups and non-AI start-ups shows that the loss cannot be attributed to a number of companies with very large losses, but that a significant proportion of AI start-ups are loss-making. Whereas, over the period 2010-2023, an average of 71% of non-AI start-ups were profitable according to EBIT, and 80.3% according to EBITDA, for AI start-ups this was 46.6% (EBIT) and 56% (EBITDA) respectively. For non-AI start-ups, the percentage of profitable companies was fairly constant. For AI start-ups, the percentage fell from 75% in 2010 to 38.7% in 2023 according to EBIT and from 75% in 2010 to 48.5% in 2023 according to EBITDA. So even according to the less stringent criterion of EBITDA, more than half of AI start-ups were loss-making in 2023. Unreported box plots show that the spread of both EBIT and EBITDA is greater for AI start-ups than for non-AI start-ups – just as the spread of net profitability in Graph 6 is much greater for AI start-ups than for non-AI start-ups. The spread of the operating result is particularly substantial downwards, but in most years the maximum (without taking into account the 0.5% extreme values) is higher for AI start-ups than for non-AI start-ups. A limited number of AI start-ups therefore manage to be among the best-performing start-ups, as is also evident from the discussion of Graph 14 in section 3.5.

In order to ascertain whether there are differences in the operating result of AI start-ups depending on their start-up year, Graph 11 compares the evolution of the average operating result of AI start-ups in their starting year and the years thereafter, for starting years from 2010 to 2017. AI companies that started their activities in 2010 appear to have had an operating result around *break-even* in their start-up year and the first years after their start. In the first year after start-up, they were profitable on average, but from the seventh year after starting they became loss-making, only returning to profitability from the twelfth year after their start.

Graph 11 Evolution of the operating result of AI start-ups by starting year
In euros (constant prices 2015)



Note: the graph shows the evolution of the average operating result (EBIT) of AI start-ups according to starting year (first year with turnover).

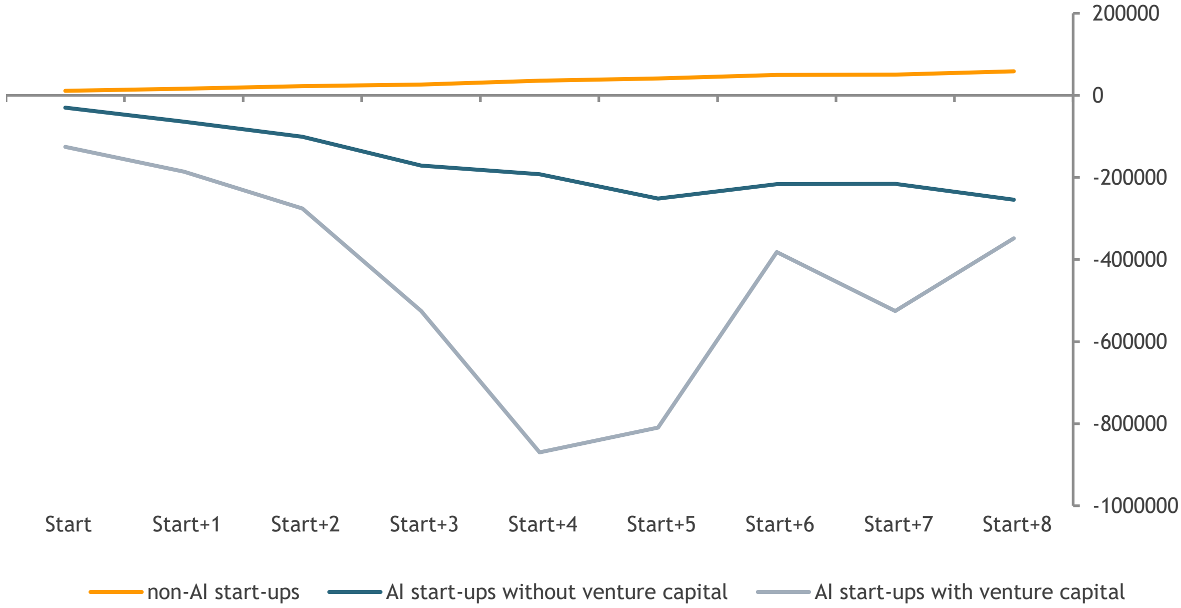
For companies that started between 2011 and 2017, we see the average operating result becoming increasingly negative in the years after their start. Only for AI start-ups from 2013 and 2014 do we notice a positive turnaround after a number of years.

If we divide AI start-ups into companies with and without venture capital, AI start-ups without venture capital appear to be less loss-making on average than AI start-ups with venture capital. Of the AI start-ups with venture capital, 21% were profitable (EBIT) six years after launch.[18] For AI start-ups without venture capital, this graph is 50%, and for non-AI start-ups, it is as high as 74%.

