Issues Note – Measuring Artificial Intelligence in Official Statistics

DETF workshop, 18 February, Session 2

Introduction and issues for discussion

This issues note is intended as a guide for discussion during the DETF Workshop of 18 February (a draft agenda is available separately), which will include a session on the measurement of artificial intelligence (AI) in official statistics. The session will focus primarily on the measurement of AI in the context of business surveys that can help determine the diffusion of AI across economy and society. These surveys raise a number of questions for statistical offices, including the definition of AI to be used in such surveys, the approach to the business surveys, as well as how to ensure international comparability .

The note also briefly alludes to some other measurement work that is underway internationally, such as the measurement of AI in science and innovation, AI start-ups, AI jobs and skills, as well as AI measurement in a macroeconomic context. Some of this work currently mainly draws on administrative and private sources, and is therefore not necessarily central to the work of national statistical offices. Nevertheless, it is briefly described here as such data are often already available and their use by NSO can be helpful in building an evidence base that can inform the policy discussions on AI. Moreover, NSOs may consider developing guidance or statistics in some of these areas at a later stage.

At the DETF workshop, delegates may wish to consider the following issues:

- ***Building on ongoing work across G20 countries, can a common operational definition of AI be agreed upon for use in surveys of ICT use by business? What further steps are needed in this regard?***
- ***How can the international comparability of surveys of ICT use by business be improved? What steps could be taken?***
- ***What role can administrative and private sources play in measuring AI? What role can NSOs play in coordinating, steering and advancing the development and production of statistics and indicators based on such additional sources?***
- ***How can the G20 best support the development of internationally comparable indicators on AI? How can the G20 support statistics capacity building related to the measurement of AI?***

Defining AI[1]

Measuring AI through official statistical surveys or from other sources requires agreeing on an operational definition of AI that describes as clearly as possible the aspects of AI that need to be measured and how to best do so. Because of the complexity of AI, the speed of AI developments and its evolving nature, researchers, statistical offices and other stakeholders may struggle with framing the question in a clear-cut way. In addition, agreeing on a common definition takes time, which is a challenge in a fast moving area such as AI: a definition of AI that is able to keep the pace with reality may need to change as AI adoption and use patterns change. Moreover, agreeing on a definition is non-trivial endeavour, as AI is often not a stand-alone technology but co-exists with and is often embedded in other technologies, sometimes in a complex fashion.

Notwithstanding the challenge mentioned above, and given the policy relevance of the questions, a range of general and operational definitions have been proposed. The section below describes how the OECD, Eurostat and statistical offices in several G20 countries define AI. It also makes a cross-country comparison that highlights recurring terms and expressions contained in such definitions, to point to a common understanding of what AI is.

OECD definition

"An AI system is a machine-based system that can, for a given set of human-defined objectives, make predictions, recommendations, or decisions influencing real or virtual environments. It does so by using machine and/or human-based inputs to: i) perceive real and/or virtual environments; ii) abstract such perceptions into models through analysis in an automated manner (e.g. with machine learning, or manually); and iii) use model inference to formulate options for information or action. AI systems are designed to operate with varying levels of autonomy." (OECD, 2019a)

While the OECD provides an AI definition in its May 2019 Council Recommendation on Artificial Intelligence, this is not to be considered a statistical and internationally-agreed operational definition of AI. A statistical and operational definition of AI

[1] This section draws on OECD (2021, forthcoming).

needs to provide pointers about what to measure and has a direct impact when implementing an AI module within ICT usage survey by businesses.

For example Eurostat, in its Community Survey on ICT Usage and E-commerce in Enterprises 2020, decided to use an "embedded approach", i.e. to include questions on AI in other relevant modules of the questionnaire such as big data, robotics etc., as the proposed definitions were found to be too complicated. It also considered that AI is not a standalone technology but co-exists with and is embedded in other technologies.

In the meantime, several statistical offices have already decided to implement an AI module within their ICT usage survey (see below). Eurostat will proceed similarly in its 2021 survey.

Some existing AI definitions, used by G20 economies in the introductory part of their AI modules, are provided below.

