Research Policy 51 (2022) 104555

Contents lists available at ScienceDirect

Research Policy

journal homepage: www.elsevier.com/locate/respol

Artificial intelligence and industrial innovation: Evidence from German firm-level data

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A R T I C L E I N F O

JEL Classifications:
O14
O31
O32
O33
L25
M15

Keywords:
Artificial Intelligence
Innovation
CIS data
Germany

A B S T R A C T

This paper analyses the link between the use of Artificial Intelligence (AI) and innovation performance in firms. Based on firm-level data from the German part of the Community Innovation Survey (CIS) 2018, we examine the role of different AI methods and application areas in innovation. The results show that 5.8% of firms in Germany were actively using AI in their business operations or products and services in 2019. We find that the use of AI is associated with annual sales with world-first product innovations in these firms of about €16 billion (i.e. 18% of total annual sales of world-first innovations). In addition, AI technologies have been used in process innovation that contributed to about 6% of total annual cost savings of the German business sector. Firms that apply AI broadly (using different methods for different applications areas) and that have already several years of experience in using AI obtain significantly higher innovation results. These positive findings on the role of AI for innovation have to be interpreted with caution as they refer to a specific country (Germany) in a situation where AI started to diffuse rapidly.

1. Introduction

Artificial Intelligence (AI) has gained great attention in innovation management and innovation policy as a new technology that may substantially change the way firms operate and innovate, with far-reaching consequences on markets, economies and societies (Agrawal et al. 2019a). AI commonly describes information-technology (IT) methods that allow machines to perform human-like cognitive functions, such as understanding, learning, reasoning and interacting (Baruffaldi et al. 2020). While AI technologies have been developed and applied for several decades (see Haenlein and Kaplan 2019), recent years saw a huge surge in the use of AI as a consequence of the advancing process of digitalisation. The digital interconnection of product, services, machines and communication devices together with the ever increasing amount of data that is generated in digitalised systems offer entirely new opportunities of exploiting data for new applications and increasing the efficiency of operations. AI is a technology that allows an effective and comprehensive use of these data sources. The development of deep learning based on artificial neural networks and other automated machine learning techniques offers a wide range of new applications in most industrial activities – from implementing data-based business models and optimising multi-machine systems to enhancing industrial research, potentially leading to a reorganisation of markets, supply chains and production systems (Nolan 2020).

At the same time, there are a number of challenges when it comes to fully utilising the innovative potential of AI (Brock and von Wangenheim 2019, Nolan 2020). Implementing AI methods often requires the adaptation of existing IT systems and raises compatibility issues. The availability and quality of data is another major challenge for effectively using AI methods, as are adequate skills of employees. As for other major new technologies in early diffusion stages, uncertainty on the technological feasibility and market acceptance of new AI applications is high. Potential users may question the credibility of decisions based on AI and may be reluctant to rely on AI-based processes. In addition, legal and regulatory issues (including data protection) as well as data security are potential hampering factors for successfully applying AI. As a consequence of these challenges, it is not guaranteed that using AI will result in more innovations or more successful innovation.

While there are high expectations about the potential of AI for disruptive innovation (OECD 2020, Brynjolfsson et al. 2019), rather

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https://doi.org/10.1016/j.respol.2022.104555
Received 8 April 2021; Received in revised form 11 April 2022; Accepted 11 May 2022
Available online 21 May 2022

little data exists on the extent to which AI is currently reshaping innovation in firms. Although some statistical offices and research institutes started to collect data on the use of AI within structural business statistics (see Montagnier et al. 2020 and Zhang et al. 2021), none of these data sources link AI use to innovation. Such a link is critical, however, to model and understand the role of AI for innovation, firm performance and wider economic impacts (Raj and Seamans 2019).

The aim of this paper is to fill this gap by providing an empirical analysis that links AI and innovative activities in firms, considering a wide variety of AI methods and application areas. We investigate both the diffusion of AI technologies in the business enterprise sector and highlight the role of AI technologies for industrial innovation. We use novel data from the German part of the European Commission's Community Innovation Survey (CIS). In Germany, the survey contained dedicated questions on the use of AI technologies, including items on the type of AI method used, the business areas where AI is applied, whether AI has been developed in-house or externally, and for how long a firm has been using AI technologies. We estimate innovation production functions to identify the share of firms' innovation output which is associated with the use of AI and extrapolate the regression results to arrive at total economy estimates. These total economy estimates provide an indication on the economic significance of AI technologies for industrial innovation in Germany at the end of the 2010 decade. It has to be mentioned, however, that these figures should not necessarily be interpreted in a strict *causal* contribution of AI to innovation, such that the firms would not had a comparable innovation performance if they had not used AI. The results should rather be read in terms of what share of total innovation activity is currently linked to the use of AI.

Our results show that AI is used by only a rather small fraction of firms (5.8% of the target population of the German CIS). For one out of four firms employing AI technology, the introduction of a world-first innovation could be linked to the use of AI. The sales generated by these world-first innovations represent about 21% of total sales with world-first innovations in AI-using firms. In terms of total economy significance, 3.2% of all firms with world-first innovations in the German business enterprise sector, and 18.1% of total sales with world-first innovations in 2018 are associated with AI use. In absolute figures these amount to €16.1 billion sales of world-first innovations. Process innovation based on AI contributes 6% to total cost savings in the German enterprise sector in 2018 (€11.4 billion).

The paper proceeds with a brief summary of the existing literature on the role of AI for innovation (Section 2). Section 3 describes how we measure the use of AI in firms and shows some descriptive results. Section 4 introduces the model used to identify innovation output that can be linked to AI and presents the estimation results. Section 5 discusses the total economy estimates and Section 6 concludes.

2. Artificial intelligence and innovation

AI is an emerging technology that has some characteristics of a general purpose technology in the sense that it can drive innovation in several ways across many sectors of the economy (Trajtenberg 2019). At the same time, it has also elements of a transversal technology (Righi et al. 2020) or may be viewed as an infrastructural, large technical system (Vannuccini and Prytkova, 2021). The specific power of AI relates to the extensive and often real-time analysis of heterogeneous data on business processes and the use of products or services in order to identify regularities and patterns, to learn what drives the analysed phenomena, and to autonomously solve problems, including newly arising ones (Taddy 2019). Through the skills of perception, cognition and problem-solving, which characterise most types of human work (Brynjolfsson et al. 2019), AI can be employed to automate processes, improve the quality of operations and enhance the features of products and services, based on self-learning algorithms.

The innovation impact of AI basically refers to three areas of innovation in firms:

- Products, services and business models: AI enables new ways of data-based business models that exploit, often in real-time, information on customers, product use and product-relevant conditions to offering new types of products and services (see Reim et al., 2020, Lee et al. 2019, Garbuio and Lin 2019, Valter et al. 2018). AI can, for example, be built-in as a software component in products and services to improve the performance of the product or offer additional service features. Autonomous driving is one of many applications in this respect. AI is also highly relevant for a more effective marketing of products and services, e.g. through identifying user patterns and developing user-specific communication of product offers.
- Production, delivery and administrative processes: AI can be used to optimise operations (particularly by automating human activities) and help humans to make the right diagnoses and decisions. For example, AI methods are used to identify patterns in production problems or defects in manufactured products and to implement predictive maintenance (Nolan 2020). Real-time fleet management or digital security applications (e.g. detecting spam or dangerous attachments to mail communication) are other examples. There is also a huge rationalisation potential of AI in administrative operations (e.g. automated responses to telephone calls and e-mails, automated invoicing) as well as in digital security, e.g. for detecting misuse of IT systems by hackers. AI also supports decision-making, e.g. for interpreting x-rays by physicians.
- R&D and innovation processes: AI is reshaping the process of research and development (R&D) through the extensive use of large (often passively generated) datasets and enhanced prediction algorithms (Cockburn et al. 2019). AI can substantially fasten and broaden R&D processes, e.g. in pharmaceuticals and chemicals (compound identification and discovering new industrial materials through neural network approaches) or in the machinery and equipment industry (e.g. through virtual factories that allow to simulate and improve production processes, Nolan 2020). Thus, AI represents a new method for research and invention. Prediction technologies and deep learning methods can influence the knowledge production process, e.g. by increasing the efficiency of searching relevant prior knowledge and by easing discovery of new results (Agrawal et al. 2019a, Bianchini et al. 2020).

In addition, the advance of AI applications drives complementary innovations often needed to leverage the full potential of AI, e.g. in digital communication (e.g. 5G), chip technology, server infrastructure, new computing approaches (e.g. quantum technology) (see Brynjolfsson et al. 2019). AI technologies may also change innovation practices and team organisation in R&D and innovation projects by demanding new forms of team work and new combination of skills in R&D projects (Raghu and Schmidt 2020) and by raising a series of questions about how to organise, conduct and evaluate AI-based research (Seeber et al. 2020).

The literature also points to a number of challenges that can limit the innovation impact of AI (Nolan 2020, Reim et al., 2020, Haefner et al. 2020). First of all, data availability and data quality are often a main barrier to successfully implement AI. High-value uses of AI typically combine diverse data types and require a constant data inflow of high quality (in terms of format, completeness, consistency and metadata information). The need for digitalising, cleaning, shaping, connecting and labelling data can easily eat up possible efficiency gains from using AI. Secondly, specific skills related to implementing AI methods are scarce and restrict firms in rolling out AI applications on a larger scale. In addition, AI projects often require a mix of skills, and setting up the necessary multidisciplinary teams can be challenging as well. Thirdly, for many firms AI is a rather new technology that is associated with uncertainty about its technological feasibility. A further challenge relates to a lack of transparency of how AI methods arrive at their results. The complex assembly of different functions and their abstraction levels impairs traceability ('black-box issue'). As a consequence, trust for AI may lack both among employees and among users when individuals do not understand how AI operates. In addition, AI applications may raise legal and regulatory issues, particularly if data from different owners are merged and the outcome of AI-based algorithms cannot be traced back to a responsible organisation or individual that can be made liable.

