Irving Fisher Committee on
Central Bank Statistics

BIS

IFC Report

No 18

Governance and implementation of artificial intelligence in central banks

2024 survey conducted by the Irving Fisher Committee on Central Bank Statistics (IFC)

April 2025

Contributors to the IFC report[1]

Bank for International Settlements (BIS)	Douglas Araujo
	Rafael Schmidt
	Olivier Sirello
BIS & Irving Fisher Committee on Central Bank Statistics (IFC)	Bruno Tissot
Central Bank of Chile (CBC)	Ricardo Villarreal

This publication is available on the BIS website (www.bis.org).

ISSN 1991-7511 (online)

ISBN 978-92-9259-847-1 (online)

[1] Respectively, Economist (douglas.araujo@bis.org); Head of IT, Monetary and Economic Department (rafael.schmidt@bis.org); Statistical Analyst (olivier.sirello@bis.org); Head of BIS Statistics and Head of the IFC Secretariat (bruno.tissot@bis.org); and Economic-Financial Analyst (rvillarreal@bcentral.cl).

The views expressed are those of the authors and do not necessarily reflect the views of the BIS, the CBC, the IFC, its members or the other institutions mentioned in this report.

The authors are grateful for comments and suggestions from Juan Pablo Cova, Robert Kirchner, Michael Machuene Manamela, Alberto Naudon and participants at the 4th IFC-Bank of Italy Workshop on "Data Science in Central Banking" (February 2025). They also thank Márcia Cavalinhos, Nicola Faessler and Ilaria Mattei for editorial support.

Contents

Executive summary

Artificial intelligence (AI) **can hold significant potential for central banks**. As an innovative technology, it is likely to provide still unexplored benefits in automation, productivity and operational efficiency. It can also offer new ways to generate insights and better support decision-making.

Against this setting, exploring **AI has become strategically important for central banks**, as highlighted by a recent survey of IFC members. They appear to be rapidly embracing innovative data science techniques in their activities, including for economic research and statistics. They are in particular actively experimenting with generative AI to enhance various tasks, such as information retrieval, computer programming and data analytics.

Yet, below the surface, many central banks are still in the initial adoption phase. This raises the **central question of *how* AI can be effectively and responsibly used** in their production processes.

A first lesson from central banks' experience is that the **deployment of this technology must be complemented by adequate governance**, which is taking shape gradually in most jurisdictions. Thus far, AI projects are primarily implemented in a decentralised way. This is certainly important to tailor applications to user needs, but it may create difficulties in terms of coordination and risk mitigation. In particular, there are significant concerns about privacy protection, cyber security weaknesses, skills shortage and ethical biases – topics that are arguably best addressed comprehensively at the overall institution level. To tackle these issues effectively, central banks can benefit from their long-established, robust and extensive experience with data management and governance, especially in the context of their official statistical functions.

A second lesson is that the **implementation of AI presents several trade-offs in terms of IT infrastructure**. One reflects the pressing need to access more computational power, which can be costly, especially in terms of IT infrastructure. Cloud services could be one solution, but their use may remain constrained by security and sovereignty concerns. Another important issue relates to the choice of closed versus open source AI models. While the former may be easier to deploy and maintain, the latter can be more cost-effective and less dependent on external vendors. A further trade-off is the deployment of in-house solutions versus off-the-shelf products, each of them featuring advantages and disadvantages in terms of customisation of applications, security, implementation costs and deployment rapidity.

Finally, another important feedback is that **leveraging innovation effectively calls for making further progress on more "traditional" data management issues**. This reflects the fact that AI-generated outputs intrinsically depend on the quality of their underlying data inputs – the well known "garbage in, garbage out" principle. From this perspective, making the most of AI opportunities requires improving the various phases of the data life cycle, from production, validation, integration and storage to dissemination and use.

Key priorities looking ahead could include (i) curating the quality of data and metadata to ensure their transparency, traceability and machine readability; (ii) improving the global data infrastructure by enhancing data access and adequate sharing and exchange of best practices among relevant stakeholders; (iii) developing modern, metadata-driven and standardised data processes and systems; and (iv) advancing user literacy in AI and general data issues.

1. Introduction

In recent years, **data science has driven remarkable innovations** offering new tools and techniques for analysing large and complex data sets (IFC (2023a)). Among these, AI, coupled with the growing availability of computational power, has great potential to reshape central banks' activities (BIS (2024)).

Clearly, **AI in central banking is not new**. This technology refers to "a machine-based system that [...] infers, from the input it receives, how to generate outputs" (OECD (2024a)). As such, it enables to leverage the increasing availability of computational resources to address tasks that traditionally require human intervention (FSB (2017)). Central banks have implemented AI in their workflows for many years already (IFC (2015a)). An example is their application of machine learning (ML) – a subset of AI based on the use of complex algorithms trained on vast amounts of data – which can perform big data analytics, with notable benefits for economic analysis, research and statistics (IFC (2021a, 2022)).

But **the recent advent of generative AI** – a class of AI that learns the patterns and structure of input content such as text, images, audio and video ("training data") and generates new but similar data without requiring much user expertise – **has pushed the adoption of this technology even further**. Specifically, the rise of large language models (LLMs) has enabled to generate human-like sentences thanks to natural language processing (NLP) techniques that capture the relationships between words. A growing number of central banks have begun experimenting with these new tools, ranging from chatbots to assistants for coding and data analytics (Araujo et al (2024), Kwon et al (2024)).

Despite its potential benefits, the embrace of AI raises a number of questions.

First, **a prominent issue relates to its responsible and safe use**. This technology is not free of limitations and risks, ranging from the generation of inaccurate, erroneous or biased outputs to the risk of increasing dependency on third-party providers. These issues could easily damage the reputation and credibility of central banks in their roles of producing reliable information and conducting evidence-based policies. Dealing with these challenges clearly puts a premium on developing well established and transparent principles ensuring adequate risk management and governance (CGRM (2025)). Fortunately, central banks can capitalise on their expertise in managing data as producers of official statistics, in particular to enhance their quality, availability, usability, integrity and security across the organisation (IFC (2021b), UNECE (2024a)). Concretely, a set of key practices and rules have been developed to ensure transparent and adequate data ownership, adherence to common standards, third-party reviews and audit tracks – with the essential foundation provided by universally accepted principles such as the Fundamental Principles of Official Statistics (UN (2014)).

Second, from a more operational perspective, **the development and deployment of AI may require the adaptation of existing IT systems**. One issue is access to sufficient computational resources. Another is ensuring the availability and reliability of data platforms to store, manage and analyse the wealth of both structured and unstructured data, which keeps expanding rapidly with the digitalisation of the economy. A related concern has to do with the adoption of cloud services, which can be a cost-effective – if not unique – way to perform complex big data analytics but which is not without drawbacks. Reflecting the above, AI implementation is characterised by various trade-offs, not least in terms of security, performance and scalability.

Another important topic for central banks is **how to adapt to the evolving data and technological landscape**, which arguably calls for a better global data infrastructure based in particular on well established statistical standards, methodologies, identifiers and registers. Priority tasks appear to involve fostering better data access, sharing and collaboration; modernising data platforms; and disseminating high-quality, standardised and machine-readable data and metadata, for instance by leveraging the Statistical Data and Metadata eXchange (SDMX) standard especially for financial and macroeconomic statistics (IFC (2025a)).

To allow for a comprehensive understanding of these issues, **the IFC conducted a survey on the use of AI and ML** at the end of 2024.[2] Specifically, it focused on the following six AI-related areas: (i) scope and interest; (ii) expectations; (iii) applications; (iv) organisational policies, governance and risks; (v) IT stack; and (vi) collaborative strategies. Taken all together, the overarching value of this survey was to be able to assess the current state of data science adoption in central banks, while also keeping sight of the main expectations and priorities looking forward, especially in terms of governance, implementation and international cooperation.

This report outlines the results of the survey as follows: Section 2 reviews the current state of AI adoption in central banks. Section 3 turns to its governance while Section 4 discusses AI impact on IT systems, including its opportunities, challenges and trade-offs. Finally, Section 5 concludes with a number of lessons from central banks' experience that can help to fully harness the benefits of AI in the evolving data and technological landscape.

2. High interest but still low adoption

Central banks have long explored data science innovations, including AI. Yet **the recent advent of generative AI** – and in particular LLMs – **has renewed interest** in how to harvest the benefits of this innovative technology that can be more easily accessed by non-specialists. As a result, resources are increasingly being mobilised to implement various use cases across the many areas of central banking. However, **full-scale adoption appears to have remained relatively low** and mostly limited to pilot projects so far.

Growing interest in AI-based applications…

Central banks are expressing a growing interest in AI according to the IFC survey, which gathered responses from 60 jurisdictions across all continents (Graph 1.A). Perhaps more notably, a large number of central banks view AI and ML as a strategic issue (Graph 1.B), with almost half of the respondents ranking it as a top priority, especially in Asia.