Eurostat definition

> *Artificial intelligence refers to systems that use technologies such as: text mining, computer vision, speech recognition, natural language generation, machine learning, deep learning to gather and/or use data to predict, recommend or decide, with varying levels of autonomy, the best action to achieve specific goals.*
>
> *Artificial intelligence systems can be purely software based, e.g.: chatbots and business virtual assistants based on natural language processing; face recognition systems based on computer vision or speech recognition systems; machine translation software; data analysis based on machine learning, etc.; or embedded in devices, e.g.: autonomous robots for warehouse automation or production assembly works; autonomous drones for production surveillance or parcel handling, etc.* [2]

Canada (Statistics Canada, 2019)

> *Artificial Intelligence (AI) refers to systems that display intelligent behaviour by analysing their environment and taking actions – with some degree autonomy – to achieve specific goals. AI-based systems can be purely software-based or embedded in a device.*

France (INSEE, 2019)

> *Artificial intelligence includes all the technologies aiming at computerization of cognitive tasks traditionally performed by humans: voice recognition, biometrics, image recognition, decision support, etc.*

Japan (Communication Usage Trend Survey 2017, Ministry of Internal Affairs and Communications)

> *AI (Artificial Intelligence) can be defined as something that can perform, learn, infer, recognize, judge, etc. through data analysis.*

Korea (2018 yearbook of Information Society Statistics, Ministry of Science and ICT and The National Information Society Agency)

> *Artificial intelligence technologies and services are machine-generated intelligence (artificial intelligence)….Refers to a technology that embodies abilities, reasoning skills, perception skills, and natural language comprehension skills……Example) AI assistant service that provides necessary information while talking by voice (S Voice and Bixby of Samsung, Q-Voice of LG, Apple's Siri, Google's Now, Microsoft's Cortana, Amazon's Alexa and Echo, SK Telecom's AI Speaker)*

In addition to the challenges inherent in agreeing on a definition of what AI is and does, it is also important to consider how to introduce the issue in surveys. Introductory definitions of AI in questionnaires are also an issue that needs being carefully considered as, overall, the propensity of respondents to neglect the texts inserted in the introductory parts of the AI modules in business surveys may at times be relatively significant. When needed, a short introductory text may help respondents provide focused and coherent answers. For AI, a short text (e.g. the OECD definition) mirrors a level of abstraction that may nevertheless be somewhat distant from a concrete implementation dimension. On the other hand, providing examples, while

---

[2] These categories closely match the 7 "Tasks" that have been identified by the OECD's ONE AI working group on the classification of AI systems, i.e. recognition; event detection; forecasting; personalisation; interaction support; goal-driven optimisation and reasoning with knowledge structures, or any combination of them embedded in a composite system (e.g. a driverless vehicle).

helping respondents formulate relevant answers in the module, is obviously lengthening the introduction and increasing the likelihood that respondents skip the introductory part. This is a trade-off that needs to be carefully managed by NSOs.

Based on an analysis of key words or expressions included in the AI definitions, it is possible to understand what stakeholders believe AI to be, as summarised in OECD (2021). This shows that the nine available definitions explored in OECD (2021) refer to AI in slightly different ways (e.g. some using “system(s)”, other using “technologies”). Furthermore, the “intelligence” feature is referred to with different expressions. Only a few include analysis of the environment or the function of prediction and goals, but all definitions explicitly – either in the body text of the definition or in the examples provided – refer to an activity or action, and most of them to machine, devices, or entity. Finally, five out of the nine definitions provide concrete examples of AI implementation.

Some of the AI definitions considered are more similar to each other than others. The Eurostat definition is very close to that of OECD, and adds examples organised around two dimensions (“pure software”/“embedded in devices”). The definitions by Canada and Sweden are very close to Eurostat’s, as they are using the same breakdown for AI systems (“can be purely software-based or embedded in device”). By contrast, they also both explicitly refer to systems that “display intelligent behaviour”, which is not included in the Eurostat definition. Differences also emerge, with some countries (e.g. France, Israel and Japan) that provide formulations relatively distant from the OECD definition.

Overall, what seemingly distinguishes most AI definitions is how the “intelligence” is captured and the associated type of actions, the reference to “various levels of autonomy” and to the “environment”, as well as the way they deal with examples.

Measuring AI in Business Surveys – a brief overview[3]

Measures of AI use in firms have recently been introduced in official statistics in a range of survey vehicles (e.g. Innovation Surveys, ICT usage surveys, General Business surveys). This paper focuses mainly on ICT usage surveys by businesses, except for Canada, where the Survey of Innovation and Business Strategy included a question on AI in 2017 (Statistics Canada, 2018), and for the United States, where the Annual Business Survey has included a Technology module since 2017.