The trade-off between great innovation potentials and substantial challenges provides an interesting ground for studying the role of AI for industrial innovation. However, only few studies have analysed the contribution of AI to innovation in firms so far as representative data on the diffusion of AI and its role in innovation processes is largely lacking (see Raj and Seamans 2019). In the absence of survey data on AI and innovation, several authors attempted to identify the use of AI methods through patent data. Fujii and Managi (2017) used a code-based approach, focussing on international patent classification (IPC) code G06N ('computer systems based on specific computational models', corresponding to US patent classification code 706 'data processing, artificial intelligence'). Cockburn et al. (2019) also used code 706, complemented by a keyword search on patent titles relating to AI. EPO (2017) used solely a code-based definition that should capture AI-related patents in the field of machine understanding. The OECD also developed a purely code-based approach that focuses on human interface, human cognition and meaning understanding (Inaba and Squicciarini 2017). Baruffaldi et al. (2020) used text mining techniques to search abstracts and patent documents that refer to AI-related papers in order to identify IPC codes that most frequently contain AI-related inventions (see Van Roy et al. 2020 for a summary of these methods in recent studies). All these studies are descriptive in nature and do not link AI use to innovation at the firm level. An exception is Behrens and Trunschke (2020) who used patent data on 'industry 4.0' technologies (a fraction of these patents relate to AI methods) to examine the impact on firms' sales, finding a stronger positive effect as compared to other patents, but which is diminishing with firm size.

Patent data, however, provide only an incomplete picture on the use and diffusion of AI as only a fraction of new AI methods are patented, and firms may implement and use AI methods based on technologies invented by others. The firm-level data used in this paper reveal that only 30% of firms that actively use AI in their products, services or operations are relying on patents to protect their intellectual property (IP). With respect to IP related to AI, this share is most likely much smaller as many AI applications are based on existing AI technology and do not represent technological inventions in their own right.

Other studies looked at specific technologies that are closely linked to AI or rely on AI technologies for analysing the role of AI in innovation. One such technology are robots. They represent a specific area of AI application with respect to the automation of processes, though not all robots are based on AI. While there are a number of studies that examine the impact of robots on productivity and other firm performance measures (Stiebale et al. 2020, Acemoglu et al. 2020a, Humlum 2019), only few works linked the use of robots to other areas of innovation. Liu et al. (2020) used industrial robot data at the sector level to examine the relation of AI and technological innovation for Chinese manufacturing. They show that the use of robots fosters other technological innovation through accelerating knowledge creation and technology spillovers.

Another strand of literature examines the use of big data and firm innovation. Although big data is only one element of AI, and big data analysis can be carried out without employing AI methods, there is nevertheless a close connection between the two. Niebel et al. (2019) analysed the relationship between firms' use of big data and innovative performance in terms of product innovation and found higher likelihood of becoming a product innovator as well as higher market success of product innovations. Ghasemaghaei and Calic (2019) showed that the characteristics of big data are positively linked to the firms' innovation competency. Ferraris et al. (2019) found a positive relation between big data analytics capabilities and firm performance which is stronger in case a firm has an effective knowledge management. Lozada et al. (2019) found a positive relation of big data capabilities and more agile processes of product and service co-creation.

To the best of our knowledge, no studies that look at the entire field of AI applications in firms and their role for innovation have been carried out yet. Neither does any existing study estimate the economy-wide relevance of AI for the innovation performance of the business sector. This paper fills this gap. In particular, we not only consider firms that developed AI technologies, but also include adopters, i.e. firms using AI that has been developed by others. This allows considering the diffusion of AI across the business enterprise sector.

3. The use of AI in firms

3.1. Data source

This study employs firm-level data on the use of AI and on innovation output in terms of new products and new processes. The database is the German part of the Community Innovation Survey (CIS).[1] The CIS is a biennial exercise coordinated by the Statistical Office of the European Commission and constitutes the official innovation statistics for the EU. The CIS is a representative, large-scale survey designed to measure innovation inputs, innovation outputs and innovation-relevant characteristics of firms and their market environment. The survey is based on the definitions and measurement concepts for innovation data as laid down in the Oslo Manual (OECD and Eurostat 2018).

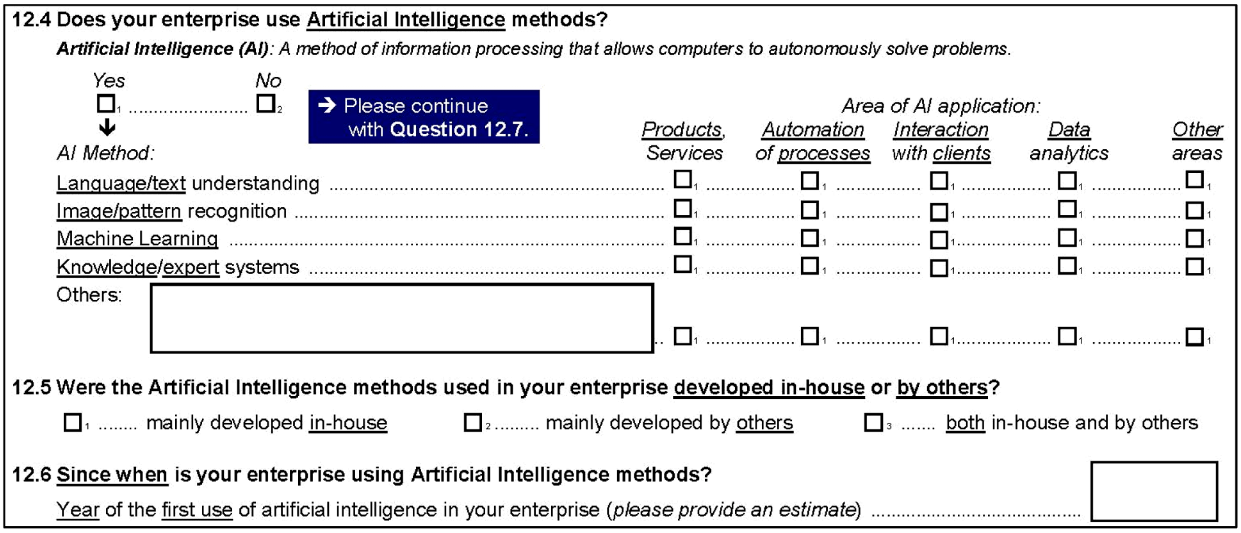
In the survey for the reporting year 2018 (CIS 2018), the CIS questionnaire used in Germany included questions on the use of AI (no other EU countries included this question).[2] The questions identified the type of AI use based on a matrix design that correlates AI methods and application areas (see Fig. 1). The phrasing was deliberately kept simple and short as the CIS questionnaire is not addressed to AI specialists, but to innovation and technology officers (in large corporations) or to general managers or firm owners (in small and medium firms). The aim was to capture the entire diversity of how AI may be used in businesses including AI applications in products and services, in production and service processes, data analytics and marketing.[3] In addition to the matrix question, information was collected on who mainly developed the AI methods used (in-house and/or external) and the first year of AI use in the firm.

Note that the measurement is focused on the *active* use of AI. Passive forms of accessing AI technology, i.e. by placing own products on online sales platforms that are operated by others who use AI methods to run the platform, or using standard software packages with embedded AI technology, are not included. To verify the understanding of AI by respondents, we conducted a follow-up telephone survey of all firms reporting AI usage in the German CIS 2018. 65% of these firms participated in the survey (see Rammer et al. 2020). Among others, we asked respondents to describe the most important AI application in the firm. The results reveal that the responding firms indeed actively use AI, i.e. they implemented AI tools in their operations or products. Not a single firm mentioned a passive use of AI as their most important application. The examples of AI use given include AI methods used in R&D, products involving AI (e.g. smart energy applications), a variety of process technology applications (error recognition, maintenance) and various business administration applications. The majority of AI usage is linked

[1] For more details on the German CIS, which is conducted as a panel survey ('Mannheim Innovation Panel'), see Peters and Rammer (2013).

[2] The questions on AI were developed by one of the authors of this article by consulting experts from industry, science and government. The AI questions have been pre-tested with a panel of industry representatives as part of a research project on monitoring digitalisation of the German economy.

[3] The use of AI in R&D, which is a widely debated issue particularly with respect to scientific R&D (Cockburn et al. 2019, Agrawal et al. 2019a, Bianchini et al. 2020) was not explicitly mentioned and is most likely be reported under 'other areas'.


12.4 Does your enterprise use Artificial Intelligence methods?

Artificial Intelligence (AI): A method of information processing that allows computers to autonomously solve problems.

Yes ☐1 .... No ☐2 ➔ Please continue with Question 12.7.

AI Method: / Area of AI application:

AI Method	Products, Services	Automation of processes	Interaction with clients	Data analytics	Other areas
Language/text understanding	☐1	☐1	☐1	☐1	☐1
Image/pattern recognition	☐1	☐1	☐1	☐1	☐1
Machine Learning	☐1	☐1	☐1	☐1	☐1
Knowledge/expert systems	☐1	☐1	☐1	☐1	☐1
Others:	☐1	☐1	☐1	☐1	☐1

12.5 Were the Artificial Intelligence methods used in your enterprise developed in-house or by others?

☐1 .... mainly developed in-house ☐2 .... mainly developed by others ☐3 .... both in-house and by others

12.6 Since when is your enterprise using Artificial Intelligence methods?

Year of the first use of artificial intelligence in your enterprise (*please provide an estimate*) ....

Source: German CIS 2018.

Fig. 1. AI questions in the German CIS 2018.
Source: German CIS 2018.

to production methods, services and product features (52%), application in administrative operations (37%), R&D (21%) and information technology (20%). AI use for marketing purposes was rather rare (5%) which is possibly due to the fact that most firms in the sample of the German CIS are in the B2B business.