Clearly, **there are many reasons why central banks place AI high on their agenda**. Versatility is a first key motive, as this technology can support a broad range of central bank-specific activities, spanning from statistical compilation to macroeconomic and financial monitoring (Araujo et al (2024)). A common use case is to extract quantitative insights from textual information, such as the discussions by the Federal Open Market Committee (FOMC) of the US Federal Reserve Board (Dunn et al (2024)). Another use case relates to new analytical capabilities, for example to identify specific patterns in data such as market dysfunction episodes (Aquilina et al (forthcoming)). Other reasons are that AI can significantly augment programming capabilities (Gambacorta et al (2024))[3] and help automate existing workflows, paving the way for increased efficiency and productivity, especially for administrative tasks (Spencer (2024)).

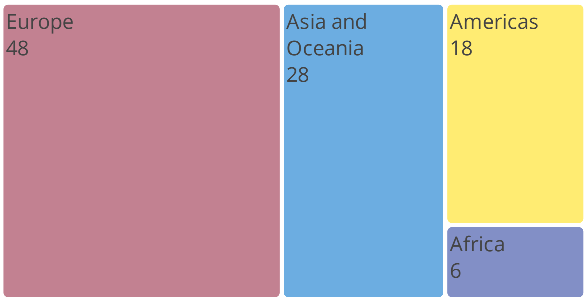
[2] See Annexes 1 and 2 for the survey questions and the list of respondent IFC jurisdictions, respectively. Responses have been collected between September and November 2024.

[3] Mirroring the broader experiences within society, as AI is increasingly used in the public and private sector (Crane et al (2025)).

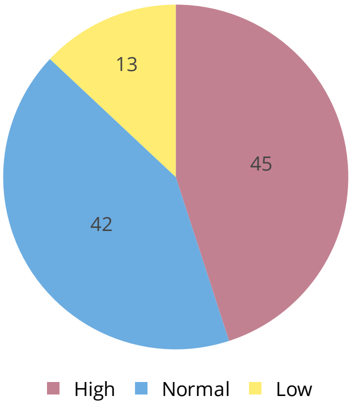
Artificial intelligence is a priority for central banks

In per cent of respondents Graph 1

A. Survey coverage



B. Evaluating AI/ML importance in strategic planning



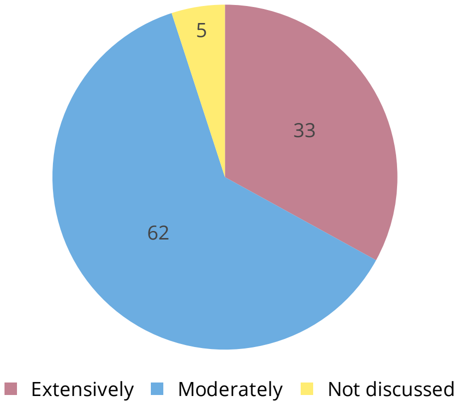
Sources: IFC survey on AI and ML (2024); authors' calculations.

Consistent with the priority given to AI exploration, **the vast majority of central banks are actively discussing its use cases** (Graph 2.A). Meanwhile, they are also concretely increasing the resources allocated to this area (Graph 2.B). Almost half of the respondents intend to invest at least 5% of their budget in AI/ML projects in the next three years, with a few planning to invest more than 10%. This marks an important change compared with current financial plans, where the share allocated to AI initiatives is generally less than 5%. Certainly, these expected budget increases may also reflect the anticipated high cost of running the new applications to be developed. Yet, cheaper solutions are emerging, with costs expected to go down over time, not least thanks to declining prices in IT computing power and the growing availability of freely accessible open models supporting data science (Araujo et al (forthcoming)).

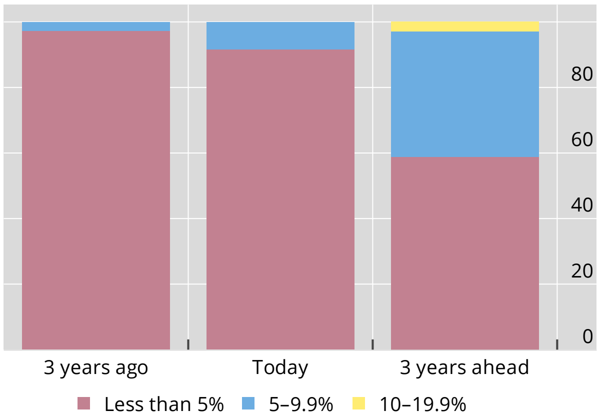
AI is an important topic for discussion in central banks, with a budget set to grow

In per cent of respondents Graph 2

A. Internal discussions on AI/ML



B. Budget allocated to AI/ML projects



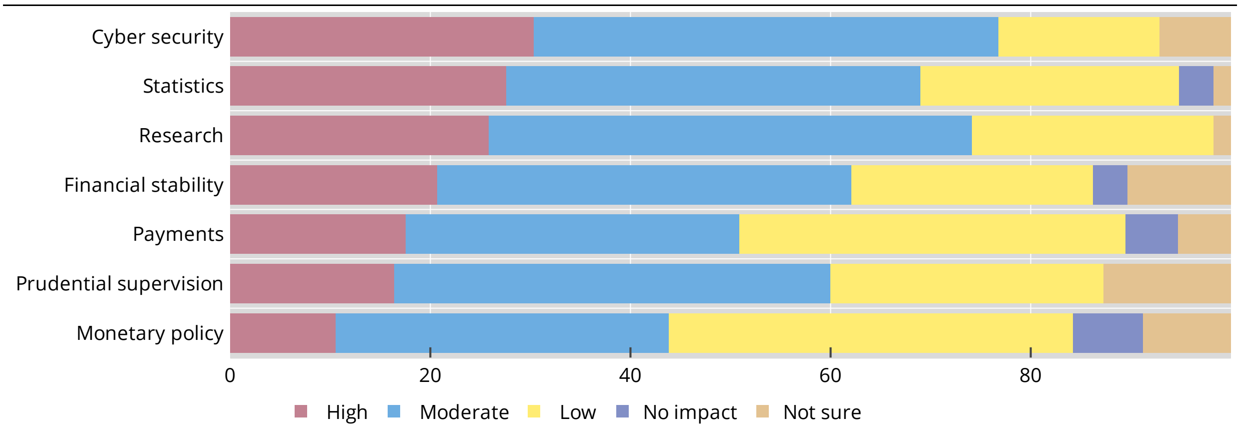
Sources: IFC survey on AI and ML (2024); authors' calculations.

The above developments suggest that **central banks generally expect significant benefits from AI in performing their various tasks** (Graph 3). Opportunities in the areas of cyber security, research and statistics are judged to be the most valuable. For instance, AI can help enhance the detection of cyber threats and reduce response time (Aldasoro et al (2024)). It can also support economic research in various ways, including by assisting with mathematical analysis, summarising literature, writing and explaining code, and helping to edit drafts (Korinek (2024)).

AI is expected to have a significant impact in general and particularly in the areas of cyber security, statistics and research[1]

In per cent of respondents

Graph 3



[1] Share of the expected impact from AI/ML (from "high" to "not sure") per each functional domain in the next two years.

Sources: IFC survey on AI and ML (2024); authors' calculations.

Turning to the central banks' statistical function, AI is also expected to bring important benefits for both data producers and users (UNECE (2023, 2025a)). The survey confirms that innovative tools can greatly support statistical compilation – in particular for data analysis and processing, at least on an exploratory basis (Graph 4.A).[4] Reported use cases also include identifying outliers and generating synthetic data (Graph 4.B), an important topic for central banks seeking to facilitate access to their micro data sets while safeguarding sensitive information (Brault et al (2024), Drechsler and Haensch (2023)).

In contrast, **central banks expect AI to have a milder – though still promising – impact on their core policy mandates**. First, a number of applications can support key tasks in the monetary policy areas, for instance inflation forecasting (Araujo et al (2024)) and macroeconomic modelling (Kase et al (2025)). Regarding financial stability, AI can help sift through textual information to better anticipate episodes of macro-financial distress (FSB (2024)) and, at the microprudential level, to support regulatory compliance and risk-based supervision (Crisanto et al (2024), Dohotaru et al (2025)) or develop stress tests (Petropoulos et al (2022)). Finally, AI is also expected to impact other areas of central banking such as payments supervision. For example, it can help detect fraud (Desai et al (2024)) or monitor money laundering in real time (BISIH (2024)).