Official survey questionnaires tackle a variety of issues, around AI adoption and uptake, following different approaches. The way businesses are asked about their use of AI is important and the structure and the variety of the items covered follows various levels of sophistication, depending on the vehicle used and the country considered. This relates for example to items such as the simple usage or adoption status, adoption barriers and obstacles, process of acquisition, types of AI technologies, fields of implementation, skills needed, or impacts. Table 1 provides an initial cross-country analysis of the issues covered in the AI measures.[4] The table is based on a detailed review of the AI survey questions presented in OECD (2021).

Overall, the table shows that coverage is relatively large for questions that relate to simple or intermediate levels of sophistication, such as AI use occurrence and AI use purposes, but that acquisitions, technologies and sectors are covered to a lesser extent. More sophisticated questions about skills and impacts are only addressed in some surveys.

AI usage or adoption status

Initially considered as an emerging technology, Artificial Intelligence usage was at the onset mainly surveyed using simple “Yes/ No” questions, such as: “In 2017, did this business use any of the following emerging technologies? => Artificial Intelligence” (Statistics Canada, 2018), or “In 2019, did your company use software and equipment incorporating AI technologies?” (INSEE, 2018). In the United States, the first measurement of business technologies did not even include the expression “Artificial Intelligence” but rather used components of AI technologies, such as Machine Learning or Natural Language Processing with their respective definitions. The question was: “In 2017, to what extent did this business use the following technologies in producing goods or services?” (US Census Bureau, 2018a and 2018b). The second measurement (US Census Bureau, 2019) uses the expression “Artificial Intelligence” and defines it as such within a more complex approach that includes motivations and impacts.

More articulated formulations of AI adoption questions in the surveys considered also seem to consider AI as an emerging technology. In Japan, questions ask about the status of AI introduction, coupled with that of the Internet of Things (IoT). In the United States, the questions differentiate between testing and using AI and between various intensity levels of AI use.

[3] This section draws on OECD (2021).
[4] It should be noted that the list of countries is not exhaustive and should be updated when further information becomes available

Table 1. Measurement of AI in official statistics, an overview for selected countries

Level of complexity

Questions	Canada	Denmark	Korea	Japan	France	Israel	Eurostat	United States
Use of AI (Y/N)	X	X	X	X	X	X	X	X
(If not) Awareness of AI			X					
(If not) Reasons for not using AI	X		X	X				X
Plan to use AI (/ in the future)			X	X			X	
(If not) Reasons for not using AI (/ in the future)							X	
Acquisition (in-house/outsourced/mix)					X	X	X	
Specific AI technologies *(e.g. Machine Learning, Deep Learning, Natural Language Recognition, ...)*	X	X					X	
Sectors (domains, fields) of implementation						X	X	
Business functions							X	
Purpose (reasons) of use / motivations for use / goals	X		X	X	X	X	X	X
Data sources and data types		X						
Skills needed						X		
Did your enterprise recruit or try to recruit AI specialists during 20xx?						X		
During 20xx , did your enterprise have difficulties filling vacant positions for AI specialists?						X		
Impacts				X				X
on Workforce – Processes and Methods								X
(number of workers / skills of workers)								X
on number of Worker Types – Processes and Methods								X
(production/non production/supervisory/nonsupervisory)								X

Source: OECD (2021), compiled from various official surveys questionnaires.

Barriers and obstacles to AI adoption

When surveyed, the reasons for not using AI relate generally to well identified issues: no business needs identified, no interest of management, lack of knowledge of available technologies, employees' lack of skills, costs (of service, equipment or implementation), security or privacy concerns, or legal barriers or concerns. Questions are also specifically addressing issues such as the insufficient communication infrastructure required for the introduction (Japan), the incompatibility with existing equipment and software (Canada), or issues around quality (Korea). The United States approach, in asking about factors that adversely affected the adoption and utilisation of AI technology, addresses similar issues but also includes the lack of maturity of the technology or the lack of reliability of the required data.

Beyond the status of AI introduction or adoption, existing surveys focus more in detail on a broader set of issues related to AI acquisition and implementation within the firm. This includes the ways through which AI is acquired by the firm, the various types of AI technologies or applications adopted, the type of business functions involved, the type of data collected and used, the sectors where AI is implemented, the associated skills needed and how to recruit AI-related human capital.

AI acquisition

As any other technological development, AI can be developed and adopted in many ways. AI systems may have been developed fully in-house (by a firm's own employees), may result from the purchase of commercial ready-to-use or customised systems, or from commercial systems ultimately modified by a firm's own employees, or may have been bought from external providers that were contracted to develop them. Also, AI can be adopted indirectly, i.e. by acquiring devices or systems that embed AI. According to recent research, AI will not be an off-the-shelf product for most firms in the near future, due to a strong need to teaming with technology partners (Brock and von Wangenheim, 2019).