Graph 12 compares the evolution of the average operating result in the start-up year and the first eight years of AI start-ups with venture capital, AI start-ups without venture capital, and non-AI start-ups. For non-AI start-ups, the average operating result is positive from the first year of activity and increases in the years after the start-up. The average operating result of AI start-ups without venture capital is negative in the start-up year, and the loss gradually deepens in the years following the start-up. AI start-ups with venture capital already have a more negative operating result on average in their start-up year than AI start-ups without venture capital. This expands further in the first years after start-up. In the fourth and fifth years after start-up, the average operating result reaches a low point, after which it gradually becomes less negative. A comparison of the distribution (unreported box plot) of the operating result shows that the evolution is not explained by a limited number of highly loss-making start-ups, but rather by a wider spread – especially towards greater losses – for AI start-ups with venture capital between the third and fifth year after launch.

[18] An analysis using EBITDA yields similar results.

Graph 12 Evolution of the operating result of AI start-ups and non-AI start-ups
In euro (constant prices 2015)



Note: the graph shows the evolution of the average operating profit (EBIT) of AI start-ups and non-AI start-ups (starting year is the first year with turnover).

The evolution of the operating result of AI start-ups with venture capital may point to the finding by Estrin *et al* (2024) that the most innovative companies take more risks and take longer to become profitable than less innovative companies.

As with the variables in Table 5, we have checked whether the difference between AI start-ups and non-AI start-ups is statistically significant for the operating result. Because the operating result can be negative, we do not use variables in logs in this section, as in section 3.2, but calculate the difference in absolute terms. Table 7 shows that the growth of both EBIT and EBITDA of AI start-ups is on average lower than that of non-AI start-ups and that the difference is also statistically significant, albeit for EBITDA at a significance level of 10%.

Table 7 The difference in operating profit growth (EBIT and EBITDA)

	EBIT	EBITDA
Difference between AI start-ups and non-AI start-ups	-27,430***	-11,137*
Number of observations	176,296	176,325
Number of control variables	251	251
Number of selected control variables	210	210
Wald chi2(14)	20.71	3.38
Prob > chi2	0.00	0.07

Note: the table shows the coefficient of a dummy variable equal to 1 for AI start-ups and equal to 0 for non-AI start-ups in a first difference estimate (average 2010-2023), with operating profit before interest and taxes (EBIT) and operating profit before interest, taxes, depreciation and amortisation (EBITDA) respectively. See text and note in Table 5 for more information about the estimation procedure. The coefficients of the difference between AI starters and non-AI starters indicate whether the coefficient differs from 0, for statistical significance of 10% (*), 5% (**) or 1% (***).

As in section 3.2, we further investigated whether certain AI characteristics can explain differences in operating profit between AI start-ups. The results are shown in Table 8. In the estimation of EBIT growth, only the positive coefficient of the number of USPTO patents is statistically significant.

Table 8 The difference in operating profit growth (EBIT and EBITDA) between AI start-ups (AI technologies and AI purposes)

	EBIT	EBITDA
AI technology:		
Text mining	24,267	36,508
Speech recognition	-1,844	27,534
Generation of written/spoken language	28,630	37,244
Image recognition, image processing	7,670	27,227
Machine learning for data analysis	23,108	31,472
Automating various workflows	29,922	41,599*
Autonomous robots, self-driving vehicles, etc.	3,967	8,438
Text-image generation	43,444	49,203
Hardware	-61,800	46,482
AI purpose:		
Marketing or sales	-34,590	-31,016
Production or service processes	-1,168	3,573
Business administration/management	-25,767	-15,359
Logistics	-16,626	4,795
ICT security	-26,844	-15,622
Accounting, financial management control	33,407	31,184
Research and development	2,813	17,497
Control variables:		
Number of sectors of use	-39,336	116,856***
Number of patents USPTO	62,069**	794,712**
Number of patents EPO	-1,139	32,160**
Venture capital	-23,730	-29,738*
Academic spin-off	27,310	13,626
Number of observations	1,398	1,406
Number of control variables	114	114
Number of selected control variables	98	99
Wald chi2(14)	21.60	34.14
Prob > chi2	0.42	0.04

Note: the table shows the coefficients of dummies that indicate whether the AI start-up uses a particular AI technology or for a particular purpose, in an estimate in first differences of , with respectively the operating result before interest and taxes (EBIT) and the operating result before interest, taxes, depreciation and amortisation (EBITDA). See text and note in Table 5 for more information about the estimation procedure. The coefficients of the difference between AI start-ups and non-AI start-ups indicate whether the coefficient differs from 0, for statistical significance of 10% (*), 5% (**) or 1% (***).