The survey also shows that **virtually all surveyed central banks already use generative AI tools** (Graph 5.A), in particular to generate text and code (Graph 5.B). Another top use case is AI chatbots – a common software application designed to converse with users – to assist with various tasks, for instance to extract, summarise, translate or draft documents (Handa et al (2025)). Some central banks have

[4] Cf IMF's StatGPT and TalkToManuals chatbots that aim to modernise data processing, dissemination and discoverability for producers and users; see Kroese (2024) and Ribarsky (2025).

developed assistants to help supervisors quickly search for relevant guidance, while others are developing tools for meeting transcripts and internal or external communication support.

The use of AI/ML by central banks' statistical functions mostly relates to data processing and analysis

Number of responses | Graph 4

A. Statistical applications of AI/ML across the phases of the data life cycle[1]

B. Large variety among the reported use cases

[1] For the main sequences of the production of official statistics as described in the Generic Statistical Business Process Model (GSBPM).

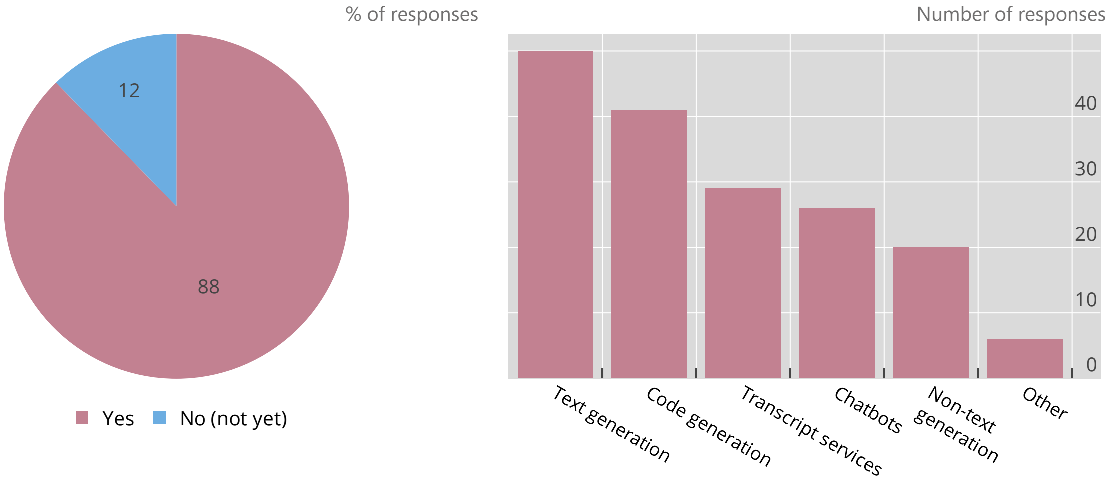
Sources: IFC survey on AI and ML (2024); authors' calculations.

Generative AI applications in central banks

Graph 5

A. Almost all reporters use generative AI…

B. …especially for text and code generation



Sources: IFC survey on AI and ML (2024); authors' calculations.

… despite a still limited number of applications in production

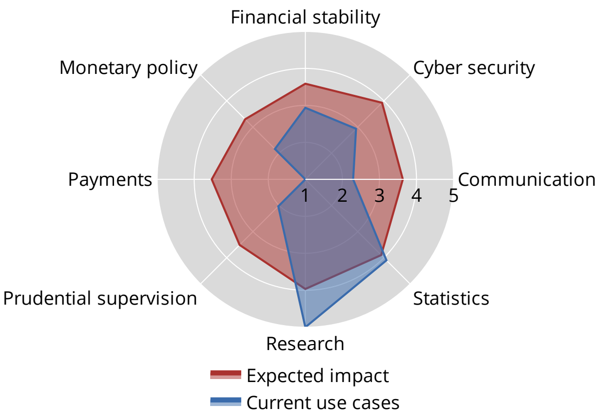
Another key highlight from the survey is that the potential of AI has yet to be fully explored, as the development of actual applications has remained relatively limited to date.

First, **there is a gap between expectations and projects actually implemented across the main functional domains of central banking** (Graph 6.A). In theory, one would expect that a higher anticipated impact would correlate with a higher number of applications. Yet, in practice, this is not always true. For example, in cyber security, the number of reported use cases is trailing expected impact, possibly reflecting significant barriers to implementation, including IT and staff resources constraints (Aldasoro et al (2024)). Other areas with a low number of concrete projects despite high hopes include payments and microprudential supervision. In contrast, the development of AI-based applications has been quite marked – and even sometimes surpassing expectations – in statistics and economic research, in particular for nowcasting, sentiment analysis and outlier detection (Graph 6.B).

Despite high expectations, current AI-based applications remain limited and primarily relate to economic research, communication chatbots and statistics — Graph 6

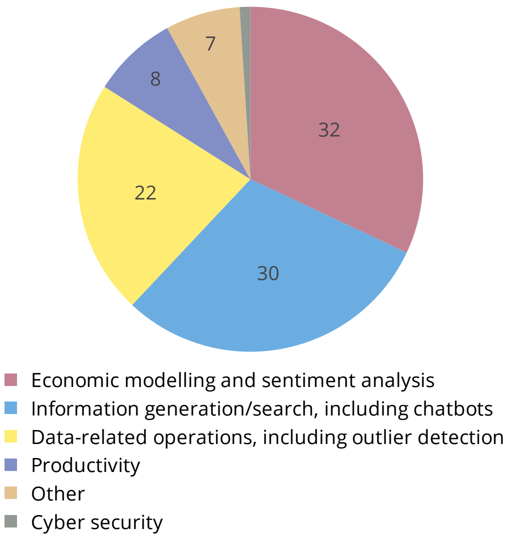
A. Expected impact and current applications of AI/ML[1]

Normalised scores, 1–5



B. Reported AI/ML use cases by application scope[2]

% of responses



[1] Expected impact is calculated as the average of the responses rated on a scale from 1 to 5 (1 = not sure; 2 = not impactful at all; 3 = slightly impactful; 4 = moderately impactful; 5 = highly impactful). The number of current use cases is presented normalised on a scale from 1 (min) to 5 (max). [2] Pilot or ongoing use cases also included. Respondents could indicate more than one answer.

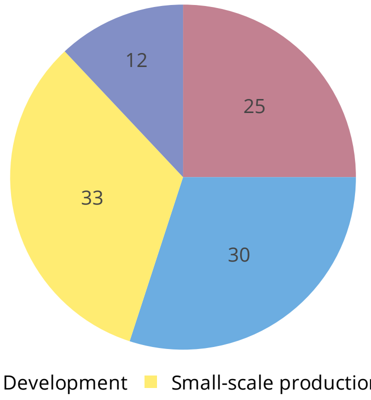
Sources: IFC survey on AI and ML (2024); authors' calculations.

Second, **most of AI-based applications have been developed on an exploratory basis instead of being deployed in actual production mode**. Specifically, just about a quarter of AI use cases effectively make it to full-scale implementation (Graph 7), while the vast majority are either in small-scale production or still in development. This suggests that central banks are still mostly experimenting with AI rather than actively using it for day-to-day operations. There could be several reasons for this. The first has to do with IT infrastructure, which can often only support a few pilot projects. Another reason is that central banks are still in the learning phase. Thirdly, most exploratory work is conducted at the level of the functional areas, while the development of full applications in production mode requires the coordination of multiple stakeholders (eg business units, IT and security departments and units in charge of budget and staff resources). However, this picture may change rapidly as central banks' IT infrastructure and governance arrangements will mature progressively to respond to the growing interest in AI techniques.

Central banks are mostly exploring AI/ML applications, with limited use for day-to-day operations[1]

In per cent of respondents

Graph 7



[1] Percentage of respondents indicating each state of AI/ML adoption ("In production" = multiple use cases deployed in production; "Small-scale production" = limited use cases in production; "Development" = few pilot projects; "No AI/ML in use" = no projects either in production or development).

Sources: IFC survey on AI and ML (2024); authors' calculations.

3. Enhancing governance

As adoption grows, central banks are increasingly recognising the importance of establishing clear principles governing the way data are managed and securely used to support multifaceted AI-based applications. In particular, a key insight from the IFC survey is that central banks have been actively working on tailoring their existing data governance and management to the specificities of AI to both mitigate its risks and promote innovation efficiently.

Central banks are maturing AI governance…

With a growing number of AI applications being considered, it is growingly felt that **adequate governance should be set up to fully harness their benefits while also mitigating the many risks**. This reflects the fact that the AI technology can be associated with hazards of various types, raising concerns over cyber activity, invasive surveillance, privacy infringements and opacity (OECD (2024c)).

One can **define AI governance as the set of principles, responsibilities, structures and**, broadly, **frameworks** that allow for an effective use of this technology while aligning it with organisational goals and risk compliance standards. In that, this concept is closely related to data governance, which is already well established in central banks to manage and ensure the quality of statistical information, in particular in terms of accuracy, availability, security and usability (Križman and Tissot (2022)). Yet, implementing AI governance in the organisation expands beyond data to address additional challenges, especially the specific risks brought in by the new technology as well as its ethical implications (Mäntymäki et al (2022); see Box A).