As a general-purpose technology, AI is not a single monolithic technology. AI systems' implementation occurs through various technologies or through applications embedding AI components.

Field of activity

Business surveys always include questions related to the sector or industry where the surveyed firm or plant operates, based on national or international industrial classifications. ICT use surveys are not an exception in this respect. An additional specific question on the field of activity for AI use is proposed by Israel (CBS, 2019). Items listed include a mix of industrial coverage (e.g. banking, financial services; transport; professional, scientific and technical activities; etc.) and generic business functions (e.g. sales and marketing, manufacturing and industrial production; information and cybersecurity; etc.). A separate, more focused question on business functions is also proposed.

Purpose of AI use: from business functions to broader economic goals

Various nodes and components of the business process and associated functions (e.g. sourcing, production, human resources management, financial flows, etc.) are increasingly digitalised, as thus constitute growing opportunities to introduce AI systems, components or applications.

Existing survey questions asking about the purpose of AI use often distinguish between specific business functions or production components: marketing, production processes, management and administration, logistics, security, human resources, etc.

To facilitate understanding and increase the accuracy of responses, in the Eurostat survey, each of the business functions detailed is accompanied by examples of possible AI implementations. For example, for marketing or sales: i) *chatbots based on natural language processing for customer support* or ii) *customer profiling, pricing optimization, personalized marketing offers, market analysis based on machine learning*; and for logistics: i) *autonomous robots for pick-and-pack solutions in warehouses*, ii) *route optimization based on machine learning,* iii) *autonomous robots for parcel shipping*, *tracing, distribution and sorting*, etc.

In Israel, the AI use purposes relate to a list of items combining precise defined tasks and/or business functions. In the United States, the survey looks at AI as one of the selected technologies used in the production of goods and services (together with e.g. cloud-based computing systems and applications, specialised software and equipment, and robotics). The question on the purpose of use focuses on the production area, and specifically on processes and methods.

Data sources and data types

Both the sources of data used (e.g. enterprise's own system, public data originating from public authorities, data from Internet), and the types of data used (numerical, text, image or sound), are among the dimensions surveyed (Statistics Denmark, 2019). They contribute to a better understanding of the importance of data acquisition and management for businesses and may help shed light on how AI becomes part of the digital transformation of firms and their business models.

Canada is also surveying how businesses are collecting data (Statistics Canada, 2019), but the focus is not specifically AI related. It concentrates rather on customer and client information (e.g. data collected directly from customers or clients, from data mining, via contracted third party, or via loyalty or reward programs).

AI skills needed

ICT use surveys regularly include questions related to the difficulties to recruit ICT specialists (e.g. Australia in 2017, Canada in 2019, Eurostat since 2014). The same question is included, but narrowed to AI specialists, by Israel (CBS, 2019). The issue of lack of skills is also one of the possible responses in the question relating to reasons for not having used AI (Canada, Korea).

AI Impacts

The impacts of AI are a widely debated issue. However, existing official surveys include only few questions related to the way AI may impact businesses. For the companies having introduced IoT and AI in 2018 (not distinguishing between both), the

Japanese survey asks about any overall perceived effect (ranging from "very effective" to "negative"). In the United States, the survey (US Bureau of the Census 2019) asks about effects (increase, decrease, no change) of AI technology adoption on numbers and on skills of workers. For numbers, this relates to global, production and non-production workers, supervisory and non-supervisory workers. For skills, this relates to the global skill level of workers, and to the scientific, technological, engineering and mathematical skills of workers.

Survey results raise comparability issues

Overall results from existing official surveys, provided in Table 2 below, show that in all the countries where AI-related questions have been included in surveys, AI is not considered (or not anymore) as an emerging technology, especially among large firms. More than five percent of large firms were using Machine Learning in the United States in 2017,[5] and more than one fourth in Denmark in 2019.

When available, data by industry also show that AI use is already significant in some industries. In 2017, results from Canada show that near one firm out of five was using AI in finance and insurance industries, and more than one out of six firms in the information and cultural industries was using AI. In the United States, Machine Learning is the first or second most used technology among a group of advanced technologies, in industries such as manufacturing, wholesale and retail trade, transportation and storage, and information. In Japan, near one firm out of five in transportation and storage as well as finance and insurance industries, has introduced AI.