It is important to note that our measure of AI use represents both the development of AI technologies and the adoption of AI technologies that have been developed by others. The AI measure captures the state of AI use at the time of the survey irrespective of the time the AI methods have been introduced. It is hence a kind of stock variable, representing the accumulated investment into AI that was in operation at the time of the survey (February to July 2019).

The German CIS 2018 targets firms with 5 or more employees in mining, manufacturing, utilities and a range of business service sectors (wholesale, transportation, information and communication, banks and insurances, professional and technical services, business support services). The survey had a sample size of 43,672 firms. Usable responses were recorded for 8,821 firms, resulting in a response rate of 20.2%. In order to evaluate a possible bias between responding and non-responding firms with respect to innovation activities, a comprehensive non-response survey was conducted, interviewing 10,250 non-responding firms (29.1% of all non-responding firms). The non-response survey revealed a higher share of innovation active firms among respondents (71.1%) than non-respondents (65.1%). For data extrapolation, this bias is corrected by using a correction factor for the firms' sampling weights (see Behrens et al. 2017 for the method used). In the following, we report weighted statistics that are extrapolated from the sample to the target population of the survey, i.e. the German manufacturing sector and business-related services. The figures for AI using firms are based on responses from 573 firms in the sample that reported to have used AI actively in their firm at the time of the survey.

Germany provides a useful empirical case for studying the link between AI and innovation. First, the German business sector is highly innovation-oriented, and a large number of firms, including small and medium-sized ones, engage in innovation (see Hollanders and Es-Sadki 2021). Secondly, AI has been a technology that received high attention in the German businesses sector. As the uptake of AI and the efforts to develop AI technologies have been slower than in some other countries (Harhoff et al. 2018), however, technology adopters are able to employ more mature AI technologies that have been tested elsewhere already. Thirdly, German firms are highly internationally oriented and consider market and technology trends across many countries in their innovation strategies. The development and adoption of AI by German businesses will hence reflect international trends in the use of AI for innovation well.

3.2. Descriptive statistics on AI usage

The analysis of firm responses to the AI questions reveals that in the first half of the year 2019, 5.8% of all firms in the target population actively used AI methods in their business operations (Table 1). This corresponds to about 17,500 firms. Only a small share of these firms developed these AI methods mainly in-house (0.9% of all firms, 16% of AI-using firms)[4] while most relied on externally developed AI methods (60% of AI-using firms). 24% used AI methods that were developed both in-house and by others. One out of five AI-using firms has first used AI

Table 1
Use of AI in firms in Germany (first half of 2019).

	Share in all firms (%)	Share in AI users (%)
Firms with any active use of AI	5.8	100.0
thereof: mainly based on in-house developed AI methods	0.9	16.1
thereof: mainly based on externally developed AI methods	3.5	60.3
thereof: based both on in-house and externally developed AI methods	1.4	23.6
thereof: first use of AI before 2011	1.2	20.5
thereof: first use of AI before between 2011 and 2015	1.1	19.6
thereof: first use of AI before between 2016 and 2017	1.9	32.6
thereof: first use of AI in 2018 or 2019	1.6	27.3

All figures were extrapolated to the total population of firms in Germany with 5 or more employees in industries (Nace rev. 2) B to E, 46, H, J, K, 69, 70.2, 71 to 74, 78 to 82.
Source: German CIS 2018.

[4] We use the term 'AI-using firm' to denote all firms that actively utilise AI technologies in their business activities, regardless whether the technology has been developed by the firm or adopted from others, following Acemoglu et al. (2020b), Babina et al. (2021) and Montagnier et al. (2020).

prior to 2011 while one out of four only recently (2018 or 2019) started to apply AI.

The share of 5.8% for AI-using firms compares quite well to the results obtained from recent business surveys on the use of AI in other countries (see Montagnier et al. 2020). For Korea (firms with 10+ employees), a share of 1.5% has been reported for the year 2017. In the same year, the share of AI-using firms in Canada (firms with 20+ employees) was 4.0%, and in Denmark it was 6.0% in 2019 for firms with 10+ employees. Higher shares than those found for the German business enterprise sector were found in France (11.0% in 2018 for firms with 10+ employees) and Japan (14.1% in 2017 for firms with 100+ employees).

The share of AI-using firms varies greatly among industries and size classes (Table 2). The industry with the highest share of AI-using firms is software and IT services (18.3%). 14.3% in consulting and advertising, and 12.2% in financial services use AI in their business operations. In manufacturing industries, highest shares are found for the electronics and electrical equipment industry (11.0%) and the chemicals and pharmaceuticals industry (8.4%). The use of AI is very rare among firms from wholesale trade (1.0%) and transportation and logistics services (1.5%). These results are partly in line with the work by Felten et al. (2021) who classified industries with respect to their AI exposure (AIIE) based on expert assessments. Experts rated the extent to which ten different AI applications are related or could be used for certain human abilities (from a list of 52 abilities). The abilities were then linked to occupations and occupations to industries. Felten et al. (2021) find highest AIIE scoring for financial services, legal, accounting and consulting services, and IT services, which is in line with our results. However, their AIIE scores are rather low for most manufacturing industries (except electronics). This may reflect the fact that our indicator is a revealed measure on the actual use of AI that also includes the adoption of AI technology, and not only in-house development of AI.

Table 2
Use of AI in firms in Germany by industry and size class (first half of 2019).

	Firms with AI use as a share in all firms (%)	Sales of firms with AI use as a share in total sales (%)
Sector (Nace rev. 2)		
Consumer goods (10-12, 14-15, 31-32)	2.2	7.6
Other materials (13, 16-18, 22-23)	2.6	10.1
Chemicals and pharmaceuticals (20-21)	8.4	30.7
Metals and metal products (24-25)	4.7	20.5
Electronics and electrical equipment (26-27)	11.0	32.8
Machinery and equipment (28, 33)	6.7	17.4
Vehicles (29-30)	5.1	38.0
Utilities, waste management, mining (5-9, 19, 35-39)	3.6	23.7
Wholesale trade (46)	1.0	7.4
Transport and logistics services (49-53)	1.5	16.5
Media services (58-60)	6.5	28.0
Software, IT services (61-63)	18.3	33.7
Financial services (64-66)	12.2	51.3
Legal, accounting, consulting, advertising serv. (69, 70.2, 73-74)	14.3	25.3
Engineering and R&D services (71-72)	6.5	15.7
Other producer services (78-82)	2.5	13.1
Size class (no. of employees)		
5 to 9	3.3	2.8
10 to 19	5.4	3.6
20 to 49	7.6	7.6
50 to 99	6.7	5.1
100 to 249	9.7	11.4
250 to 499	15.7	15.4
500 to 999	21.6	35.6
1,000 and more	30.8	65.5

All figures were extrapolated to the total population of firms in Germany with 5 or more employees in industries (Nace rev. 2) B to E, 46, H, J, K, 69, 70.2, 71 to 74, 78 to 82.
Source: German CIS 2018.

These figures are mainly driven by the AI usage behaviour of small firms since those represent the largest number of all firms in any industry, and small firms show substantially lower AI use rates (3.3% for firms with 5 to 9 employees, 5.4% for firms with 10 to 19 employees) compared to large firms (30.8% for firms with 1,000 or more employees). For assessing the economic relevance of AI use, the share of sales in an industry that is represented by AI-using firms provides a more accurate picture. In financial services, more than 50% of the industry's total sales were obtained by AI-using firms. In manufacturing of vehicles, this share is 38%, and in the software and IT industry, it is 34%. These figures demonstrate that AI-using firms generate high sales volumes. It does not imply that any of these sales are due to AI use. Among the group of large firms with 1,000 or more employees, AI-using firms represent 66% of all sales of this size class. Among micro firms (5 to 9 employees), AI-using firms contribute only 2.8% to the size class' total sales.

The most frequently used AI method in German firms in 2019 was machine learning (55% of all AI-using firms). AI-based image and pattern recognition methods were used by 49% of firms, and 46% had implemented knowledge and expert systems based on AI (Table 3). AI methods for language and text understanding were used by 30% of the firms. AI methods were most often applied to products and services (60% of AI-using firms) and for the automation of processes (56%). 34% used AI for data analysis.

4. Estimating the relationship between AI and innovation

The main aim of the paper is to assess the role of AI for the firms' innovation performance. For this purpose, we employ an innovation production function (Mairesse and Mohnen 2002) and regress a variety of variables of firms' innovation outcome on whether the firm uses AI (and in what way) while controlling for other variables that may drive innovation outcomes.

A firm's choice of whether and how to apply AI methods is clearly related to a firm's innovation strategy. AI is a technology that helps to realise certain performance features of products and business operations. A firm will decide on the use of a certain technology based on its internal resources, user needs and market trends, and the strategies of its competitors that best exploits its assets and generates profitable assets for the future. The choice of an innovation strategy (such as technology leadership, cost advantage through more efficient processes or niche market orientation through product differentiation and customised products) and the choice of technology represent two aspects of a single strategic decision process.

The goal of this paper is not to establish evidence of causality running from AI to innovation outcomes. This would require either an instrumental variable approach or the exploitation of some exogenous variation in the use of AI which we currently do not have at hand. We, therefore, see our study rather as an explorative study where we suggest potential causal relationships that could be studied in more rigorous econometric works in the future. We limit the ambition of our regression analysis to controlling for the most important variables driving innovation outcomes in general, and also firms' other (non-AI) digitalisation efforts within its innovation strategy in particular, in order to identify innovation that is closely linked to the use of AI. While we outline below that we are using a rich set of covariates which mitigates endogeneity concerns due to omitted variables, we cannot rule out that some remaining unobserved factors may drive innovation outcomes, the use of AI as well as other digitalisation efforts and key innovation input variables simultaneously. Remaining endogeneity concerns may only be

Table 3
AI methods and applications areas of AI in firms in Germany (2019).