Box A

Implementing AI governance

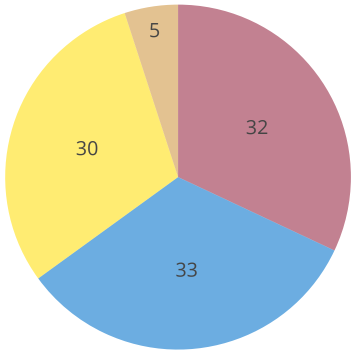
This box summarises surveyed **central banks' experiences in operationalising AI governance**, focusing on four core components, namely data governance, organisation, rules and risk management:

1. **Data governance** involves adequate documentation to clarify policies, standards and procedures, inter alia, that ensure data quality – especially in terms of accuracy, transparency and provenance, security and responsible use. Common solutions typically include establishing comprehensive data management systems, documenting data (eg through metadata on the sources, version and curation), maintaining asset inventories (eg data catalogues) and metadata registries, using standards and enabling efficient data exploration for both humans and machines, for instance through application programming interfaces (APIs).
2. **Organisational structures** are very often interdisciplinary and range from dedicated centralised solutions (eg steering committees/commissions, programme management offices, multi-modal structures) to hub-and-spoke systems (ie overall network with multiple functional hubs) and fully decentralised approaches (eg governance set up at the level of the business lines). Accountabilities for AI can also be assigned to existing roles (eg chief data/information/technology officer) and/or units (eg IT department) or, on the contrary, to newly created functions. Some central banks have also adopted more informal organisational setups, such as communities of practice or cross-functional networks.
3. **Guidelines and policies** commonly include terms of use for AI systems, including their modalities, interfaces and data (eg models, third-party dependencies, upstream/downstream data). Survey's responses also refer to guidelines for responsible AI use, privacy standards, explainability requirements and, more broadly, international principles such as the Fundamental Principles of Official Statistics. In addition, specific attention is put on documenting the methods and/or processes to regularly assess AI outputs for accuracy, reliability and fairness (eg human oversight, automated evaluation, reviews of input contents).
4. **Risk management** frameworks are critical to assess risks and conduct ongoing monitoring of AI systems. Reported solutions include regular audit of AI systems for vulnerabilities, evaluation of the robustness of safety measures, the development of incident response procedures, business continuity plans and processes to promote and maintain skills (ie to prevent erosion of knowledge due to overreliance on AI systems). They are typically implemented by leveraging existing risk management frameworks (such as the three lines of defence, "3LoD").

A key highlight of the survey is that the **governance of AI appears to be still in its early phase in many central banks**. Only about a third of the respondents have a policy for the use of AI and a very tiny minority of them have made it publicly available (Graph 8). In contrast, the majority is either only just starting to develop AI policies or simply does not have any plans to do so for the moment. This trend is especially pronounced in emerging market economies (see Box B). A key reason for this could be the gap between the high speed of innovation, on the one hand, and the slower pace of designing and formalising institutional arrangements, on the other hand (OECD (2024c)). The latter typically takes time to develop, as it involves several stakeholders and must be consistent with available resources and strategic priorities.

Most central banks do not have or are only just elaborating their policies for using AI

In per cent of respondents Graph 8



Sources: IFC survey on AI and ML (2024); authors' calculations.

...to mitigate risks effectively...

The survey shows that **central banks are well aware of the risks posed by AI**. Indeed, they rank the need to address the associated operational risks at the top of their priorities (Graph 9.A). Specifically, they see data privacy and cyber security as primary issues (Graph 9.B), recognising the importance of safeguarding their information in secure IT environments.

Fortunately, **central banks have developed a number of solutions to mitigate such risks effectively**, thanks to their long-standing experience in managing data. First, they often have established comprehensive risk management frameworks, which can be instrumental in defining AI risk profiles, evaluating projects and protecting information accordingly (CGRM (2025)).[5] A typical example relates to information classification rules, which can be easily adapted from existing data governance frameworks to address AI/ML risks specifically, for instance for dealing with data breaches or information leakages.

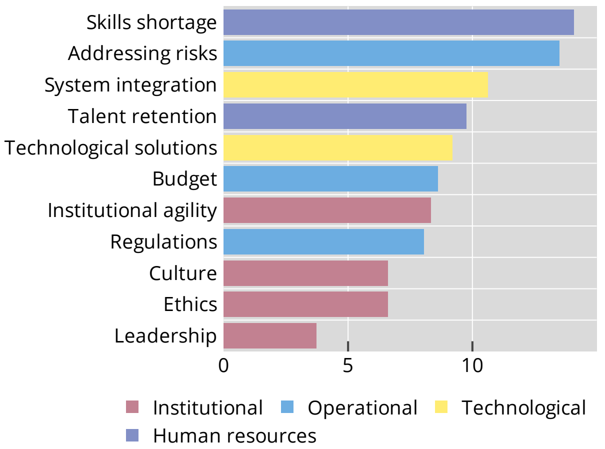
A second solution is to **restrict the use of AI tools**. This appears to be a popular solution among central banks for confidentiality reasons, as indicated by three quarters of the respondents (Graph 10.A). In practice, such restrictions can be implemented in various ways, ranging from web filtering solutions to block specific external domains to the prohibition of AI tools in restricted areas. Another often cited solution is to permit the use of AI services with confidential information only within separate and secure environments, such as on-premises infrastructure often without internet access.

[5] The setup of such risk management frameworks can benefit from existing guidelines, such as those produced by the US National Institute of Standards and Technology (NIST); see NIST (2024).

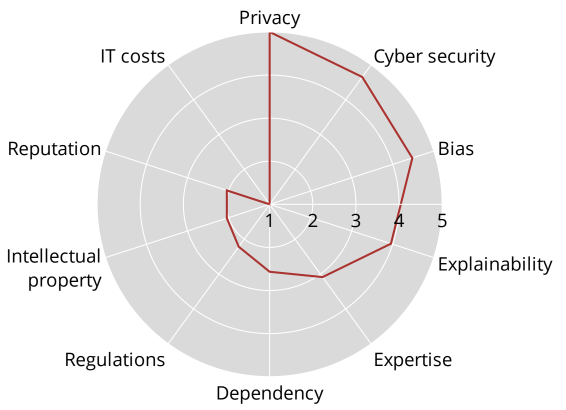
Central banks face significant challenges and risks in adopting AI/ML

Graph 9

A. Skills shortage and addressing risks are key barriers



B. Privacy, cyber security and biases are top concerns[1]



[1] Normalised scores from 1 to 5 (1 = not sure; 2 = not impactful at all; 3 = slightly impactful; 4 = moderately impactful; 5 = highly impactful).

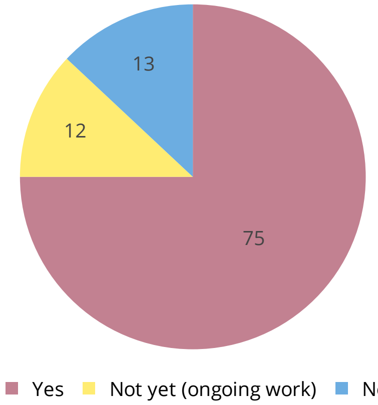
Sources: IFC survey on AI and ML (2024); authors' calculations.

Restrictions and policies to ensure the safe and ethical use of AI in central banks

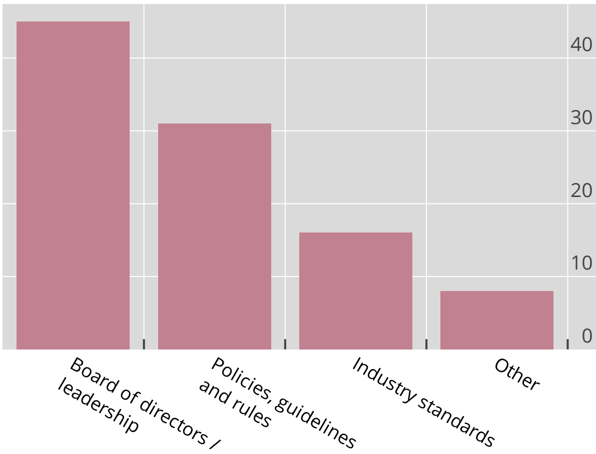
In per cent of respondents

Graph 10

A. Most central banks have restrictions on AI tools



B. Boards of directors often oversee responsible AI



Sources: IFC survey on AI and ML (2024); authors' calculations.