The Wald test shows the limited explanatory value of the variables included in the EBIT estimate. The estimate of EBITDA growth has more explanatory value. For example, AI start-ups that use AI technology suitable for automating various workflows have a statistically significant (10%) higher growth in operating profit (EBITDA) than AI start-ups that do not. The more sectors AI start-ups are active in, the faster their EBITDA increases. This also applies to the number of patents, both USPTO and EPO. AI start-ups with venture capital have lower EBITDA growth, although the coefficient is only statistically significant at 10%.

The only statistically significant coefficient for both EBIT and EBITDA is that of the number of USPTO patents, which therefore appear to contribute to the growth of the operating result.

3.4. Productivity

Productivity, the ratio between output volume and the amount of inputs used to achieve it, is probably the measure most commonly used by economists to assess the performance of companies.[19]

Measuring or estimating productivity has long been the subject of methodological debate. A commonly used measure is labour productivity, for example, turnover or value added per employee or per hour worked. Labour productivity only takes labour into account as a factor of production. A measure that also takes into account other factors of production such as capital, energy and materials is multifactor productivity (MFP).[20] The growth of MFP is considered an indicator of technological progress. Although MFP is in principle to be preferred to labour productivity, there are many methodological problems that complicate reliable calculation or estimation. In our analysis, we will consider four productivity measures: turnover per employee (full-time equivalent - FTE), value added per employee (FTE), MFP estimated using a panel estimation (OLS) and MFP estimated according to Wooldridge (2009). For both MFP estimates, value added is considered as the output measure. Multifactor productivity was estimated by industry (NACE 2-digit level). The coefficients of the MFP estimation are often quite problematic. In the Wooldridge estimation, the coefficient of the capital production factor is usually very low or even negative. This estimation procedure fits in with the control function approach, which attempts to remedy the endogeneity problem of a standard OLS estimation, but this approach has its own limitations (for a recent discussion, see de la Cal Medina 2025 and Doraszelski & Li 2025).

Table 9 shows the results of an estimation of productivity growth according to the four different measures. According to the estimates, the average productivity growth for three of the four measures of AI start-ups is statistically significantly higher than that of non-AI start-ups. In terms of value added per employee, there is no statistically significant difference in productivity growth between AI start-ups and non-AI start-ups. According to the Wald test, all variables included in the estimation of the first difference in value added explain little of the variation in productivity growth. AI start-ups in the United States do not appear to experience significantly higher growth in labour productivity than non-AI start-ups (Dinlersoz, Dogan & Zolas 2024). Calvino & Fontanelli (2024) find a positive link between the use of AI and productivity for French companies that develop AI themselves, in contrast to companies that use AI applications that they have not developed themselves. The higher productivity compared to non-users is mainly explained by the fact that the most productive companies use more AI than less productive companies.

[19] An important point of current debate, beyond the scope of this paper, is what contribution AI will make to productivity and whether AI, as a technology with general applicability, will be able to reverse the downward trend in productivity growth that has been observed in most rich countries for decades.

[20] Also called total factor productivity (TFP).

Table 9 The difference in labour productivity and multifactor productivity growth

	Turnover/FTE	Value added/FTE	MFP (OLS)	MFP (Wooldridge)
Difference between AI start-ups and non-AI start-ups	0.06**	0.03	0.07***	0.08**
Number of observations	159,783	161,400	163,206	152,355
Number of control variables	251	251	251	251
Number of selected control variables	207	220	198	194
Wald chi2(14)	5.58	1.10	31.76	5.83
Prob > chi2	0.02	0.30	0.00	0.02

Note: the table shows the coefficient of a dummy variable equal to 1 for AI start-ups and equal to 0 for non-AI start-ups in a first differences estimation (average 2010-2023), with, respectively, turnover per full-time equivalent (FTE) employee, value added per FTE, multifactor productivity (MFP) estimated using OLS, and multifactor productivity estimated following Wooldridge (2009). See text and note in Table 5 for more information about the estimation procedure. The coefficients of the difference between AI start-ups and non-AI start-ups indicate whether the coefficient differs from 0, for statistical significance of 10% (*), 5% (**) or 1% (***).

Table 10 shows the results of an estimation that attempt to explain the productivity growth of AI start-ups on the basis of AI characteristics. Although, with the exception of value added per employee, there are statistically significant coefficients for the various estimates, there is no agreement between the alternative productivity measures. We therefore present the results for information purposes without paying much attention to the specific characteristics, especially since there is not only a difference in significance but sometimes even in the sign of the same coefficient. The Wald test shows that the variables considered in the estimation of value added per FTE and MFP following Wooldridge (2009), which also uses value added as an output measure, have little explanatory value.