AI method	*Area of application*					Total
	Products, Services	Automation of processes	Interaction with clients	Data analysis	Other areas	
Language/text understanding	15.1	9.5	7.9	7.0	5.5	30.3
Image/pattern recognition	24.1	30.8	4.9	11.3	3.3	48.9
Machine learning	32.3	30.4	9.1	16.7	4.3	54.6
Knowledge/ expert systems	24.9	19.1	9.8	16.4	4.4	46.2
Total	59.9	55.6	22.0	33.9	11.1	

All figures were extrapolated to the total population of firms in Germany with 5 or more employees in industries (Nace rev. 2) B to E, 46, H, J, K, 69, 70.2, 71 to 74, 78 to 82.
Note: The totals sum up to more than 100% as each firm could report multiple methods and areas of application.
Source: German CIS 2018.

ruled out in the future when either panel data become available, or when other exogenous variation in the use of AI can be utilised.

4.1. Conceptual model

The conceptual model that guides the design of the empirical estimations consists of three main groups of variables. Innovation output is measured by a series of variables on new or improved products or processes that have been introduced to the market or implemented in the firm. These innovation outcome variables are related to the use of AI, other digitalisation efforts of the firm and other determinants including innovation input measures, general firm capabilities and market characteristics (see Fig. 2). The details are described in the following subsections.

4.2. Dependent variables and descriptive statistics

As one of the main purposes of this paper is a first explorative analysis on where AI is intertwined with the innovation process in the business sector, we use a relatively large set of dependent variables that shed light on different dimensions of the innovation supply chain. We distinguish product from process innovation (based on the fourth edition of the Oslo Manual which merged organisational and marketing innovations into product and process innovation, see OECD and Eurostat 2018) and use a number of subcategories of each innovation type. Product innovations are new or improved products that differ significantly from a firm's previous products and include both physical goods, services and digital products. We subsequently distinguish product innovations by their degree of novelty with respect to a firm's market. We separate new-to-market innovations from innovations that are only new to the firm. For new-to-market innovations, we further separate world-first innovations from those that are only new to a regional or sectoral sub-market. The importance of these innovations for the firm is measured by their respective shares in the firm's total sales.

Process innovations are considered separately from product innovations. A firm is a process innovator if it has implemented at least one new or improved process (including new logistics methods, new IT methods, new methods for administration, new organisational methods, new forms of workplace organisation and new marketing methods) in the preceding three year period that differs significantly from the firm's previous processes. Process innovations can then be further separated into cost-reducing process innovations and others (the latter may result in higher quality of the produced goods but not lower unit cost, for example). The economic returns of cost-saving process innovations are approximated by the share of unit cost reduction.

All subsequent descriptive statistics are weighted results, i.e. the numbers are extrapolated from the sample to the population of firms using sampling weights. Table S1 in the Supplementary Material provides descriptive statistics for the sample of firms that were used for model estimations. Note that the mean and standard deviation of the variables are calculated using weights as we also employ weighted regressions. A correlation matrix of model variables is presented in Table S2 in the Supplementary Material.

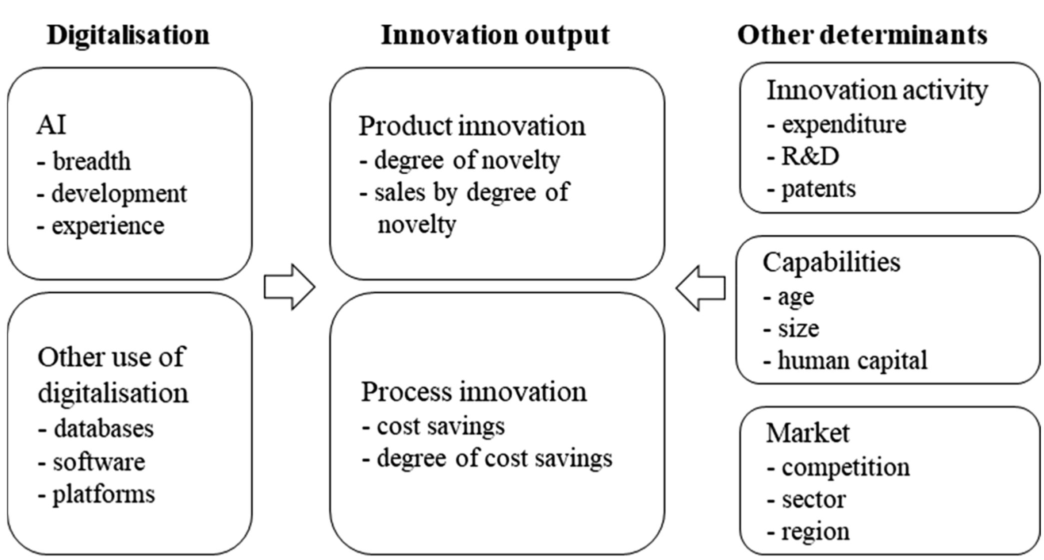


Fig. 2. Variables considered for identifying the role of AI for innovation output in firms.

4.3. Product innovation

For product innovation, we first use a dummy variable (*PDI*) indicating whether the firm introduced a new good or service (that differs significantly from the firm's previous goods or services) to its portfolio in the time period 2016-2018. On average, about 61% of firms with some AI activity report a product innovation. In the subsample of firms without AI activity this share amounts only to 35% (see Table 4).

The CIS data allow to separate product innovations by their degree of novelty in a firm's market. A product innovation can either be only new to the firm (*PDI new firm*), i.e. the product innovation is an imitation or adaption of other firms' products, or it can be new to the market that the firm is serving (either in geographical or product space) (*PDI new market total*). This market novelties can be further divided into world-first innovations or new sub-markets (*PDI new sub-market* and *PDI world first*). Among the AI-using firms about 19.4% report to have had a market novelty of which 8.3% only had sub-market novelties and about 11.1% reported world-first innovations. These shares are higher than in the group of firms without AI activity, where they amount to about 8.8% that can be divided into 5% for sub-markets and 3.8% for world-first, respectively.

In addition to the dummy variables of the product innovation types, we also study the volume of new product sales. The survey also allows splitting the total sales of the firms into the following sub-categories:

1. Sales with unchanged products (goods and services)
2. Sales with product innovations
2a. Sales with innovative products that were only new to the firm's portfolio
2b. Sales with market novelties
2bi. Sales with novelties only new for regional or sectoral sub-markets
2bii. Sales with world-first innovations
Total sales: 100%

When looking at the sales shares rather than just at the event of product introductions, differences between AI-using firms and others are also striking. For instance, in the population of AI-using firms, almost 21% of total sales are achieved with new products, while this figure is only 13% in the group of firms not using AI. The share of sales with world-first innovations is more than twice as high in the sub-population of AI users (2.9% vs. 1.3%).

4.4. Process innovation

For process innovation, we use a dummy variable, *PCI total*, indicating whether the firm has introduced a process innovation during 2016-2018. On average, about 75% of firms with AI activity report to have introduced at least one new process. Among the firms without AI activity this share amounts only to 51% (see Table 5).

Table 4
Descriptive statistics of product innovation variables (weighted results).

	Firms with AI activity Mean	Firms without AI activity Mean
	Dummy variables	
PDI total	0.607	0.346
PDI new firm only	0.413	0.258
PDI new market total	0.194	0.088
PDI new sub-market	0.083	0.050
PDI world first	0.111	0.038
	Sales shares	
PDI share_all	0.207	0.125
PDI share_newfirm	0.152	0.098
PDI share_newmarket	0.055	0.027
PDI share_newsubmarket	0.026	0.014
PDI share_worldfirst	0.029	0.013

Note: Figures represent weighted results for 17,448 AI-using firms and 282,190 not AI-using firms within the firm population of the German CIS.

Table 5
Descriptive statistics of process innovation variables (weighted results).

	Firms with AI activity Mean	Firms without AI activity Mean
	Dummy variables	
PCI total	0.746	0.514
PCI no cost	0.481	0.393
PCI cost reduction	0.265	0.121
	Share of unit cost reduction	
PCI cost share	0.052	0.034

Note: Figures represent weighted results for 17,448 AI-using firms and 282,190 not AI-using firms within the firm population of the German CIS.

In addition, the process innovation variable can be split into two categories, i.e. whether the process resulted in a reduction of unit costs of production (*PCI cost reduction)* or not (*PCI no cost)*. The latter could imply higher work safety, or higher quality of the production process and the like. We observe higher shares of AI-using firms for both dimensions. When looking at the share of the reduction in the unit cost of production, we also find that AI-using firms achieve higher amounts with 5.2% versus 3.4% (see Table 5).

It will be interesting to see whether these descriptive findings regarding product and process innovation performance differences between AI users and other firms, hold in multiple regression analyses when we control for the firms' general innovation strategy by accounting for several innovation input dimensions, other digitalisation efforts and additional structural firm characteristics.

4.5. Empirical measures of AI

The role of AI for a firm's innovation output is measured by an indicator on AI use. In addition to the AI indicator, we also examine whether heterogeneity in the use of AI is associated with different innovation outcomes. In addition to the AI indicator variable, we explore possible effects of AI measures that can be formed out of the survey data introduced in Section 3.2. First, we consider the breadth of AI usage. We define *AI breadth* as the count of items of AI methods and AI applications areas:

- AI methods: (i) language or text understanding, (ii) image or pattern recognition, (iii) machine learning, (iv) knowledge or expert systems.
- AI application areas: (i) products or services, (ii) automation of processes, (iii) interaction with clients (iv) data analysis, (v) other applications (including R&D).