A third option is to **design adequate policies to deal with AI-specific issues**. A key focus has been ethical issues, such as biases and the lack of explainability (Graph 9.B), reflecting the importance given to using *trustable* AI models (Ali et al (2023)) as well as to securing the fairness, quality and transparency of the information managed by central banks to support their mandates. In practice, the survey shows the board of directors plays a key role at the organisational level in overseeing and raising awareness about AI ethical issues. It is supported in this endeavour by existing policies, practices and principles (Graph 10.B), with due consideration of widely recognised international standards supporting data governance, such as the Fundamental Principles of Official Statistics (Willis-Núñez and Ćwiek (2022)).

Box B

AI governance in central banks across regions

While nearly all central banks worldwide have a deep interest in AI, one question is whether their governance approach differs significantly between those located in emerging market economies (EMEs) and those in advanced economies (AEs) – noting that a large number of respondents to the IFC survey are from Europe.① This box provides a comparative view of the two groups.

A first result is that **development and deployment of AI are equally important priorities for central banks irrespective of their location**. Specifically, the survey shows a strong interest in this topic among EMEs, especially in Asia and Oceania (Graph B1.A). This also materialises in significant budget commitments: around half of EME respondents anticipate investing at least 5% of their financial resources in AI/ML in the next three years, against less than a quarter of AEs (Graph B1.B).

However, **as regards AI governance frameworks, around half of EME respondents appear to lack dedicated guidelines**, whereas most AEs have begun developing them (Graph B1.C). Moreover, many EMEs still had no intention to develop any AI policies at the time of the survey.

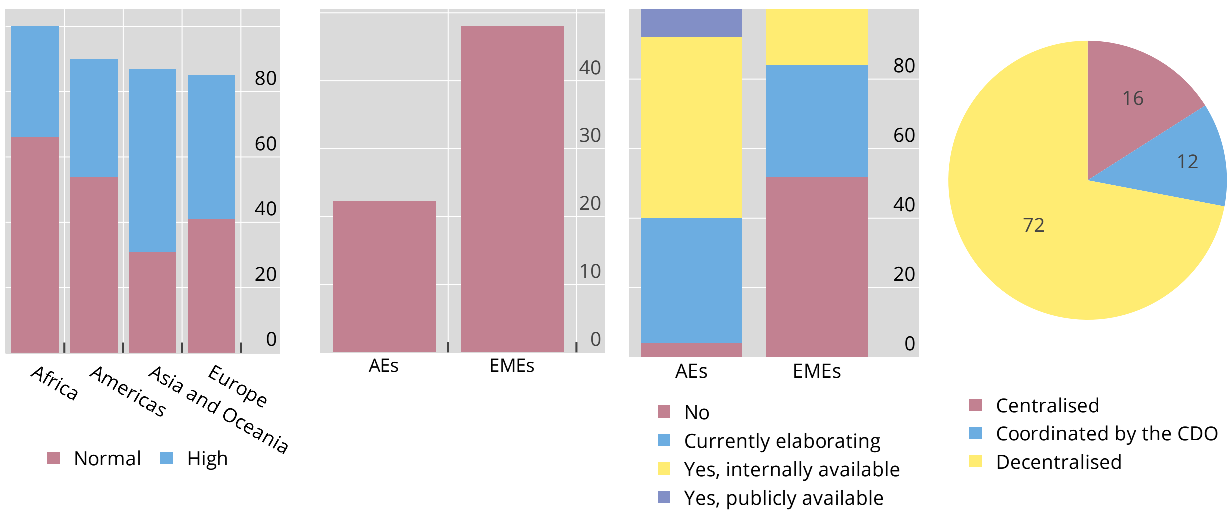
Another highlight is that **only a small share of EME respondents have set up an overarching AI coordination function** (28% versus 52% for AEs). They have been taking a highly decentralised approach to the management of AI projects (including pilot projects), reported to be the case for 72% of them (versus 63% for AE respondents; Graph B1.D).

Lastly, the diversity of the above picture underlines the value for central banks in AEs and EMEs to share experiences and best practices in advancing AI implementation.

EME central banks highly value AI, but their governance appears less developed

In per cent of respondents — Graph B1

A. There is strong interest in AI from all central banks, especially in Asia… | B. …which is also confirmed by expected large budget increases…[1] | C. …but most of them are not developing AI policies… | D. …while AI projects are managed in a decentralised way



[1] Percentage of respondents which expect to invest at least 5% of their budget in AI/ML projects in the next three years.

Sources: IFC survey on AI and ML (2024); authors' calculations.

① AEs here comprise Australia, Canada, Denmark, euro area jurisdictions, Japan, Norway, Sweden, Switzerland and the United States. EMEs include all other IFC respondents (see Annex 2).

...but also to promote innovation

While their primary focus is often risk mitigation, comprehensive governance frameworks can also help coordinate and foster innovation. A key reason is that they can provide a **common approach to addressing complex AI-related business needs** more consistently and effectively, by developing synergies and avoiding overlaps and/or inconsistencies.

Thus far, the survey shows that **around two thirds of AI/ML use cases have been implemented on an ad hoc basis** by the various business areas in central banks, compared with only a fifth managed by a dedicated unit (Graph 11.A). Such a decentralised approach certainly provides greater agility and speed in implementing tailored solutions that are relevant to user needs, reducing the risk of having overly ambitious plans that consume resources without delivering concrete business value. However, the heterogeneous proliferation of use cases across the organisation can also be sub-optimal. For one, the lack of coordination can hinder the sharing of experiences between business areas. In addition, AI-related risk management practices may not be sufficiently supervised, and the strategic objectives set at the organisation level might not be properly enforced.

AI is mostly managed in a decentralised way, calling for effective coordination

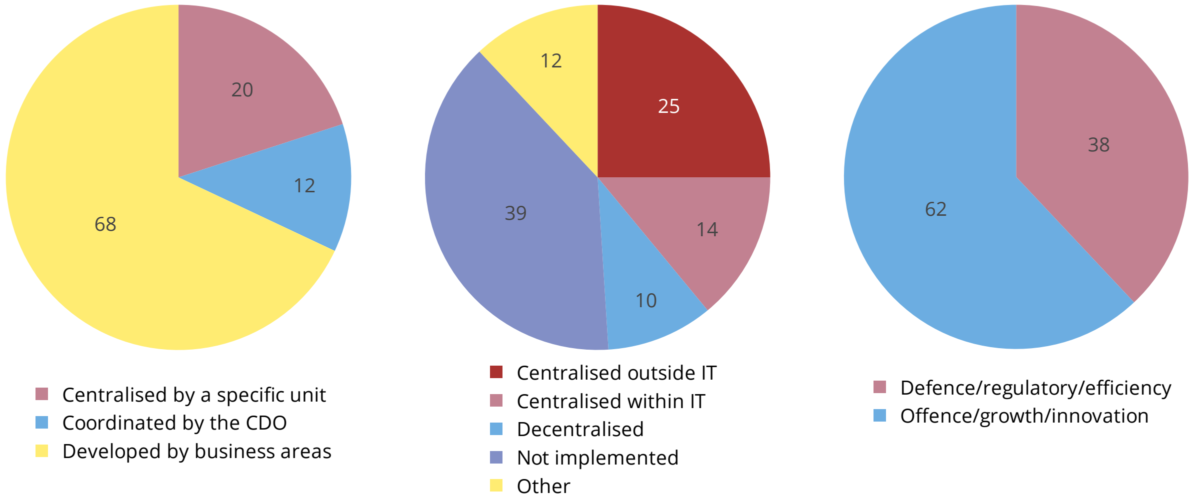
In per cent of respondents

Graph 11

A. AI/ML projects are mostly developed at the level of business areas...

B. ...suggesting that bank-wide AI governance structures are still in development...

C. ...although central functions such as the CDO can help coordinate and promote innovation



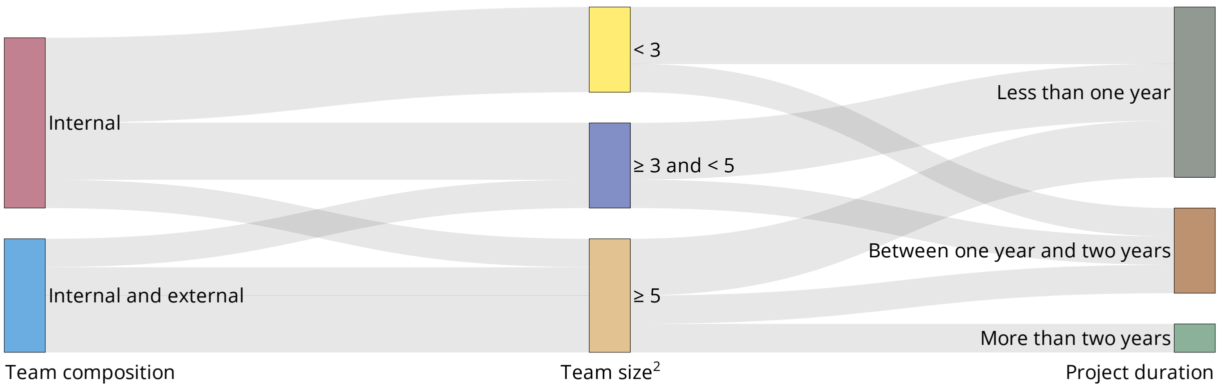
Sources: IFC survey on AI and ML (2024); authors' calculations.