Table 10 The difference in the growth of labour productivity and multifactor productivity (AI technologies and AI purposes)

	Turnover/FTE	Value added/FTE	MFP (OLS)	MFP (Wooldridge)
AI technology:				
Text mining	0.25	-0.06	-0.15**	0.02
Speech recognition	-0.05	-0.33	-0.04	-0.42*
Generation of written/spoken language	0.09	-0.16	-0.07	-0.17
Image recognition, image processing	0.02	-0.18	0.02	-0.27**
Machine learning for data analysis	0.11	-0.07	-0.07*	-0.13
Automating various workflows	0.04	-0.08	0.00	-0.17
Autonomous robots, self-driving vehicles, etc.	0.15	-0.20	-0.01	-0.17
Text-image generation	0.06	-0.12	-0.12*	-0.20
Hardware	-0.03	-0.42	0.11	-0.36
AI purpose:				
Marketing or sales	-0.27***	-0.02	-0.02	0.00
Production or service processes	-0.17*	0.04	-0.05	0.10
Business administration/management	-0.31***	-0.10	-0.01	0.00
Logistics	-0.37***	-0.03	-0.05	0.03
ICT security	-0.43***	-0.19	0.01	-0.19
Accounting, financial management control	-0.19	0.11	-0.02	0.10
Research and development	-0.19	0.03	-0.02	0.19
Control variables:				
Number of sectors of use	0.17***	0.06	-0.02	0.08
Number of patents USPTO	-0.05	0.05	0.05**	0.05
Number of patents EPO	0.12	0.04	0.07	0.03
Venture capital	-0.05	-0.09	-0.06	0.14
Academic spin-off	-0.04	-0.13	-0.22***	-0.01
Number of observations	1,506	1,060	1,507	1,027
Number of control variables	114	114	114	114
Number of selected control variables	96	89	98	89
Wald chi2(14)	45.50	17.25	31.09	15.42
Prob > chi2	0.00	0.70	0.07	0.80

Note: the table shows the coefficients of dummies that indicate whether the AI start-up uses a particular AI technology or for a particular purpose, in an estimate in first differences with, respectively, the turnover per full-time equivalent (FTE) employee, the value added per FTE, multifactor productivity (MFP) estimated with OLS and multifactor productivity estimated with the Wooldridge procedure. See text and note in Table 5 for more explanation of the estimation procedure. The coefficients of the difference between AI start-ups and non-AI start-ups indicate whether the coefficient differs from 0, for statistical significance of 10% (*), 5% (**) or 1% (***).

3.5. Business dynamics

The dynamics of a sector or industry are usually analysed on the basis of entry and exit, the survival rate of companies, their average growth rate and the number of high-growth companies (gazelles).[21] Compared to other EU countries, Belgium has relatively low entry and exit rates, a relatively high survival rate and high average growth for start-ups, but few high-growth enterprises (Dumont 2021). With regard to high-growth companies, Eurostat calculates growth on the basis of the number of employees. This can be explained in part by the greater availability of administrative business data on employees than on turnover or value added, but also by the importance that policymakers attach to the contribution of start-ups in terms of job creation.[22] As mentioned earlier, there is some tension between the objectives of policymakers and the 'lean start-up' strategy of entrepreneurs, although section 3.2 shows that AI start-ups grow faster than non-AI start-ups in terms of the number of employees.

The most recent data from Statbel show that of the companies established in 2018 (first registration as VAT-liable), 64% were still active in 2023. Although start-ups in Belgium have a relatively high survival rate compared to start-ups in other EU countries, this means that one-third of start-ups in Belgium voluntarily cease trading within five years, either through dissolution or liquidation, or are forced to do so through bankruptcy. A number of start-ups disappear from the administrative data due to a merger by acquisition or a merger by the creation of a new entity, which can be seen as a successful exit.

Graph 13 shows, for the 744 Belgian AI start-ups, the number of bankruptcies, liquidations or dissolutions and the number of mergers or acquisitions, based on Crossroads Bank for Enterprises data on the legal situation (and date). For mergers and acquisitions, we used additional information, mainly media reports on mergers or acquisitions of Belgian start-ups. It is striking that the discontinuation of AI start-ups only began in 2018. This would mean that all AI companies established between 2010 and 2013 were still active five years later. This seems unlikely and may indicate a ‘survivorship bias’ in our data on AI start-ups.[23] It is possible that in the first few years after 2010, companies were established that would meet our definition of AI start-ups but that ceased their activities after a few years. In all likelihood, these companies no longer have a website, nor is any other online information about their AI production still available. It is therefore plausible that a number of AI start-ups from the early period are no longer active and are counted among the non-AI start-ups. Given their limited number compared to genuine non-AI start-ups, the impact of this bias on the calculation of the performance of non-AI start-ups is negligible. By incorrectly excluding them from the AI start-ups, the performance of AI start-ups is likely to be overestimated.