The breadth may thus range from 1 (only one method used in one application area) to 20 (all four methods used in all five application areas). On average, the firms using AI have a breadth of 2.7, with a maximum value of 15. This means no firm exhausts all possible combinations of application areas and AI methods.

Furthermore, we consider *AI experience*, measured by the number of years that have elapsed since a firm's first used of AI technology. The average AI usage amounts to 5.1 years and the maximum to 29 years (i.e. AI technologies were first used in 1990).

Finally, we also consider a set of three dummy variables indicating whether the firm developed the AI technology mainly in-house, in-house and in collaboration with others, or whether the AI technology has been mainly developed by others and the focal firm is a mere adopter. From all firm observations used for model estimations, 56% only adopt AI technology developed by others. 18% develop AI mainly internally, and 26% report that AI has been developed both in-house and by others, which include both collaborative developments as well as the combination of only in-house developed AI methods and AI methods developed by others.

4.6. Supplemental digital capabilities and resources

AI methods are one technology to utilise the opportunities of digitalisation. Effectively leveraging the potential of AI requires additional digital capabilities and resources, which can both support the contribution of AI to innovation, and enable and advance innovation in their own right. We consider three such capabilities and resources: databases and data analytics, software programming capabilities, and digital platforms. It is possibly important to include these other digital capabilities and resources in the empirical model in order to avoid that their contributions to innovation is captured by the AI variables:

- The availability and quality of large data sets is one, if not the key, prerequisite for an effective use of AI (Agrawal et al. 2019b, Obschonka and Audretsch 2019). The availability of big data, capacities to analyse these data, and data management capabilities that generate 'smart' data can create a number of innovation opportunities (George et al. 2014, Wamba et al. 2017), independent from using or not using AI technologies. We use an indicator on whether firm invested into setting-up, maintaining and analysing own databases (including the purchase of external data).
- Software programming capabilities are another digital competence that both can spur innovation in a variety of ways (see for example Arora et al. 2013) and support the effective implementation of AI applications in existing IT systems and data structures. The critical role of software activities and proprietary software has been stressed in the literature on intangibles (Corrado et al. 2021) and competition (Bessen 2020). We consider firms that have their own in-house programming capacity or purchased programming services externally as being equipped with software programming capabilities.
- Digital platforms are a tool for collecting data that are highly relevant for innovation-oriented AI applications (particularly with respect to social media), but they can also initiate new innovation approaches, particularly in re-organising marketing and interaction with business partners (Sedera et al. 2016) and developing new business models (Brousseau and Penard 2007, Täuscher and Laudien 2018). We use two items from a question on the use of different channels for acquiring knowledge (social web-based networks or crowd-sourcing, open business-to-business platforms or open-source software) to proxy a firm's use of digital platforms.

4.7. Further control variables

Aside from digitalisation, there are many firm and market characteristics that may influence innovation output. We consider three groups of variables:

- *Innovation input*: Following Crépon et al. (1998), we use the amount of innovation expenditure relative to a firm's sales as variables characterising the type of R&D activity of a firm (continuous or occasional) to capture a firm's input to innovation that will affect the type and scale of innovation output.
- *General firm capabilities*: Based on the extensive empirical literature on the determinants of innovation output (see Cohen 2010 for an overview), we include firm size, firm age and a human capital variable (share of graduated employees) for capturing heterogeneity among firms' capabilities to develop and successfully introduce market innovations. For the models on the economic returns from innovation, we also include the amount of marketing efforts, measured by marketing expenditure per employee. Higher marketing efforts are likely to increase sales independently from possibly superior characteristics of the innovative product or service.
- *Market characteristics*: There is ample evidence that the type and intensity of competition in a firm's market can be a major driver or barrier for innovation decisions and the outcome of innovation (Varian 2019, Aghion et al. 2005, Cohen and Levin 1989). We use an index on the intensity of competition that captures the relevance of various characteristics of the firm's market environment. In the survey, the firms respond to the following eight characteristics of their competitive environment by rating each item into the categories "3: applies fully", "2: applies somewhat", "1: applies very little", "0: does not apply". The index is the sum of the scores on the statements (see Rexhäuser and Rammer 2014 for further details on the index):
  - products become outdated quickly;
  - the technological development is difficult to predict;
  - products/services from competitors are easily substituted for those of your enterprise;
  - major threat to market position because of entry of new competitors;
  - competitor's actions are difficult to predict;
  - demand development is difficult to predict;
  - strong competition from abroad;
  - price increases lead to immediate loss of clients.
- In addition, industry and regional dummies control for further market characteristics possibly affecting innovation outcomes.

Table S1 in the Supplementary Material shows descriptive statistics (and the definition) for all model variables. All variables are measured using data collected in the German CIS 2018 (except for age which is calculated using the firm's year of foundation as documented in Creditreform data, see Bersch et al. 2014). The total number of observations for model estimations varies between 6,738 and 6,283 for different dependent variables.

As we are interested in establishing the significance of AI for innovation outcomes at the macroeconomic level, we run weighted estimations. Sampling weights either indicate the number of other firms that are represented by a firm in the sample (for innovation output variables that refer to the number of firms, e.g. firms that introduced a certain type of innovation), or the volume of sales that is represented by a firm in the sample (for economic returns from innovation such as sales with product innovation). The weights are calculated for the sample of the German CIS using 63 strata (21 industries, 3 firm size classes) from the firm population data obtained from the business register of the Federal Statistical Bureau of Germany.

5. Estimation results

5.1. Base models on AI use

In the base models, we use a dummy variable for AI use. The results on the associations between AI use and innovation outcomes are shown in Table 6 (type of product innovation), Table 7 (process innovation) and Table 8 (economic returns from product innovation).

Table 6 shows the average marginal effects of AI use on the introduction of product innovations that were obtained from weighted Probit regressions. We find that firms employing AI technology are 8.5% more likely to introduce a product innovation than firms that do not use any AI. As the average probability to have a product innovation among AI-using firms is about 60.7%, the economic magnitude of the AI contribution is sizeable. It amounts to about 16% [= 8.5 / (60.7-8.5)]. When looking at the types of product innovation, we find that the firms employing AI are at the forefront of innovation, as the association of AI with product innovation mainly shows for market novelties and there especially for world-first innovations. The result for world-first innovation shows a 2.3% points higher likelihood. The average value in the sample of AI-using firms amounts to 11.1%, and thus the marginal effect reflects an increase of about 26% [= 2.3 / (11.1-2.3)].

We also obtain interesting results for the control variables: the other digitalisation variables, i.e. software capabilities, data capabilities, and platform use, are positive and significant in the regressions. All are significant in the equation for any type of product innovation ('total'),

Table 6
Marginal effects of AI use on the introduction of product innovation by degree of novelty (results of sampling-weighted Probit regressions).

	Product innovation				
	Total	Only new to firm	New to market	Only new to regional or sectoral market	World first
AI use	0.085***	0.024	0.025*	-0.005	0.023***
	(0.031)	(0.028)	(0.013)	(0.012)	(0.007)
Software capabilities	0.073***	0.071***	0.013	0.008	0.005
	(0.017)	(0.017)	(0.010)	(0.009)	(0.006)
Data capabilities	0.078***	0.031*	0.043***	0.032***	0.011**
	(0.018)	(0.018)	(0.010)	(0.009)	(0.005)
Platform use	0.096***	0.081***	0.018**	0.015*	0.004
	(0.015)	(0.015)	(0.009)	(0.008)	(0.006)
Continuous R&D	0.267***	0.038*	0.157***	0.101***	0.070***
	(0.021)	(0.022)	(0.011)	(0.011)	(0.008)
Occasional R&D	0.188***	0.098***	0.099***	0.062***	0.054***
	(0.021)	(0.022)	(0.012)	(0.010)	(0.009)
Innovation exp. / sales	0.256***	0.129**	0.067***	0.008	0.042***
	(0.063)	(0.052)	(0.022)	(0.022)	(0.011)
Share of graduates	0.014	-0.012	0.026	0.003	0.022**
	(0.033)	(0.033)	(0.019)	(0.017)	(0.011)
Age (ln # years)	-0.017**	-0.008	-0.008	-0.006	-0.002
	(0.009)	(0.009)	(0.005)	(0.004)	(0.002)
Size (ln # employees)	-0.002	0.001	-0.003	-0.005*	0.002
	(0.006)	(0.006)	(0.003)	(0.003)	(0.002)
# observations	6,475	6,475	6,475	6,475	6,475
Wald Chi^2	947.0***	366.0***	904.2***	422.3***	619.3***
Log Likelihood	157,804	158,505	66,625	53,401	31,057
Pseudo R^2	0.18	0.07	0.28	0.17	0.34

Robust standard errors in parentheses. ***, **, *: significant at p<0.01, <0.05, <0.1.
All regressions include 20 industry dummies, 14 regional dummies, a competition index and an intercept.
Data source: German CIS 2018.

Table 7
Marginal effects of AI use on the introduction of process innovation by type of impact (results of sampling-weighted Probit regressions).