The above trade-offs suggest that there can be merit in having either **a centralised or federated structure for governing AI across the various business areas**. Indeed, the survey shows that 39% of the respondents have established an AI-specific central structure (Graph 11.B), often assigning it to functions outside the IT department, such as the chief data officer (CDO) or digital innovation officer (Graph 11.C). On the other hand, a smaller share of central banks coordinate AI projects through a more federated approach, that is by delegating several responsibilities to individual business areas within an overall comprehensive framework (UNECE (2024a)). However, this overall picture may be changing quickly looking ahead, considering that more than half of the central banks reported having not yet established any AI governance function at the time of the survey.

In any case, **the rationale for establishing bank-wide AI governance may depend on how related projects are being developed**, especially in terms of their frequency, time frame and team size. Thus far, the reported use cases feature a limited duration, with most projects lasting less than one year. However, a significant share of central banks appear to be involving quite large teams in their AI initiatives (Graph 12), which puts a premium on strong organisational coordination, not least to ensure clear accountability, securely manage information and provide adequate documentation.

Most of the large AI projects involve external staff and last less than two years

Number of responses[1] Graph 12



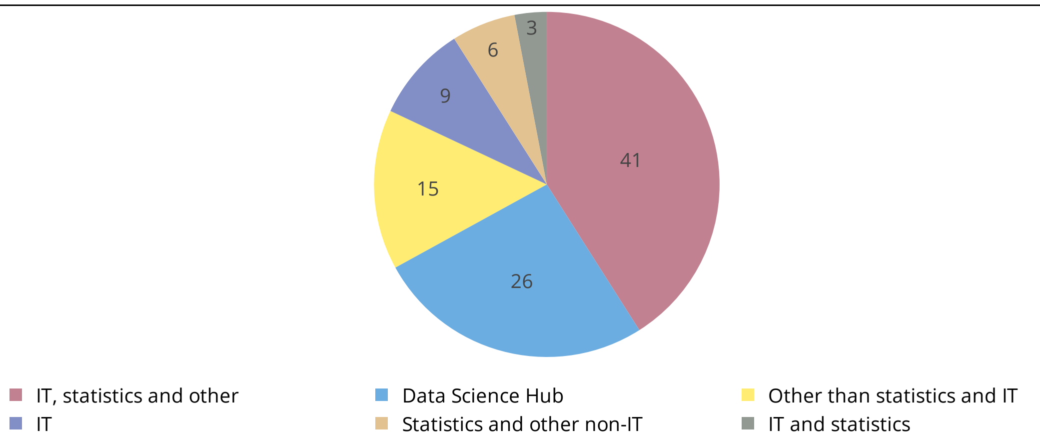
[1] The size of the flow represents the overall count per collected use case. [2] Team size refers to staff full-time equivalents (FTEs).

Sources: IFC survey on AI and ML (2024); authors' calculations.

Indeed, a related lesson from the survey is that **AI projects typically entail strong partnerships**, with almost half of them spanning over at least three departments (and often involving IT or statistics teams; Graph 13). Such synergies can be facilitated by a comprehensive governance framework to

AI/ML projects typically involve strong collaboration across departments

In per cent Graph 13



Sources: IFC survey on AI and ML (2024); authors' calculations.

overcome functional barriers or "silos", as well as by the establishment of steering committees or programme management offices.

Ultimately, and independently of the organisational structure to be adopted, a key objective should be to **foster knowledge-sharing on AI projects across the organisation**, especially to facilitate the upskilling of staff – an important priority for most central banks (see Graph 9.A above). This underlines the important role played by coordinating functions to both foster business-level agility and ensure common awareness in the organisation about the benefits and risks of AI. To this end, some central banks have also adopted flexible structures, such as organisation-wide task forces or commissions on AI comprising a mix of senior leaders and experts.

4. AI impact on IT systems: opportunities, challenges and trade-offs

The opportunities offered by AI are a good reminder of the importance of modernising business and IT processes to drive higher automation, productivity and performance. Yet, while central banks have already gained substantial experience in developing comprehensive IT and data platforms, the integration of AI systems into their existing infrastructures appear to have generated multiple challenges, with the need to address important trade-offs.

AI as a driver for modernising information processes in central banks

One prominent highlight of the survey is that **AI can be instrumental in strengthening a wide range of central bank processes, starting with IT tasks** (Graph 14.A). As computer programming is often very structured and repetitive in nature (Chui et al (2023)), there is ample scope for improving productivity through greater automation, for instance in coding through software copilots (Kuhail et al (2024), Moradi Dakhel et al (2023)).[6]

A second key area for central banks is **data management and processing**. AI and ML have proved to be helpful in streamlining many time-consuming phases of the data life cycle, for instance by automating data collection, transformation ("data wrangling") and quality checks. They can also greatly support data analysts by providing real-time insights on large and/or complex "big data" sources and tapping into novel data types (IFC (2023a)). In particular, generative AI, especially NLP-based tools and LLMs, can be instrumental in converting unstructured textual information – which is typically heavily used in central banking – into structured inputs, allowing for enhanced analysis.

Third, albeit to a lesser degree, the survey suggests that AI can also have a **positive impact on the wider range of central banks' administrative and communication activities** (IFC (2023b), UNECE (2025a)). For instance, generative AI can help optimise text-based routine tasks such as translation, summarisation or information extraction. AI-powered solutions can also support communication specialists to design and produce non-textual material, such as images, audio and video, in an efficient and more creative way (Graph 14.B).

[6] A software coding copilot is a type of AI-based tool designed to assist software developers (much like a copilot in an aircraft) in writing code, for instance through suggestions and auto-completion. While they have many advantages, copilots can raise issues in terms of licences and software copyrights, cyber attacks and the risk of inadequate business controls, especially when used without any human involvement.

Challenges of integrating AI into existing IT systems

The integration of AI into existing IT systems can be a complex and challenging process, not least because of the risk of disrupting current solutions. It also poses major technical, financial and operational issues, including the need for massive computational resources and scalable data platforms.

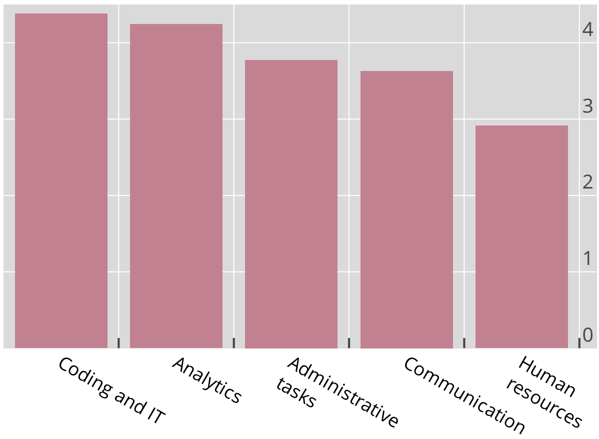
First, **the development and deployment of AI-based tools may require substantial investments in high-performance computing infrastructure**, especially in terms of advanced graphics card processing.[7] Other challenges include soaring energy consumption and large carbon footprints (Wang et al (2024), Garg et al (2025)). Yet there are ways of reducing the costs related to compute-intensive tasks. A prominent one is to rely on model inference to generate content based on a pre-trained model instead of training a new model, as the latter requires heavy computing resources. Another is to rely on cloud services, which may enable the use of customised hardware on demand, thus facilitating greater computation without significant in-house investments (see Box C).

Another significant issue is **the need for scalable data platforms**, for at least two reasons. First, AI applications require powerful IT infrastructures to be able to process vast amounts of data in real time, while also ensuring reliability, availability and performance. Second, they also necessitate platforms that handle unstructured data types, such as text from news, social media, earnings reports or trading communications. As a result, a growing number of central banks are investing in modern data storage solutions, including NoSQL databases[8] and cloud-based storage (IFC (2020)).

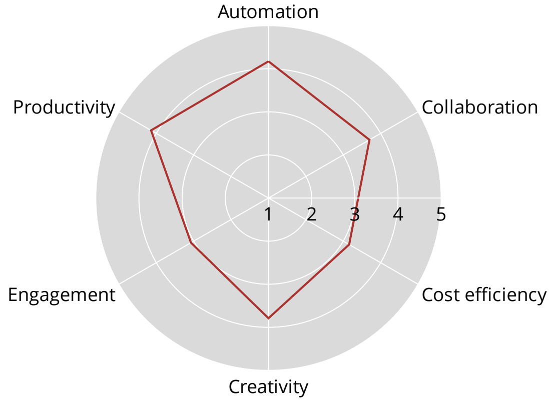
AI can drive greater automation and productivity, particularly for computer programming and data analytics[1]

Normalised scores, 1–5 Graph 14

A. AI's largest impact is expected to be in coding and analytics



B. Automation and productivity are the most anticipated benefits



[1] Normalised scores from 1 to 5 (1 = not sure; 2 = not impactful at all; 3 = slightly impactful; 4 = moderately impactful; 5 = highly impactful).