In total, 74 AI start-ups ceased trading from 2018 onwards due to bankruptcy, liquidation or dissolution, and 26 were involved in a merger or acquisition. This information allows us to determine whether the likelihood of an AI start-up ceasing trading can be explained by business economics variables or the AI characteristics we have identified. As there are relatively few mergers and acquisitions, the estimation

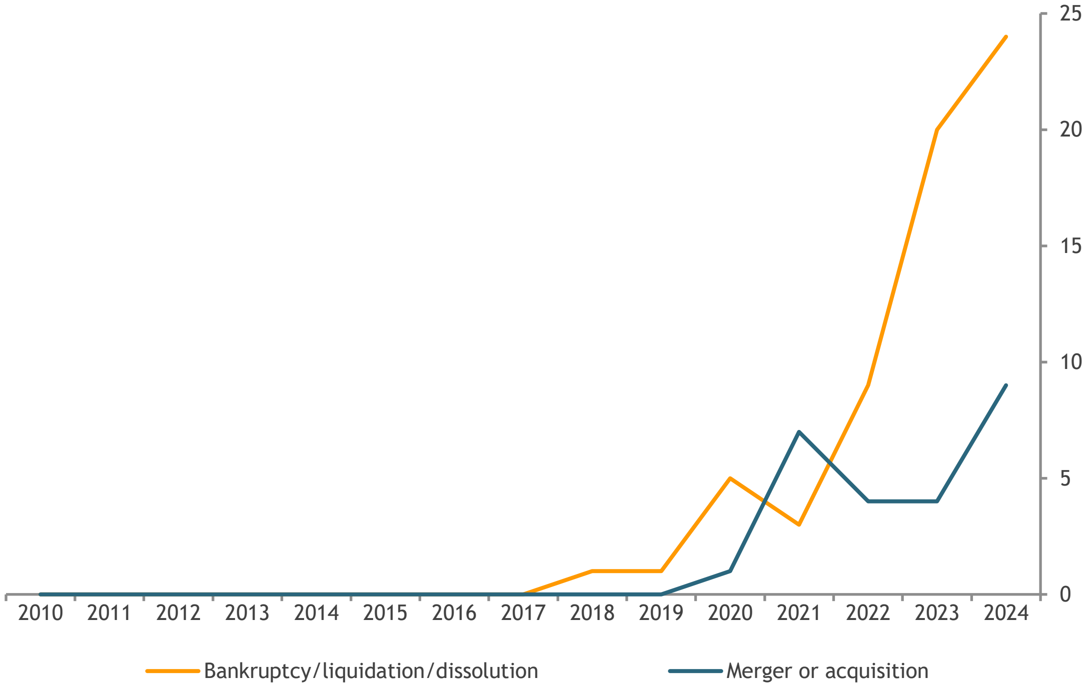
[21] Calvino, Reijerink & Samek (2025) provide a recent overview of studies on the potential impact of generative AI on business dynamics.

[22] Among researchers, the usefulness of policies specifically targeting high-growth companies is increasingly being questioned (Hart, Prashar & Ri 2020; Coad *et al* 2024; Hamilton and Ng 2025).

[23] AI start-ups in the United States have a lower survival rate than non-AI start-ups (Dinlersoz, Dogan & Zolas 2024).

results should be interpreted with caution. Dinlersoz, Dogan & Zolas (2024) also point to the limited number of mergers and acquisitions of AI start-ups in the United States during the period 2004-2023.

Graph 13 Number of exits of AI start-ups by legal situation (2010-2024)



Note: the information is based on data on the legal status and date of legal status from the CBE and additional information on mergers and acquisitions.

Table 11 shows the estimation results in which we explain, on the one hand, the probability of an AI start-up going bankrupt, being liquidated or dissolved and, on the other hand, the probability of an AI start-up being taken over or entering into a merger, based on information about the AI technology used or the purpose of the AI applications offered.