	Process innovation		
	Total	Not leading to cost reduction	Leading to cost reduction
AI use	0.080**	-0.017	0.042**
	(0.034)	(0.030)	(0.017)
Software capabilities	0.139***	0.107***	0.056***
	(0.017)	(0.019)	(0.013)
Data capabilities	0.122***	0.067***	0.037***
	(0.019)	(0.020)	(0.012)
Platform use	0.109***	0.073***	0.034***
	(0.016)	(0.017)	(0.011)
Continuous R&D	0.206***	0.071***	0.095***
	(0.022)	(0.024)	(0.014)
Occasional R&D	0.221***	0.086***	0.099***
	(0.024)	(0.025)	(0.015)
Innovation exp. / sales	0.130*	0.144**	0.023
	(0.067)	(0.060)	(0.034)
Share of graduates	-0.011	-0.009	0.002
	(0.035)	(0.036)	(0.025)
Age (ln # years)	-0.038***	-0.024***	-0.014**
	(0.009)	(0.009)	(0.006)
Size (ln # employees)	0.025***	0.004	0.017***
	(0.006)	(0.006)	(0.004)
# observations	6,738	6,738	6,738
Wald Chi^2	952.0***	390.3***	545.8***
Log Likelihood	166,857	182,036	100,540
Pseudo R^2	0.18	0.07	0.13

Robust standard errors in parentheses. ***, **, *: significant at p<0.01, <0.05, <0.1.
All regressions include 20 industry dummies, 14 regional dummies, a competition index and an intercept.
Data source: German CIS 2018.

and some variation occurs in the regressions on the different sub-types. Generally, we can conclude that the firms' digital affinity plays a role in product innovation and it seems useful to control for other IT-related variables as otherwise some general effects of IT affinity might be miss-assigned to our focal variable of AI. If the other IT usage would be omitted and their contribution would thus be in the error term of the econometric model specification, serious endogeneity concerns would arise.

We also find that all innovation input measures are positive and statistically significant in all models. The share of graduates is only positively associated with world-first product innovations. Interestingly, after controlling for AI, digitalisation and innovation inputs, we do not find strong size or age effects in the regressions. Size is positive for cost-reducing process innovation but negative for the sales share of product innovation. The former result is in line with the product life cycle argument by Klepper (1996) and the cost-spreading argument by Cohen and Klepper (1996). The latter result is largely driven by the fact that small innovative firms more often renew their entire product offerings through product innovation, resulting in a higher sales share compared to large firms with more diversified product portfolios (see Kleinknecht et al. 2002, Rammer et al. 2009). The effect of the competition index is inversely U-shaped (not shown in table), which is in line with findings of other studies (Aghion et al. 2005). However, the inflexion point of the curve is at the very right of the data distribution and that implies that the product innovation propensity basically increases with competition. This is only found in the regressions on any kind of product innovation and the "only new to the firm" regression, though. Competition does not affect the introduction of market novelties which may create a temporary quasi-monopolistic position of the firm.

The results on process innovation are shown in Table 7. AI use is associated with an 8% higher likelihood to have any type of process innovation. When looking at cost-reducing process innovations versus others, it turns out that the AI technology is relevant for cost-reducing process innovations but not for others. Firms with AI technology are 4.2% more likely to introduce cost-reducing processes. Of course, in the context of process innovations, AI might be part of the innovation itself.

Table 8
Coefficient estimates of AI use on sales of product innovation (by degree of novelty) and cost reduction from process innovation (results of sampling-weighted OLS regressions).

	Sales share from product innovation					Share of unit cost reduction owing from process innovation
	Total	Only new to firm	New to market			
			Total	Only new to regional or sectoral market	World first	
AI use	0.027*	0.011	0.017**	0.004	0.013**	0.008**
	(0.015)	(0.013)	(0.008)	(0.006)	(0.006)	(0.004)
Software capabilities	0.007	0.009	-0.002	-0.001	0.000	0.004**
	(0.007)	(0.006)	(0.003)	(0.002)	(0.002)	(0.001)
Data capabilities	0.041***	0.030***	0.010***	0.005*	0.005**	0.006***
	(0.008)	(0.007)	(0.004)	(0.003)	(0.003)	(0.002)
Platform use	0.023***	0.024***	-0.001	0.002	-0.003	0.004**
	(0.007)	(0.006)	(0.003)	(0.002)	(0.003)	(0.002)
Continuous R&D	0.097***	0.060***	0.037***	0.028***	0.009***	0.012***
	(0.011)	(0.010)	(0.006)	(0.005)	(0.004)	(0.003)
Occasional R&D	0.055***	0.044***	0.011**	0.011***	0.000	0.011***
	(0.012)	(0.011)	(0.005)	(0.004)	(0.003)	(0.003)
Innov. exp. / sales	0.202***	0.116***	0.087***	0.033**	0.054***	0.021**
	(0.035)	(0.029)	(0.022)	(0.015)	(0.018)	(0.008)
Share of graduates	0.044**	0.024*	0.020	0.001	0.018	0.006
	(0.018)	(0.014)	(0.013)	(0.006)	(0.011)	(0.004)
Age (ln # years)	-0.015***	-0.011***	-0.003**	-0.002	-0.001	-0.003***
	(0.003)	(0.003)	(0.002)	(0.001)	(0.001)	(0.001)
Size (ln # empl.)	-0.010***	-0.006***	-0.004***	-0.003***	-0.001	0.000
	(0.003)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
Marketing expend.	0.001	0.001	0.000	0.000	0.000	0.000
	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
Patent use	-0.006	-0.019**	0.014**	0.002	0.012***	-0.004*
	(0.010)	(0.008)	(0.006)	(0.005)	(0.004)	(0.002)
# observations	6,283	6,283	6,283	6,283	6,283	6,626
F statistics	15.65***	12.35***	4.45***	2.81***	2.59***	5.17***
R^2	0.17	0.14	0.12	0.07	0.08	0.07

Robust standard errors in parentheses. ***, **, *: significant at p<0.01, <0.05, <0.1.
All regressions 20 industry dummies, 14 regional dummies, a competition index and an intercept.
Data source: German CIS 2018.

With respect to control variables, we find comparable effects as in the product innovation regressions. The controls on other IT usage, i.e. software and data capabilities and platform use, are positively related to process innovations. Also, the two R&D dummies have positive and statistically significant marginal effects. Interestingly, we find that older firms are less likely to introduce new processes. This might either imply that their production processes are well calibrated or that they become inflexible over time.

For identifying the relationship between AI use and economic returns from innovations (sales with product innovation, cost reduction from process innovation), we run weighted OLS regressions accounting for sampling weights (see Table 8).

We find a relatively strong association between the use of AI and the sales shares of innovations with higher degrees of novelty. While there is only a weakly significant link to product innovations in general and no link to sales of products that a just new to a firm's portfolio (i.e. adoption or imitation), the sales of market novelties increase 1.7 percentage points with AI, and the share of world-first innovation sales is associated with a 1.3 percentage points increase in case firms employ methods of AI. As the sample averages of these variables are 5.5% and 2.9%, respectively, the use of AI is associated with an increase of 45% [= 1.7 / (5.5-1.7)] and about 81% [= 1.3 / (2.9-1.3)], respectively.

The reduction of unit costs in firms with AI use is 0.8 percentage points higher. As the average value of cost reduction is 5.2%, the marginal effect of AI is also not negligible in relative terms. The at first sight rather small coefficient of 0.008 accounts for a relative change of about 18% [= 0.8 / (5.2-0.8)].

With respect to the control variables, we find quite similar results as in the Probit regressions on the corresponding dummy variables of the different innovation categories. Therefore we do not discuss those in detail. As we here accounted for sales volumes we had added controls on marketing expenditure and patent use but the results remain somewhat inconclusive. Marketing is never statistically significant. Patent use, however, shows a negative sign in the imitation regression which is not surprising as patenting firms might rather be innovation leaders and not imitators. This is consistent with the fact that we find strong effects of patent use on market novelties and especially world-first innovations that might be successfully protected by the firms' intellectual property rights.[5]

5.2. Models on AI characteristics

We run a series of additional estimations for different characteristics of AI use to analyse heterogeneity among AI users: (i) the origin of the development of AI technology (in-house, others, in-house + others), (ii) breadth of AI use and (iii) firms' experience with AI (number of years AI has been used). For reasons of brevity, the results shown in Table 9 only summarise the average marginal effect of the main variables of interest in the regressions, i.e. the AI variables. The results of the controls are omitted as they are almost identical to the results presented above. Each column in the subpanels of the table (AI development, breadth of AI use, experience in AI use) is based on a separate regression, either Probit or OLS.

World-first product innovations are mainly associated with in-house development of AI technologies. This seems intuitive. If the adoption of

[5] As a robustness check, we re-run the model estimations for dependent variables measured in t+1, using data from the German CIS 2019 in order to analyse lagged relations. The results are reported in the Supplementary Material and confirm our base model results.

Table 9
Marginal effects / coefficients of AI characteristics on product and process innovation outcome (results of sampling-weighted Probit and OLS regressions).