Sources: IFC survey on AI and ML (2024); authors' calculations.

[7] Examples include central processing units (CPUs), graphics processing units (GPUs), tensor processing units (TPUs) and neural processing units (NPUs, also known as AI accelerators or deep learning processors). AI/ML applications may also require highly performant and scalable configurations, such as multi-node clusters for distributed computing.

[8] For instance, to deal with unstructured information with such "not only SQL" databases.

Box C

Cloud services and AI in central banks: balancing benefits and risks

Over the past few years, central banks have progressively expanded their use of cloud services, benefiting from their flexible, modular and scalable solutions. With the growing adoption of AI, the cloud has gained even greater traction as a cost-effective means of meeting the demand for more computing power, for instance for high-performance graphics processing units (GPUs).①

Cloud services, also abbreviated to "cloud", refer to a model of delivering computing resources, software applications and data storage over the internet, on demand and on a pay-as-you-go basis, allowing users to access and utilise computing resources without the need for physical infrastructure or maintenance.② There are multiple models of cloud deployment. On the one hand, clouds can be public whenever their services are open for use by everyone, like those offered by Alibaba, Amazon Web Services, Google, IBM and Azure. On the other hand, private or community cloud services can be used exclusively by specific organisations, offering greater autonomy and control over sensitive data and infrastructure. Between these two extremes, there are also hybrid forms which feature the scalability of public clouds while also enabling the stringent security and compliance functionalities of private ones.

Clouds can also be categorised into three groups depending on the level of management and control offered to clients. First, software as a service (SaaS) is a fully managed service, with the third-party provider responsible for all aspects of the application, from installation to maintenance and upgrades. By contrast, infrastructure as a service (IaaS) allows clients to manage and configure virtualised computing resources such as servers, storage and networking. Finally, platform as a service (PaaS) falls in between, offering a managed platform for developing, running and managing applications, where the client controls the application and data but not the underlying infrastructure.

With the spread of AI applications in central banks, **outsourcing computational infrastructure to the cloud has become a pressing issue**.③ A key reason for this is that the cloud enables the use of customised hardware on demand, thus facilitating greater computing power without significant in-house investments. A second advantage is scalability, which makes it possible to add computational power while keeping costs relatively low.④ Indeed, the survey shows that one third of respondents are using the cloud for regular business activities, including as an architectural choice for AI/ML applications (Graph C1.A). Furthermore, most cloud services enhance operational resilience and facilitate software updates and maintenance, thus ensuring the latest features and security patches.

However, **the journey towards the cloud does not come without challenges**. A key concern is data privacy and security, especially when operations are outsourced to third-party vendors. Further, cloud services may be targeted for cyber attacks due to their high-profile nature, possibly undermining the protection of central banks' sensitive data. Another important issue is data sovereignty.⑤ Use of the cloud may entail loss of control over one's data, especially when hosting facilities are not bound by commercial agreements and/or are located outside the central bank's reach, potentially raising legal and geopolitical risks. Another concern is the high market power concentrated in few providers, as limited competition could hinder the ability to negotiate contracts and lead to unfair pricing practices.⑥

Reflecting the trade-offs above, **central banks appear in practice to prefer on-premises cloud**, allowing them to manage their infrastructure in private data centres. The survey shows that two thirds of respondents either do not allow (26%) or are only experimenting with (39%) external providers (Graph C1.A), while more than 40% of respondents prefer on-premises self-deployed solutions (Graph C1.B and C1.C).

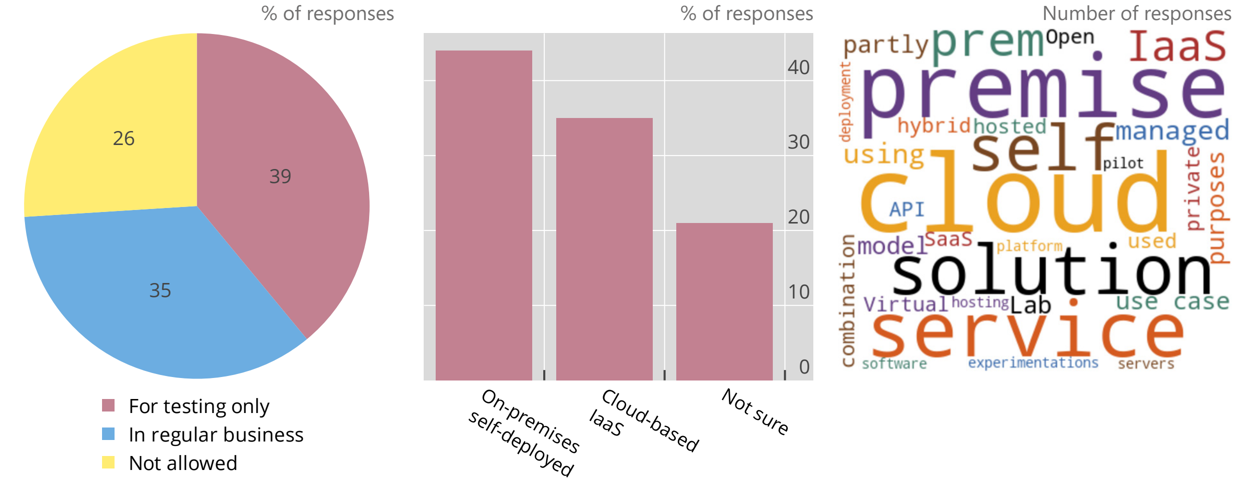
① See IFC (2020). ② See UNECE, *Cloud for official statistics*, March 2024; for an overview of public cloud use, see Gartner, "Gartner forecasts worldwide public cloud end-user spending to surpass $675 billion in 2024", press release, 20 May 2024. ③ See OMFIF (2023). ④ See N Haefner, V Parida, O Gassmann and J Wincent, "Implementing and scaling artificial intelligence: A review, framework, and research agenda", *Technological Forecasting and Social Change*, vol 197, December 2023. ⑤ See S Verhulst, "Operationalizing digital self-determination", *Data and Policy*, vol 5, no e14, April 2023. ⑥ See United Nations Commission on International Trade Law, *Notes on the main issues of cloud computing contracts*, 2019.

Central banks are using or testing cloud services but prefer on-premises solutions — Graph C1

A. Access to cloud services is being progressively adopted…

B. …but on-premises solutions are the top architectural choice for AI/ML…

C. …although several options are being evaluated by central banks



Sources: IFC survey on AI and ML (2024); authors' calculations.

Trade-offs in terms of IT choices

The above opportunities and challenges imply that central banks may face a number of trade-offs when deciding on their IT infrastructure, namely in-house versus generic market solutions and security versus performance.

The first trade-off is whether to **develop customised software solutions or use off-the-shelf products**. The former, typically developed in-house, are arguably better tailored to user requirements but may require significant investment in terms of resources, expertise and time. By contrast, off-the-shelf applications curated by third-party vendors are often quicker to deploy, less costly to implement and easier to maintain, yielding significant advantage for rapidly evolving AI-based applications. However, proprietary solutions come with limitations, including third party dependency – with potential over-reliance of the customer on the vendor for maintenance, updates and support – as well as reduced scalability, adaptability and flexibility to address specific business cases. Hence, a key objective is to strike a balance between these often conflicting objectives. For one, developing a modular and interoperable architecture can reduce dependency by allowing the organisation to integrate various components from multiple vendors. Moreover, the use of open source software (OSS) can enhance flexibility to meet business needs and reduces the risk of vendor lock-in (Box D).

Balancing security with performance is the second key trade-off when it comes to the implementation of AI solutions in central banks. On the one hand, ensuring the security of AI systems, for instance through encryption and access control techniques, is essential when handling sensitive information. On the other hand, strict security measures can lead to excessive latency, low processing power and a limited supply of innovative AI-based tools, hence potentially limiting users' capacities). A possible way forward is to design AI systems to balance both aspects. Concrete options include leveraging techniques such as secure-by-design methodologies, threat modelling and continuous monitoring.

Box D

Open source versus closed source AI

Like any software, **AI models can be either open source or closed source**. The choice of one approach over the other has significant implications for their development, deployment and maintenance.