AI start-ups active in the field of autonomous robots, self-driving vehicles or autonomous drones have a statistically significantly higher probability of bankruptcy, liquidation or dissolution than AI start-ups that do not use these technologies. AI start-ups that focus their applications on production and service processes, on the other hand, have a lower probability of bankruptcy, liquidation or dissolution. The more sectors AI start-ups have customers in, the lower the risk of bankruptcy, liquidation or dissolution. AI start-ups that focus on applications in ICT security or in accounting and financial management control are statistically significantly more likely to be taken over. Table 3 in section 2.1 shows that these are the two least common objectives among Belgian AI start-ups. These are therefore more specific market niches. It is striking that AI start-ups with venture capital are less likely to be taken over or merged – which is clearly the ambition of many venture capital providers – and academic spin-offs are more likely.

Table 11 Probability of exit of AI start-ups by legal situation (AI technologies and AI purposes)

	Bankruptcy/liquidation/dissolution	Merger/acquisition
AI technology:		
Text mining	0.02	0.94
Speech recognition	0.16	0.01
Generation of written/spoken language	-0.69	0.04
Image recognition, image processing	0.25	-0.49
Machine learning for data analysis	0.00	-0.02
Autonomous robots, self-driving vehicles, etc.	1.11**	-
Text-image generation	-	1.34
Hardware	0.80	-
AI purpose:		
Marketing or sales	-0.20	-0.32
Production or service processes	-1.20***	-0.35
Logistics	-0.42	0.6
ICT security	-	1.58*
Accounting, financial management control	-	1.50**
Research and development	-0.73	0.22
Control variables:		
Number of sectors of use	-0.16**	-0.13
Venture capital	-0.43	-1.85*
Academic spin-off	0.08	2.12***
Number of observations	522	555
LR chi2(14)	21.43	24.03
Prob> chi2	0.09	0.06
Pseudo R2	0.08	0.14

Note: the table shows the results of a logistic estimation in which the dependent variable is equal to 0 for AI start-ups that did not go bankrupt or into liquidation and were not taken over or merged, and equal to 1 for AI start-ups that went bankrupt or into liquidation (second column) and companies that were involved in a merger or takeover (third column). Statistical significance is indicated by * (10%), ** (5%) and *** (1%). For AI technology and AI purpose, the most common category is always taken as a reference (automating various work-flows or assisting in decision-making for technology and organising business administration or management for purpose). The LR chi2 test considers as its null hypothesis that the explanatory variables together cannot explain the variation in the variable to be explained. The p-value of the test, Prob> chi2, represents the probability of the LR value if the null hypothesis is correct. Pseudo R2 is an alternative to the R2 of a least squares estimate, which indicates what part of the variation of the dependent variable can be explained by the explanatory variables. However, as the term 'Pseudo' indicates, the interpretation in a logistic estimate is not so clear-cut.

Table 12 shows the results for estimates in which we explain these probabilities using information about the sectors in which the customers of the AI start-ups operate. Due to the relatively limited number of Belgian AI start-ups that have ceased trading, there is an identification problem in the estimates.

Some coefficients cannot be estimated, for example because no AI start-up using a particular technology, for a particular purpose or with customers in a particular sector, ceased its activities during the period under review. Table 12 shows the results of the estimates in which we examine whether there are statistically significant differences in the probability of bankruptcy, liquidation or dissolution or the probability of a merger or acquisition of AI start-ups between the sectors in which the customers of the AI start-ups operate. Companies that focus on the government and the non-profit sector are less likely to go bankrupt, be liquidated or dissolved. Start-ups with different AI objectives are also less likely to cease trading.

Table 12 Probability of exit of AI start-ups by legal situation (user sectors)

	Bankruptcy/liquidation/dissolution	Merger/acquisition
Sectors		
Legal	0.00	2.45***
Government + non-profit	-2.14**	0.54
AR/VR	1.57	4.28***
Control variables:		
Number of AI technologies	-0.05	-0.27
Number of AI purposes	-1.00***	0.24
Venture capital	-0.71	-1.80
Academic spin-off	0.5	2.19***
Number of observations	508	374
LR chi2(14)	37.51	36.65
Prob> chi2	0.23	0.16
Pseudo R2	0.14	0.24

Note: the table shows the results of a logistic estimation in which the dependent variable is equal to 0 for AI start-ups that did not go bankrupt or into liquidation and were not taken over or merged, and equal to 1 for AI start-ups that went bankrupt or into liquidation (second column) and companies that were involved in a merger or takeover (third column). Statistical significance is indicated by * (10%), ** (5%) and *** (1%). The sector that occurs most frequently as the sector of users, retail and distribution, is considered the reference. See note to Table 11 for more explanation of the estimation procedure.