Table 2. Percentage of businesses using AI technology, recent years

firm's size band	**Canada[1] 2017** *20+*	**Denmark[2] 2019** *10+*	**France[3] 2018** *10+*	**Japan[4] 2017** *100+*	**Korea[5, 7] 2017** *10+*	**Korea[6, 7] 2018** *10+*
All	**4.0**	**6.0**	**11.4**	**14.1**	**1.5**	**2.1**
10-49		4.8	10.8	-	1.5	1.6
Small (20-99)	3.2		11.3			
50-99		6.7	12.3			
100-249		12.1	14.3	-		
100-299			13.1	14.2		
(Medium) 50-249			13.1	-	1.1	3.6
(100-249)	7.1		14.3			
Large (250+)	10.1	23.5	20.7	-	5.4	13.9
300+			23.2	13.6		

Notes: 1. Statistics Canada, SIBS 2017. 2. Statistics Denmark 2019. Refers to ML or AI. 3. INSEE 2019. Preliminary results. 4. Communication Usage Trend Survey. 5. 2018 Yearbook of Information Society Statistics. 6. 2019 Yearbook of Information Society Statistics. 7. The data of Korea are based on the establishment level, not on the firm level.
Sources: see OECD (2021) for the full details.

Explaining differences

The results provided in the two tables above highlight significant differences between countries, which may have been caused by a number of factors. First, the coverage of the surveys, intended as target population surveyed (e.g. business units surveyed can be enterprises or establishments), industries and firm size. For example, in Korea, the unit surveyed refer to the establishment, not to the enterprise. And in Japan, firms employing less than 100 employees were not surveyed, which clearly pushes the share of firms using AI upward (see third point below). Second, and as previously underlined, the structure of the questionnaires, the heterogeneity of the AI definitions used and the different nature, wordings and scope of questions, may also contribute to explain some of the differences emerging across countries. Third, as frequently observed for other emerging technologies, early birds in AI adoption are primarily large firms and firms from the ICT and high tech sectors. In addition, AI is often a part of a firm's digital transformation journey. It may get combined or merged with other technologies such as big

[5] See US Bureau of the Census, Annual Business Survey 2018, Digital Technology Module Tables, https://www.census.gov/data/tables/2018/econ/abs/2018-abs-digital-technology-module.html

data analysis, IoT and cloud computing. The uptake of those complementary technologies may contribute to explain differences in development and adoption within and across countries. Overall, the brief review above and the more detailed assessment available in OECD (2021) shows that there is a strong need for international comparability in AI measurement, but that the road is paved with obstacles.

Other measurements of AI in the digital economy – some highlights[6]

Existing official measures are often struggling to keep up with the rapid pace of technological developments, including AI. At the same time there is a pressing need to identify and share indicators to shed light on where and how AI is developed, used, by whom, how fast, and in which sectors. To be able to deliver up-to-date policy relevant statistics, official statistical information systems will need to build partnerships with businesses and academia. Moreover, while surveys of business use are currently the main focus of NSOs' activities related to measuring AI, other sources of administrative and private data can provide important complementary information on a country's strengths in artificial intelligence, including the broader business environment for AI.

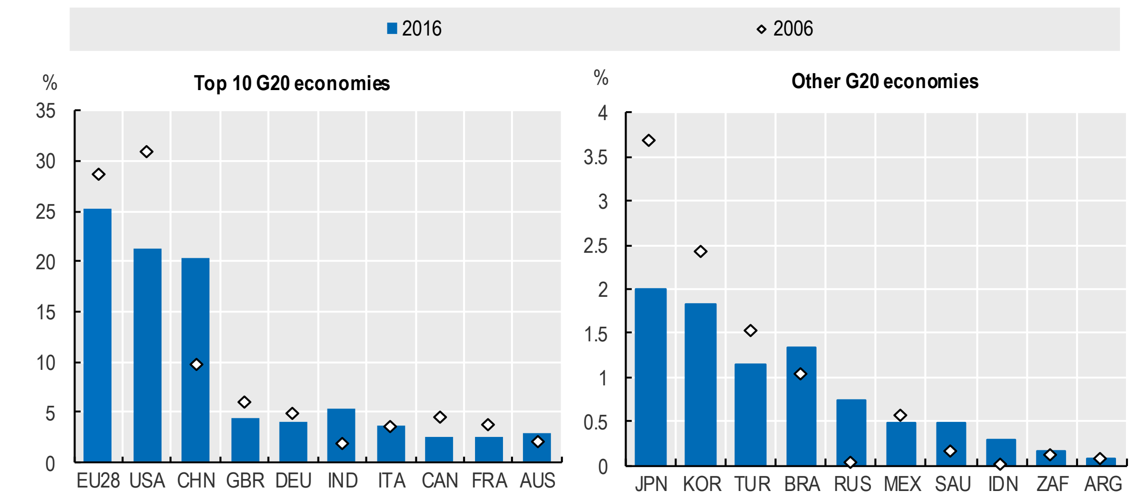
For example, Baruffaldi et al (2020), propose an operational definition of AI based on the identification and measurement of AI-related developments in science, algorithms and technologies. The analysis is based on information contained in scientific publications, open source software and patents and results from collaboration with the Max Planck Institute for Innovation and Competition (MPI Munich). The work also benefitted from advice from leading AI scientists and from patent experts. The three pronged approach devised by Baruffaldi et al (2020) relies on an array of established bibliometric and patent-based methods, and is complemented by an experimental machine learning (ML) approach implemented on purposely collected open source software data. The approach produces an encompassing operational definition of AI. As in the case of survey work, such a definition can only account for past and present developments, and will need to be periodically revised and refined, as AI evolves. Some of the key findings and details of the approaches in Baruffaldi et al (2020) are:

- The identification of the science behind AI developments is based on a bibliometric two-step approach, whereby a first set of AI-relevant keywords is extracted from scientific publications classified as AI in the Elsevier's Scopus® database. This set is then augmented and refined using text mining techniques and expert validation. This two-step approach leads to identifying 168 groupings of AI-related terms (and variations thereof, e.g. convolutional neural networks and neural networks). Scientific publications and conference proceeding articles are finally tagged as being AI-related if they contain in their abstract at least two AI keywords related to different groupings. This is done to contain the number of false positives and minimise over identification. This approach was used, among others, for an indicator on scientific publications presented in the G20 report "*A Roadmap toward a Common Framework for Measuring the Digital Economy"* (OECD, 2020b, Figure 3).
- As AI is ultimately implemented in the form of algorithms, and in the impossibility to access data related to private firms' AI software, Baruffaldi et al. (2020) use open-source software's information about software commits (i.e. contributions) posted on GitHub (an online hosting platform) to track AI-related software developments and applications. Such data are combined with information from papers presented at key AI conferences to identify "core" AI repositories. Machine learning techniques are trained using information for the thus identified core set are used to explore the whole set of software contributions in GitHub to identify all AI-related repositories.
- Information contained in patent data is used to identify and map AI-related inventions and new technological developments embedding AI-related components, independently of the technological domain in which they occur. Text mining techniques are used to search abstracts and patent documents referring to AI-related papers. This leads to identifying the International Patent Classification (IPC) codes most frequently allocated to AI-related inventions. Such list of IPC codes, upon validation by patent examiners and experts in the field, is refined so that some IPC codes are considered in full as being AI-related, whereas identification of other patent codes needs to rely on keyword searches on patents. Finally, experts agreed to implement refined keyword-only searches to identify AI developments happening in other technology areas. An example of the findings of such work is shown in Figure 4, updating the results presented in Baruffaldi (2020).

Figure 3. Top-cited scientific publications related to AI, 2006 and 2016

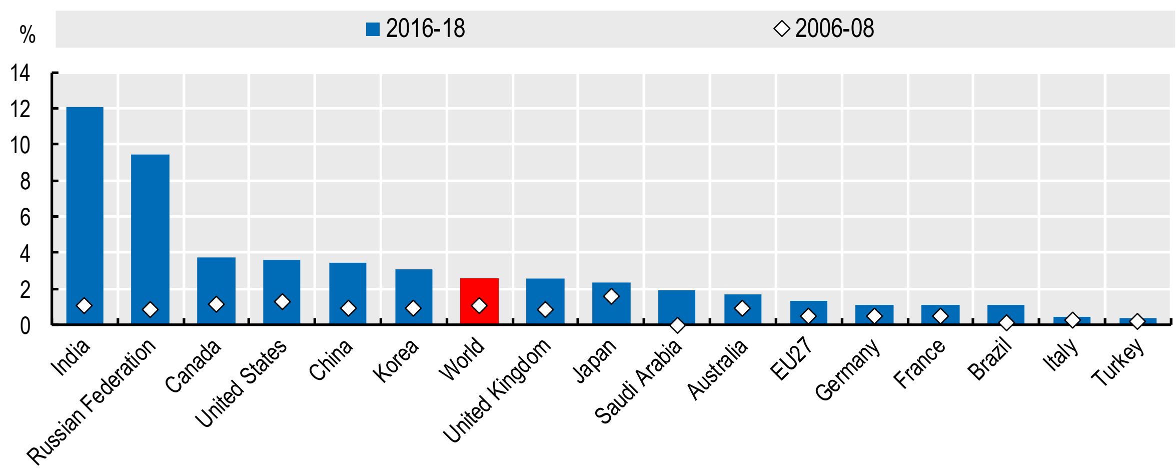
Number of AI-related documents among the 10% most cited publications, fractional counts