	Product innovation (Probit)			Process innovation (Probit)		Sales share from product innovation (OLS)			Share of unit cost reduction due to process innovation (OLS)
	Total	New to market		Total	Leading to cost reduction	Total	New to market		
		New to regional/ sectoral market	World first				New to regional/ sectoral market	World first	
AI development[a)]									
Mainly	-0.015	0.036	0.035***	-0.104*	0.021	0.010	0.030	0.045*	0.009
in-house	(0.066)	(0.025)	(0.013)	(0.061)	(0.031)	(0.043)	(0.028)	(0.027)	(0.009)
Mainly	0.119***	0.019	0.008	0.155***	0.064***	0.022	0.005	0.004	0.006
others	(0.041)	(0.019)	(0.010)	(0.049)	(0.024)	(0.017)	(0.008)	(0.005)	(0.004)
In-house +	0.026	0.024	0.028**	0.083	0.026	0.056	0.041	0.015	0.019
others	(0.055)	(0.021)	(0.011)	(0.059)	(0.027)	(0.039)	(0.025)	(0.014)	(0.012)
Breadth of AI use[b)]									
Breadth	0.145***	0.046	0.117**	0.091	0.137***	0.016*	0.005	0.004	0.006**
	(0.054)	(0.053)	(0.059)	(0.056)	(0.045)	(0.009)	(0.006)	(0.004)	(0.003)
Breadth^2	-0.013**	0.001	-0.001	-0.004	-0.011**	-0.001	0.000	0.000	-0.000**
	(0.006)	(0.005)	(0.005)	(0.006)	(0.004)	(0.001)	(0.001)	(0.001)	(0.000)
Inflexion#	6				6				5
Experience in AI use[b)]									
AI experience	0.057*	0.067**	0.100***	0.052*	0.021	0.007*	0.006**	0.004*	0.001
	(0.032)	(0.031)	(0.033)	(0.031)	(0.028)	(0.004)	(0.003)	(0.002)	(0.001)
AI experience^2	-0.002	-0.002	-0.003*	-0.002	-0.000	-0.000*	-0.000*	0.000	0.000
	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
Inflexion#			18			12	13	13	
AI methods[a)]									
Language/text	-0.017	-0.017	0.011	0.002	0.026	-0.283	-0.282	0.062	0.172
understanding	(0.059)	(0.023)	(0.012)	(0.069)	(0.033)	(0.202)	(0.201)	(0.227)	(0.178)
Image/pattern	0.084	0.010	-0.003	0.083	0.037	0.289	0.028	0.113	0.216
recognition	(0.052)	(0.019)	(0.010)	(0.056)	(0.026)	(0.176)	(0.148)	(0.160)	(0.140)
Machine	0.060	0.030	0.028***	0.089	0.005	0.193	0.036	0.272	0.018
learning	(0.050)	(0.020)	(0.010)	(0.057)	(0.027)	(0.174)	(0.183)	(0.184)	(0.152)
Knowledge/	-0.025	0.014	0.008	-0.031	0.024	-0.072	0.151	0.011	0.119
expert systems	(0.050)	(0.022)	(0.012)	(0.057)	(0.026)	(0.172)	(0.187)	(0.209)	(0.142)
AI application areas[a)]									
Products,	0.063	-0.026	-0.000	0.016	0.043*	0.18	-0.292*	0.021	0.273**
services	(0.051)	(0.020)	(0.010)	(0.055)	(0.025)	(0.172)	(0.176)	(0.182)	(0.139)
Automation of	0.113**	0.048**	0.029***	0.097*	0.058**	0.382**	0.247	0.236	0.329**
processes	(0.053)	(0.021)	(0.011)	(0.054)	(0.027)	(0.180)	(0.161)	(0.173)	(0.147)
Interaction	-0.070	0.047	0.009	-0.040	-0.041	-0.188	0.361	0.401	-0.178
with clients	(0.065)	(0.029)	(0.015)	(0.074)	(0.038)	(0.222)	(0.240)	(0.266)	(0.209)
Data	-0.019	-0.020	-0.002	0.057	-0.017	-0.128	-0.134	-0.114	-0.134
analysis	(0.061)	(0.025)	(0.011)	(0.063)	(0.030)	(0.210)	(0.219)	(0.211)	(0.170)
Other areas	0.004	0.047	0.035**	0.092	-0.004	0.012	0.408	0.513*	-0.042
(incl. R&D)	(0.074)	(0.031)	(0.016)	(0.116)	(0.048)	(0.248)	(0.268)	(0.284)	(0.266)

All regressions include a full set of controls (software capabilities, data capabilities, platform use, continuous R&D, occasional R&D, innovation expenditure, share of graduates, age, size, competition, marketing, patent use) as well as 20 industry dummies, 14 regional dummies and an intercept.
a) marginal effects; b) coefficient estimates. Robust standard errors in parentheses. ***, **, *: significant at p<0.01, <0.05, <0.1.
Data source: German CIS 2018.

AI would be supplier-induced, for instance, these suppliers will almost surely also deliver AI technology to others. If AI is an integral part of the innovation, it will be unlikely that world-first innovation can be made with technology that is available to many other users. Interestingly, AI mainly developed by others is very positively associated with product and process innovation in general, though. This might be an indication that firms seeking some technological advancement of their products and processes in the dimension of AI may well rely on business partners, possibly such as suppliers or IT consultants, to upgrade their products and processes.

When exploring the role of AI breadth and AI experience, we largely confirm the earlier results of the baseline regressions where an AI dummy was used, but also find some interesting nuanced results. We allow for non-linear effects by including also the squared values of breadth and experience in the regressions (Table 9).

We generally find positive effects of both AI breadth and AI experience on the innovation output variables. However, we find decreasing marginal returns in several regressions, i.e. the squared value of the coefficient is negative, and the curve thus describes an inverse U-shape. As average marginal effects might be somewhat misleading in such situation, because marginal effects may change signs in the data range, we report the coefficient estimates along with the inflexion point of the estimated curve when the squared term is significant in the regression. Otherwise, the relationship is basically linear.

For instance, the effect of AI breadth on product innovation is basically an upward-sloping curve until AI breadth reaches the value 6. The value 6 corresponds to the 90% quantile in the data. We therefore conclude that the relationship between AI breath and product innovation is basically positive for the majority of data points. The flat part and especially the negative part of the curve are induced by some very high values of AI breadth. One possible explanation is the presence of a 'coordination failure' when it comes to the integration of a new technology across all dimensions of a firm.[6] In case of AI, this would either require AI-specific knowledge in all business functions of a firm (from

[6] We want to thank an anonymous reviewer for pointing us to this explanation.

accounting and production to marketing and human resource management) or substantial technology support of business areas that do not have this knowledge. Both may complicate an effective exploitation of AI technologies.

The other results on both breadth and experience are remarkably similar. First, the relationship between AI and innovation performance is statistically significant also when using breadth and experience, confirming the results found in our base model that used the AI dummy. Generally, we find that both a broader use of AI and a longer experience in using AI are positively associated with performance. The inflexion points of the U-shaped curves are remarkably similar in all cases at around 12 years. The only exception is the regression on the likelihood of world-first innovations and experience. There the curve peaks at 18 years which is beyond the 95% quantile of the experience distribution. In all other cases, the estimated curves peak at the 90% quantile. The somewhat lower innovation outcomes for firms that started to use AI very early may mirror some 'lock-in' in older types of AI technology that are not sufficient for generating an innovative advantage. In addition, the result may indicate decreasing returns from AI in stimulating new innovation over time.

In addition, we tested whether the role of AI use for innovation output systematically differs by the AI method used or by the area of application. The results are reported in the lower part of Table 10 and show that no single AI method is driving our results, except for machine learning methods which seem to be the most relevant AI method when it comes to developing world-first innovations. This result implies that it is foremost the firm's decision to use AI that is linked to superior innovation results, but not the choice of a specific method of AI. The choice of AI method is most likely driven by the business model and the business operations of the firm which offer specific opportunities for AI use. In terms of application areas, AI used for process automation (e.g. AI in robotics or industry 4.0 concepts) has the most significant role as a driver of innovation output. For developing and successfully marketing world-first innovations, AI in other areas also shows statistically significant coefficients, which may be linked to the use of AI in R&D.

5.3. AI and uncertainty of innovation outcome

The estimation results presented above reveal that firms using AI methods in their business operations yield higher innovation outputs. This finding already takes into account the likely negative consequences of AI use on innovation output resulting, for instance, from a higher technological risk, more time-consuming development projects, difficulties in integrating AI-based solutions into existing IT systems or requiring very specific and scarce skills for developing and implementing AI methods. In case AI-using firms were facing these difficulties and were not able to successfully complete AI-based innovations, this result would be mirrored in lower innovation output.

Table 10
Extent to which product and process innovations met expectations, by AI usage.

	Product innovators		Process innovators	
	AI-using	Not AI-using	AI-using	Not AI-using
Expectations exceeded	10.0	6.3	3.9	2.7
Expectations met	47.4	45.1	44.6	40.8
Expectations partially met	32.2	33.3	37.7	40.8
Expectations not met	0.7	2.7	0.9	2.4
Too early to assess	9.7	12.6	12.9	13.4

Note: tabulation of net sample.
Source: German CIS 2018.

Nevertheless, higher output of AI-based innovations may be associated with a higher variance in output, e.g. a higher rate of project failure on the one hand, but higher returns from innovation in the case of successful market introduction.[7] Whether such higher variance is at place is important for research and innovation policy since it may lead more risk-averse or financially constrained firms to refrain from exploring AI in order to avoid high costs of failure. In order to explore this issue, we first run regression models on the likelihood of project cancellation (as a measure of negative innovation output), using the same set of independent variables as in the models on positive innovation output, including the AI indicator and, alternatively, the indicator on AI breadth. Project cancellation is measured as a dummy variable, taking the value 1 if a firm reported to have abandoned or stopped before completion of at least one innovation project during the reference period.

The results (see Table S4 in the Supplementary Material) show no statistically significant association between the use of AI and project cancellation. For the breadth of AI use, we find a weakly significant positive effect of about 0.5%, i.e. with every additional combination of AI method and application area, the likelihood of cancelling at least one innovation project increases by 0.5 percentage points (with the average share of firms reporting innovation project cancellation being 16.9%).

As a second test, we use information on whether product and process innovations met the firm's expectations. Such a question was included in the CIS 2018 for the first time, both for product and process innovations. In case the use of AI results in a higher variance of high-performing and underperforming innovations, we would expect a higher share of AI-using firms both for innovations that exceed expectations, and for innovations that fell short of expectations. A cross-tabulation (Table 10) shows that AI-using firms more often report product and process innovations that exceeded expectations, but they less frequently report that product and process innovation did only partially or not at all meet their expectations.

5.4. Macroeconomic extrapolations

The nature of the CIS as a representative survey based on a random sample allows to calculate total economy estimates on innovation output that is linked to the use of AI. Such economy totals are useful for assessing the economic significance of AI as a driver of innovation. The totals also allow comparison with other data from business statistics, in particular with the tabulated results of the CIS for the entire business enterprise sector as reported by Eurostat.