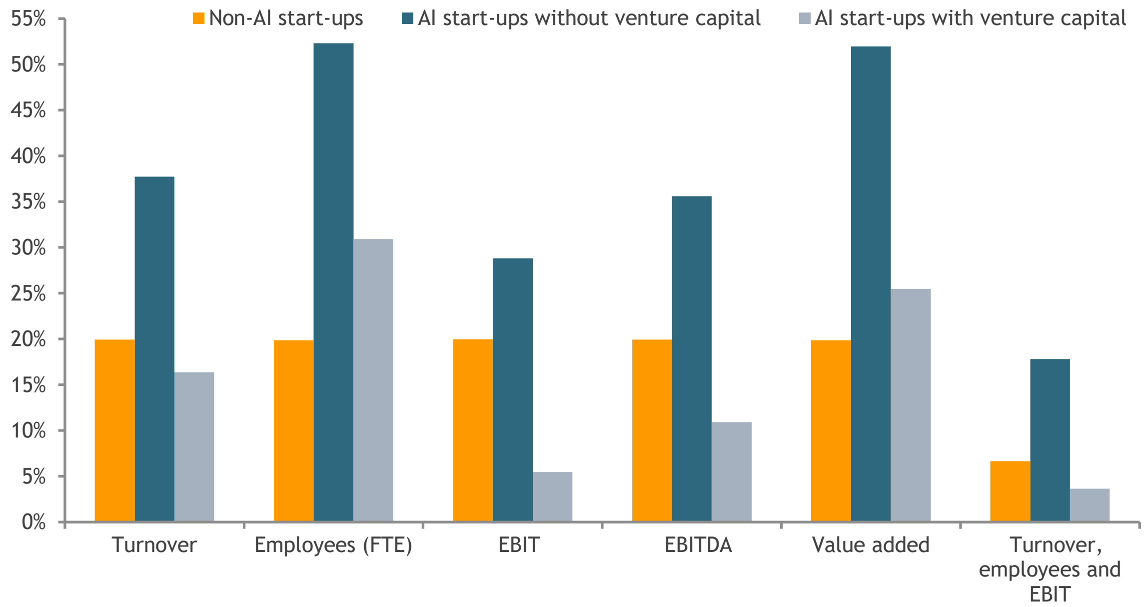
AI start-ups that have customers in the legal sector or in the field of Augmented Reality/Virtual Reality are more likely to be involved in a merger or acquisition. In the estimates shown in Table 12, a considerable number of sector variables are not included because no AI start-ups with customers in those sectors have exited, due to bankruptcy, liquidation or dissolution, or due to a merger or acquisition. The result of the LR test also points to the limited explanatory value of these estimates.

Studies on the prediction of failures, mergers and acquisitions usually include financial ratios. We have also carried out estimations using indicators of profitability, liquidity and solvency (see section 3.1). These variables have a statistically significant coefficient in some estimations but the inclusion of the ratios have no impact on the statistical significance of the AI characteristics that we are interested in. Separate estimates also show that the coefficients of the number of patents (EPO or USPTO) are not statistically significant. In order to limit the number of explanatory variables, these variables are therefore not included in the estimations reported in Tables 11 and 12.

The results of the estimation of the growth of start-ups, discussed in sections 3.2 and 3.3, relate to averages. For a number of business variables, there appears to be a greater spread for AI start-ups than for non-AI start-ups. Instead of looking at average effects, we can focus on the fastest growers, which are likely to attract a lot of interest from policymakers.

To identify the most successful start-ups during the period 2010-2023, we consider the top 20% of all start-ups with the highest turnover, the highest number of employees, the highest operating profit (EBIT and EBITDA) and the highest added value in 2023. These are therefore the companies that, since their inception (from 2010 onwards), have managed to grow into the largest start-ups in various dimensions. Graph 14 shows the percentage of three groups of start-ups (non-AI start-ups, AI start-ups without venture capital and AI start-ups with venture capital) that belonged to the top 20% in 2023. If this percentage is higher than 20%, that group of start-ups is relatively overrepresented in the top 20%. A percentage lower than 20% indicates underrepresentation. The last three bars in Graph 14 show the percentage of the three groups of start-ups that are among the top 20% in terms of turnover, number of employees and operating profit (EBIT).[24] This is a relatively small group of start-ups, which, based on the situation in 2023, can be considered the most successful start-ups. Since non-AI start-ups make up the majority of all start-ups, the percentage for non-AI start-ups will fluctuate around 20%, except for the last criterion, because this concerns start-ups that rank in the top 20% for each of the three variables considered. Approximately 7% of all start-ups belong to the most successful start-ups.

Graph 14 Percentage of AI start-ups and non-AI-start-ups among the top 20% largest startups in 2023



Note: the graph shows the percentage of AI start-ups and the percentage of non-AI start-ups that belong to the 20% of all start-ups with the highest level of the various variables in 2023. The last three bars show the percentage of AI start-ups and non-AI start-ups that are among the top 20% for turnover, number of employees and operating profit (EBIT) in 2023.