6 This section draws heavily on Baruffaldi (2020).



Source: OECD calculations based on Scopus Custom Data, Elsevier, Version 1.2018 and 2018 Scimago Journal Rank from the Scopus journal title list (accessed March 2018), January 2019.

Figure 4. AI-related inventions in total patents, G20 economies, 2006-08 and 2016-18



Note: Data refer to IP5 patent families in AI-related technologies, by earliest filing date and applicant's location, using fractional counts. Only G20 economies owning more than 500 IP5 families in the time periods considered are included. Data for 2018 are incomplete.
Source: Updated from Baruffaldi, et al. (2020), based on OECD, STI Micro-data Lab: Intellectual Property Database, http://oe.cd/ipstats, February 2021.

There are many other examples of administrative and private sources being used to track the development of AI. For example, OECD (2019) used the private dataset Crunchbase to explore private equity investments in AI-related start-ups. The OECD is currently investigating the use of the Preqin private dataset to estimate and visualise private equity investments in AI start-ups in real-time. Yet other private sources, like Glass AI and Burning Glass, can also provide helpful insights.

The OECD AI Observatory (OECD.AI) currently presents interactive data visualisations covering AI trends and developments on a range of topics. For example:

- It tracks the labour supply of AI skills using LinkedIn Economic Graph, including penetration of AI skills by country, industry, gender and over time; the rate of growth of AI hiring by country and over time; as well as the international migration of AI talent;[7]
- Using data from Adzuna, OECD.AI provides real-time indicators of AI skills demand in 16 countries, including by type of skill, country, and skill bundle;[8]

[7] See: https://oecd.ai/data-from-partners?selectedTab=AIJobsAndSkills
[8] See: https://oecd.ai/data-from-partners?selectedTab=AIJobsAndSkills

- National and international AI research trends – including by gender – from Microsoft Academic Graph and Elsevier and patenting activity from Microsoft Academic Graph;[9]
- Trends in open source software development from Github;[10]
- and domestic and international AI-related search trends over time, from Google trends.[11]

Moreover, extensive work is currently underway at the OECD to develop new evidence and indicators on the impact of AI on work, innovation, productivity and skills, in the so-called AI-WIPS project.[12]

Many AI indicator reports are also being produced by academic institutions and the private sector, e.g. the AI Index produced by Stanford University's Institute for Human-Centered AI,[13] or the Global AI Index by Tortoise Media.[14]

As with the development of other emerging technologies, some of the indicators presented in academic and private studies may eventually be complemented or replaced by official statistics as these become more widely available. At the same time, academic and private sources are likely to remain important in the tracking of rapidly-evolving technologies such as AI. Statistical offices and governments may therefore wish to consider whether they should play a role in guiding the development of statistics and indicators based on such sources, e.g. by developing statistical quality frameworks.

The measurement of AI from a macro-economic perspective

From a macro-economic perspective, the measurement of AI is a constantly developing challenge faced by all national statistical offices. Similar to other challenges brought on by the introduction of new technologies and digitalisation, the creation and use of AI in the economy forces statisticians to consider if the current standards and classifications are still fit for purpose. That is, are they able to provide an accurate representation of the level of production associated with AI, but just as importantly, do they contain the specific information desired by users.

The use of AI in production usually involves investment by firms in order to create a tool that can be used repeatedly in the production process; due to this, there is only limited concern regarding the question of its inclusion in macro-economic outputs. Fundamentally, this type of expenditure on AI should be captured in one of the established asset classes that already exist within the 2008 System of National Accounts (2008 SNA). Alternatively, if purchased as an input into production, there are numerous digital products for which it is likely allocated to.