For calculating total economy estimates, each firm in the sample has been assigned a weight w that gives the number of firms out of the total number of firms (F) in the business enterprise sector in Germany for the firm i's stratum j (combination of sector and size class) that is represented by a responding firm (r_i), while taking into consideration a likely response bias nr between innovative and non-innovative firms in stratum j (see Behrens et al. 2017 for more details):

$$w_i = \frac{F_j}{\sum_i^N r_{ij}} nr_j$$

These weights are used to estimate the total number of AI-using firms in Germany (which is about 17,500) and their total sales (about €1,235 billion) as well as the number of AI-using firms that have introduced different types of product and process innovation (about 10,600), and the volume of sales for different types of product innovation (about €256 billion) as well as the amount of cost reduction from process innovation (about €64 billion). The marginal effects estimated for the AI variable are used to then calculate the number of firms that have introduced a certain type of innovation as a result of using AI, as well as the volume of

[7] We are grateful to an anonymous reviewer for drawing our attention to this issue.

innovative sales and cost reductions that can be assigned to the use of AI. We use marginal effects from the base model, and only consider marginal effects that are statistically significant.

Table 11 reports the results of these calculations. The number of firms that introduced certain types of innovations with the use of AI are non-negligible, but not large. We estimate that almost 1,500 firms introduced new products because of their AI use, all else constant. Out of those, 436 achieved market novelties which are to a large extent also world-first innovators (401 firms). Similarly, almost 1,400 firms could implement new processes that were associated with the use of AI, and 733 firms among those achieved also reductions in unit cost of production.

When looking at the total sales with product innovations that are associated with the use of AI, we calculate an amount of €33.3 billion. Compared to the total sales of the AI-using firms (€1,235 billion) and their total innovation sales (€256 billion) this number is not high (13% for the latter comparison). These rather low shares reflect that many AI-using firms would have innovated also in the absence of applying AI, and that only a small share of innovative firms in Germany are actually using AI.

When looking at world-first innovations −which may reflect the technological frontier in many sectors− the relative significance of AI-related innovations is high. For instance, almost 45% of the total world-first innovation sales of AI-using firms are related to AI. These sales represent 18.1% of all world-first sales of German firms. The relationship between sales of market novelties and AI is also high. From these extrapolations, we generally conclude that the use of AI seems still expandable but that the role of AI in frontier innovations such as market novelties and especially world-first innovations starts to be essential.

6. Conclusions

This paper analysed the extent to which the use of AI is linked to innovation results of firms in Germany. We employed data from the German part of the CIS 2018 which included a number of questions on how and where firms were using AI. We examined the contribution of various AI variables to different dimensions of product and process innovation outcomes. We found that AI plays a significant role for introducing innovations and obtaining economic returns from these innovations. AI is particularly relevant for more ambitious product innovations like product innovations that were new to a market. The most prominent role of AI was found for world-first innovations. AI methods are also closely linked to process innovation leading to cost savings (see Acemoglu and Restrepo 2018).

Firms that developed AI by combining in-house and external resources obtained significantly higher original innovation results, i.e. market and especially world-first novelties, than firms that mainly used externally developed AI methods (though the latter is the largest group among AI-using firms). Firms that apply AI in a broad way and that have already several years of experience in using AI tend to obtain higher innovation outputs. We did not find marked differences between the four types of AI methods distinguished in the data (language/text understanding, image/pattern recognition, machine learning, knowledge/expert systems) while we found some evidence that AI used in business processes (e.g. robotics, industry 4.0 concepts) is more closely linked to superior innovation performance.

The estimated marginal effects of AI use were also used to produce total economy figures, utilising the representative nature of the survey. While only 5.8% of all firms in the German business enterprise sector are actively using AI, the sales of new-to-market products that are linked to AI use represent 11.9% of total new-to-market sales in Germany. For world-first innovations, the sales share that can be linked to AI use is even 18.1%. These results demonstrate that it is a rather small group of firms that are able to reap substantial benefits from AI. The total economy figures also suggest that investing into AI pays off. The estimated sales volume of product innovations that can be linked to the use of AI in the German economy −€33.3 billion− compares to expenditures on the development and implementation of AI (including purchases of externally developed AI) of about €4.8 billion in 2019 (see Rammer et al. 2020). In case AI-based innovations were able to realise the same profit-to-sales ratio as the average firm in Germany (6.7%), the sales of AI-based products would have paid back about half of the investment made for developing and implementing AI technologies. Cost savings from AI-based process innovation (€11.3 billion) further add to the returns from investing into AI technologies. The finding of substantial outputs achieved with AI-related innovations is supported by the result that AI-using firms more often report innovations that exceeded expectations, but less frequently innovations that did only partially or not at all meet the firm's expectations.

The results should be interpreted with caution, however, when it comes to drawing a general conclusion on the likely impact of AI on innovation. Our results refer to just one country in a specific situation of the diffusion of a new technology. The time period considered in this paper represents an early stage of rapid AI diffusion across firms. The most recent results of the German Innovation Survey reveal that by 2021, the share of AI using firms in Germany rose to 10.1% (from 5.8% in 2019, see Rammer 2022). In such a situation, there are probably more high-return applications of AI available that drive the high figures of innovation outcomes than in later-stage periods of technology diffusion.

Our findings are relevant for government policies aiming at supporting the use and diffusion of AI technologies in several respects. First, our results point to a dual nature of AI in industrial innovation. On the one hand, spurring the introduction and sales of novel products will increase firm's competitiveness, with likely positive effects on profitability, growth and the demand for (skilled) labour. On the other, cost savings may also increase competitiveness, but reduce labour demand, particularly for low-skilled labour. This dual nature was also found in a recent paper of Balsmeier and Woerter (2019) who investigated the link between digitalisation and employment. Understanding this dual nature is important in public debates on the economic impacts of AI which often focus only on the positive (enabling new business models) or only on the

Table 11
Estimated innovation output of the German business enterprise sector in 2018 that can be linked to AI (only statistically significant contributions).

	Output linked to AI (weighted results[a]) (1)	*Unit of measure*	Share in total innovators (and innovation output) of AI-using firms (%) (2)	Share in innovators (and innovation output) of all firms (%) (3)
Product Innovation (PDI) - total	1,483	*k# firms*	14.0	1.4
PDI - new-to-market	436	*k# firms*	12.9	1.5
PDI - world-first innovations	401	*k# firms*	20.7	3.2
PCI - total	1,396	*k# firms*	10.7	0.9
PCI - unit cost reduction	733	*k# firms*	15.9	1.9
Sales with product innovations (SPI)	33.3	*bn€*	13.0	4.4
SPI - new to the market	21.0	*bn€*	30.7	11.9
SPI - world-first innovations	16.1	*bn€*	44.8	18.1
Cost reduction	11.4	*bn€*	17.7	5.7

Source: German CIS 2018.
[a] Firms with 5 or more employees in industries (Nace rev. 2) B to E, 46, H, J, K, 69, 70.2, 71 to 74, 78 to 82.

negative (job losses).

Secondly, our macroeconomic estimates on the role of AI for innovation output at the total-economy level inform about the significance of AI-related innovations. These economy totals can be related to other macroeconomic figures on AI activities at country levels, e.g. the amount of public funding or total industry investment in AI technologies. Thirdly, the positive effects of breadth and experience in AI use suggest that it takes time until significant returns can be obtained, and that a more comprehensive approach to AI is beneficial for obtaining higher returns. This is an important finding for policy with respect to realistic expectations about the time horizon of AI diffusion and AI's contribution to economic performance.

An important challenge for policy when it comes to support emerging technologies is a likely trade-off between high potential impact on innovation and productivity on the one hand, and high uncertainty and high variance of the impact on the other (Rotolo et al. 2015). In the case of AI, such a pattern has been found for AI applications in scientific research (Bianchini et al. 2020). Our findings provide no clear evidence of a higher uncertainty and output variance, though our database does not allow a differentiated analysis of this issue. This finding may be linked to the fact that our study looks both at the development of new AI technologies in firms, and the adoption of existing AI applications, or at the use of AI technologies that have been developed by others for the firm. The majority of AI-using firms in our sample are adopters, who arguably face lower uncertainty and are better able to focus the use of AI on those applications that promise highest returns.

The results of this paper are a first step to quantify the role of AI for industrial innovation which needs to be further developed, extended and broadened by future research. This is particularly true for impacts on firm competitiveness, productivity and employment. Our findings are limited by the fact that we have to rely on a cross-sectional database. Even though we made an effort to identify the contribution of AI to innovation output – first by measuring AI as a stock variable of all AI technologies adopted in the past that are still in use, and secondly by employing a rich set of covariates and by a robustness check looking at future innovation outcomes – we cannot rule out endogeneity issues. Unfortunately, instrumental variables approaches were not really feasible with the data at hand. Panel data could help in the future to shed more light on causality. Panel data would also enable investigations into the temporal nature of the link between AI and innovation and whether the findings of this study also hold for other periods in the diffusion of AI. In addition, international comparisons would be useful to evaluate the role of economic framework conditions such as digital infrastructures or availability of specific skills for the role of AI for industrial innovation.

While our results provide some insights under which circumstances the use of AI in innovation transfers into higher innovation output, there are still many more analyses needed to better understand the role of AI for industrial innovation. One key research question is, how to identify promising AI-based innovation projects. Another one relates to the role of various challenges, e.g. the availability of skills and data, compatibility with other IT systems, technological and market uncertainty, and legal and regulatory issues, for successfully exploiting the potential of AI in innovation.

Declaration of Competing Interest

None.

Acknowledgments

The authors are grateful to three anonymous reviewers who provided highly helpful comments. The usual disclaimer applies. We acknowledge support from the German from the German Federal Ministry of Economic Affairs and Energy through the research project "Measurement of the Digitalisation of the German Economy". The data used in this paper have been collected in the context of the research project "Mannheim Innovation Panel" which received funding from the German Federal Ministry of Education and Research. We also gratefully acknowledge financial support from the Flemish Science Foundation (FWO, grant G077218N).

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.respol.2022.104555.

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