AI start-ups without venture capital are overrepresented in the top of all start-ups for all dimensions considered in Graph 14. This is most evident for turnover, where 38% of this group belongs to the top 20%, and for the number of employees and added value, with a percentage of 52% in each case. AI start-ups without venture capital are also clearly overrepresented among the 7% most successful companies. AI start-ups with venture capital are slightly overrepresented in the top 20% of all start-ups in terms of number of employees and added value. In terms of operating result (EBIT and EBITDA), they are significantly underrepresented in the top 20%. This also applies to the top 7% of most successful start-ups.

It should be noted, however, that in 2023, the average age of both non-AI start-ups and AI start-ups without venture capital was six years. Both groups of start-ups can therefore be compared effectively. For AI start-ups with venture capital, the average age in 2023 was only four years. This could partly explain why they are currently less represented among start-ups with the highest turnover, and especially among start-ups with the highest operating profit. There is also a striking difference between AI start-ups with and without venture capital in terms of capital structure. In 2023, AI start-ups with

[24] Since value added largely coincides with the wage bill plus operating profit, we will disregard it.

venture capital had higher financial independence on average and lower average debt per employee than AI start-ups without venture capital. AI start-ups without venture capital therefore appear to have fewer problems obtaining credit than AI start-ups with venture capital. This could indicate that AI start-ups with venture capital focus on activities with greater potential but also greater uncertainty, which is of course consistent with the essence of venture capital and in line with Estrin et al (2024), who find that the most innovative companies take longer to become profitable than less innovative companies.

The relatively small percentage of AI start-ups that can be considered highly successful (i.e. 7%) is strikingly consistent with the findings of Challapally et al (2025). In the United States, only 5% of companies currently seem to be succeeding in getting a sufficient return on their investments in Generative AI, whereas for the vast majority of companies - both users and AI producers - these investments have little impact on their operating results. This recent study by MIT researchers shows that only a small proportion of AI projects that are launched are successfully implemented. The best-performing AI producers focus on limited but high-quality applications rather than broad functionality. They scale by continuously learning from feedback, with domain knowledge and integration into the workflow being more important than flashy user experiences. Successful AI producers start with the less crucial parts of the workflow and, after significant adjustments and demonstrating added value, expand to core processes. They must take sufficient account of the fact that customers want AI applications to conflict as little as possible with the company's existing processes, software and data. Challapally et al (2025) give three examples of successful applications: AI speech technology for summarising and transferring telephone calls, document automation for contracts and forms, and code generation for repetitive technical tasks. According to the researchers, the limited return on current AI investments is due to the fact that companies spend more resources on visible front-office applications in marketing and sales, while investing less in applications for back-office functions, which nevertheless yield a higher return.

Conclusion

AI developments are moving fast. As start-ups struggle to define a future-proof strategy, policymakers face the challenge of creating clear rules and guidelines to ensure the responsible use of AI and steer these developments in the socially desirable direction.

The development of large AI models, which form the basis of generative AI, with applications such as ChatGPT, is dominated by a relatively small group of large companies. The market for commercial applications of large AI models is currently much more dynamic, with thousands of start-ups worldwide. It is mainly in this market that the Belgian start-ups that we have identified are active.

Belgian AI start-ups are clearly more focused on growth than Belgian non-AI start-ups. They mainly aim for rapid growth in turnover, which is often accompanied by a sharp increase in the number of employees. For many of these companies, profitability remains elusive for the time being. In the first few years after their starting, the losses of AI start-ups often increase, and only from the fifth year onwards is there a slight improvement.

Among the small group of exceptionally successful start-ups - companies that simultaneously achieve high turnover, have many employees and are highly profitable - AI start-ups without venture capital are clearly overrepresented. AI start-ups with venture capital, on the other hand, are underrepresented. This can be explained in part by the fact that these start-ups were, on average, established more recently than non-AI start-ups and AI start-ups without venture capital, but perhaps also because they are among the most innovative companies with a higher risk profile, which take longer to become profitable than less innovative companies.

As 2023 is the most recent year in our analysis, we are missing the developments in 2024 and 2025, which have undoubtedly brought substantial shifts in the AI ecosystem. The primary aim of our study is to map out Belgian start-ups in AI production. The ultimate economic impact of AI will - apart from further developments that are difficult to predict, such as the possible achievement of Artificial General Intelligence (AGI) - be largely determined by the extent to which companies adopt AI applications and adapt them to their business-specific processes. In order to assess this impact, information is needed on the use of AI by companies. The identification of Belgian companies active in AI production will help to identify Belgian companies that use AI. This is what we will focus on in future research.

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