From a capital perspective, since AI is computer based and involves the creation of software, a large amount of AI would seem consistent with the existing description used in the 2008 SNA for computer software as *"computer programs, program descriptions and supporting materials for both systems and applications software."* This broad description covers expenditure on any and all computer programs, from a simple word processer to an advanced supervised machine learning program[15]. That said, this asset category is predominately used for assets that are actively contributing to the production process and while much AI is already doing this a significant amount of expenditure on AI is still in the developmental phase. In these cases the SNA would still be capturing the production involved in developing AI, but more likely within the Research and Development (R&D) asset class. This class includes *"creative work undertaken on a systematic basis to increase the stock of knowledge, and use this stock of knowledge for the purpose of discovering or developing new products."*

While the existing 2008 SNA is likely capturing the expenditure, it is therefore fulfilling the goal of ensuring an accurate representation of AI in the economy. However, it does not currently assist with the secondary concern of doing so at an appropriate level. To address this, a greater effort must be made to delineate expenditure related to AI as it is contained in the products mentioned above.

[9] See: https://oecd.ai/data-from-partners?selectedTab=AIResearch
[10] See: https://oecd.ai/data-from-partners?selectedTab=AICoding
[11] See: https://oecd.ai/data-from-partners?selectedTab=AISearchTrends
[12] See: https://oecd.ai/work-innovation-productivity-skills
[13] See: https://hai.stanford.edu/research/ai-index-2019
[14] See: https://www.tortoisemedia.com/2019/12/03/global-ai-index/
[15] Additionally in circumstances where the AI software is embedded in a larger piece of equipment, for instance loaded into the electronics of a vehicle, then the cost of the AI may be incorporated into the overall value of the machinery. This would be the same for all tangible fixed assets.

From a national accounts perspective, a possibility might be to break down the Supply and Use Tables by creating “of which” type delineation for certain products: this could be preferable to an entirely separate classification as users would still be able to see not only the different type of AI being produced (i.e. as software, R & D, embedded in other products) but also the breakdown between that which is capitalised or consumed.

Such a proposal, however, leads onto the practical difficulties of including AI in macro-economic statistics. As outlined previously, many of the established surveys and government data, which make up the majority of source data used by NSOs, do not provide information from an economic statistic perspective. As such, many of the survey questions or administrative information focus on the characteristics of the AI development, such as: is the firm utilising AI or not? For what purpose? What will be the impact of its development? These questions, while providing important information for policy development do not assist in valuing the asset or the level of production required to create it.

To truly make AI visible in the national accounts, NSO’s could and should take an active role in influencing the development of source data which provides the level of detail required. Part of this role is fundamentally linked to the development of a definition that assists with the collection of this information. Business often provide expenditure information based on accounting classifications; therefore, if a definition for AI is based on (to use two definitions mentioned earlier in the paper), specific characteristics that the program is capable of, such as *“displaying intelligent behaviour by analysing their environment and taking actions – with some degree autonomy – to achieve specific goals”* or *“perform, learn, infer, recognize, judge, etc. through data analysis”* it’s unlikely that businesses will be able to delineate expenditure in their accounts based on such specific characteristics.

That said, one possibility in this space may involve the expected lifespan of the asset, as firms often delineate assets (and the expenditure on them) based on this characteristic. While all AI is different, it’s possible that due to AI’s learned skills, unlike other fixed asset classes, AI actually becomes more valuable over time, as more data is provided for learning, thereby extending its useful life. While this will not always be the case, as some specific tasks that are learnt may simply become obsolete, the potential for AI to exhibit a useful life much longer than standard assets, provides a reason for it to be separately accounted for both in business and macro-economic accounts.

Such possibilities are still some time off, but it is important to continue to review such possibilities so that statistical classifications continue to evolve and appropriate reflect the technology it is tasked with measuring. Such a commitment is the NSO’s best chance to continue to provide data and information that is accurate and meeting user’s demands.

References

Baruffaldi, S., et al. (2020), "Identifying and measuring developments in artificial intelligence: Making the impossible possible", *OECD Science, Technology and Industry Working Papers*, No. 2020/05, OECD Publishing, Paris, https://doi.org/10.1787/5f65ff7e-en.

OECD (2019), *Artificial Intelligence in Society*, OECD Publishing, Paris, https://www.oecd.org/publications/artificial-intelligence-in-society-eedfee77-en.htm .

OECD (2020), *A* Roadmap *Toward a Common Framework for Measuring the Digital Economy*, http://www.oecd.org/sti/roadmap-toward-a-common-framework-for-measuring-the-digital-economy.pdf

OECD (2021, forthcoming), “AI Measurement Issues in ICT Usage Surveys – A Review”, *OECD Digital Economy Papers,* OECD Publishing, Paris.

UN, European Commission, IMF, OECD, World Bank (2009), “System of National Accounts 2008”, New York, 2009. Available at: https://unstats.un.org/unsd/nationalaccount/docs/sna2008.pdf