On the one hand, **closed source** applications refer to software or models whose underlying code and architecture are proprietary and only accessible to developers or owners. Commercial vendors typically provide support, maintenance and updates. In exchange, users are often required to adhere to licensing agreements and may be limited in their ability to customise the solution.

On the other hand, **open source** approaches can comprise the software framework used to build and deploy AI models.① They can be used for any purpose and can be inspected or modified without restrictions. For example, models such as BERT and RoBERT are freely available and can be adapted for various NLP tasks. Another key advantage is the limited development cost, as open source models offer greater flexibility, portability and transparency, particularly because everyone can scrutinise their specifications. However, they also present some notable limitations. They often require more expertise and resources to develop and maintain, as users are responsible for ensuring the integrity and security of the code. Moreover, knowledge about possible vulnerabilities may be more easily accessible to malicious actors.②

Reflecting the above trade-offs, **central banks have in practice adopted a hybrid approach, implementing both open and closed source AI models** (Graph D1.A). The survey suggests that they tend to favour

Central banks use both open and closed AI models and prefer open source ones for cost and dependency reasons

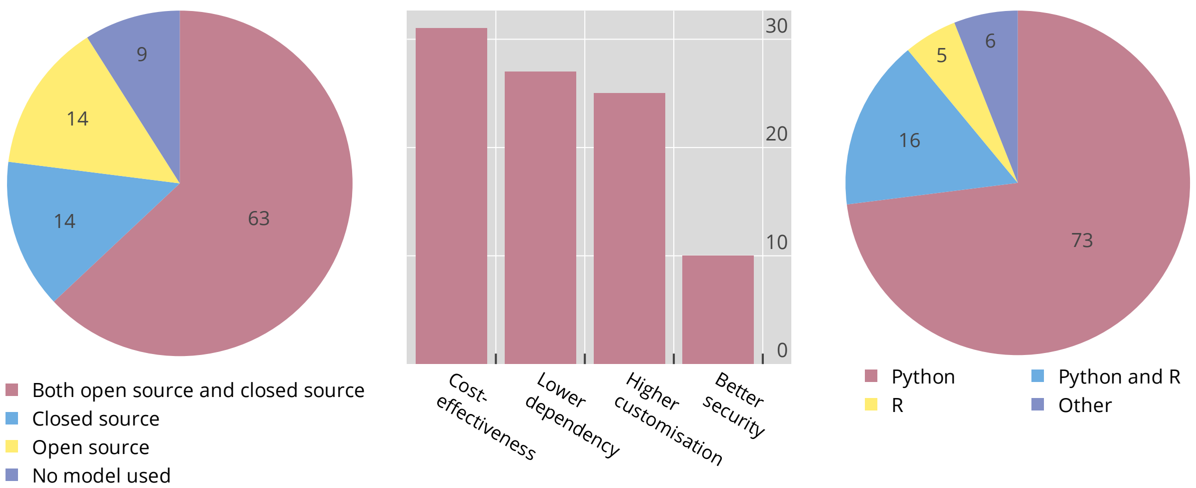
In per cent

Graph D1

A. Both closed and open source models are used

B. Cost-effectiveness and lower dependency are critical factors in choosing open source AI

C. Python is the top programming language for AI/ML



Sources: IFC survey on AI and ML (2024); authors' calculations.

open source AI due to cost-effectiveness, reduced vendor dependence and customisation reasons (Graph D2.B). From this perspective, having a dual approach makes it possible to strike a balance, leveraging the benefits of open source while also taking advantage of the support and reliability offered by closed source solutions when needed.

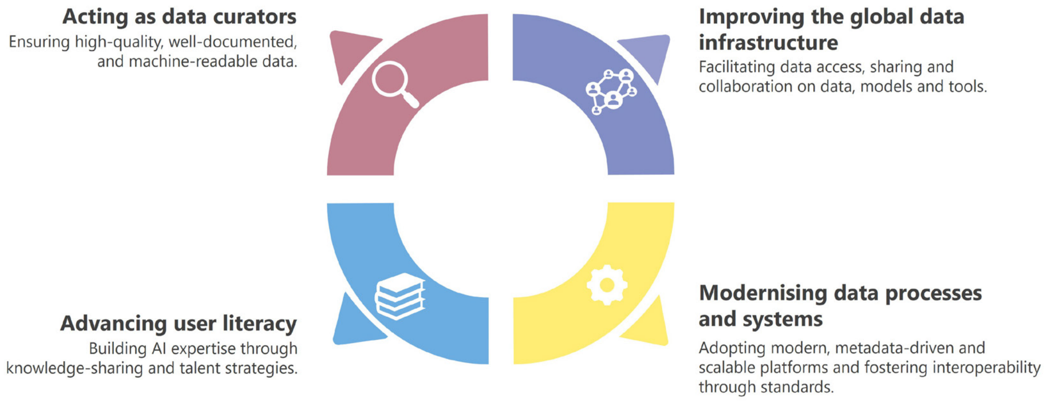
Turning to programming languages, central banks clearly report favouring the use of open source ones. Specifically, Python appears to be the top choice for AI/ML applications for almost three quarters of use cases, sometimes in combination with other languages such as R, Java and Julia (Graph D1.C). Python's popularity can be attributed to its simplicity, readability and flexibility as well as the extensive range of tools and libraries available. Noteworthy examples include TensorFlow, Keras and PyTorch, which can support the design, development and deployment of a wide range of AI-related applications, from data analysis and ML to automation and web development.

① According to opensource.org, "Open Source AI is an AI system made available under terms and in a way that grant the freedoms to: use the system for any purpose and without having to ask for permission; study how the system works and inspect its components; modify the system for any purpose, including to change its output; and share the system for others to use with or without modifications, for any purpose". ② See E Seger et al, *Open-sourcing highly capable foundation models: an evaluation of risks, benefits, and alternative methods for pursuing open-source objectives*, Centre for the Governance of AI, September 2023.

5. A roadmap to promote innovation in the evolving data and technological landscape

Making the most of the opportunities provided by AI calls for establishing a clear roadmap ahead, with four main areas of focus: (i) securing the quality of the statistical information; (ii) improving the global information infrastructure, especially as regards adequate data access and sharing as well as collaboration in terms of best practices; (iii) developing modern, metadata-driven and interoperable data management processes; and (iv) advancing user literacy in data science and AI (Graph 15).

Making the most of AI in central banks: a roadmap Graph 15



Source: authors' elaboration.

Acting as data curators

As AI-generated outputs are shaped by the quality of their input data, **securing and enhancing the quality of statistical information** appear to be key priorities. In practice, however, AI is mostly trained on vast data reservoirs that are poorly documented and that originate from non-authoritative sources outside of the rigorous standards of official statistics. Hence, there is a risk that poor data quality and scarce metadata can misdirect the training of models and, potentially, drive AI to generate misinformation (Garrett (2024), Sirello et al (forthcoming)). The survey suggests that central banks could play a useful role on this front by acting as reference "data curators" along with the other institutions responsible for official statistics.

First, they have been leading efforts to **strengthen information documentation**, that is the data about the data, or "metadata". Concretely, this means using information standards, version control, persistent identifiers and OSS formats (Gottron and Suranyi (2025), US DoC (2025)). Data and metadata should also be open, findable, accessible, reusable and interpretable, following the FAIR data principles (UNESCO (2023), Wilkinson et al (2016)).

A second, important consideration is to **make the information machine-readable**, as users may increasingly access it indirectly through AI systems or machines (UNECE (2025b)). In addition to better standardised data and metadata information, this calls for disseminating AI-relevant information to help both developers and users to better understand the sources and underlying assumptions of the models used (Mitchell et al (2019), McMillan-Major et al (2024)).[9] Another option is to ensure that dissemination tools such as data portals can be easily scraped and crawlable to feed algorithms and models.

Ultimately, central banks have also an interest in **securing the quality of information in the broader data ecosystem**, not least because of the growing volume of private data feeding into AI systems. As producers of official statistics, they have a long-standing track record in disseminating high-quality data following universally recognised principles.[10] Along with statistical offices, they can leverage this experience to play a data curator role in the broader data ecosystem, for instance by setting guidelines and identifying, monitoring and closing data gaps (Križman and Tissot (2022)). This may also call for setting up a **global data framework** to improve the availability and reuse of high-quality data in the AI age (UN HLAB-AI (2024)).

Improving the global data infrastructure through adequate data access, sharing and collaboration

AI is fundamentally a data-intensive technology. Thus far, most models have been trained on publicly available information, including official and non-public sources such as the internet. Yet, these resources are finite, and some data providers are increasingly restricting access to their data (Villalobos et al (2022)). This raises the risk of data bottlenecks and, ultimately, of a "tragedy of the data commons" (Jones (2024), Verhulst (2024), Longpre (2025)).

Against this background, **facilitating data access and adequate sharing clearly emerges as priority moving forward**. Fortunately, central banks have extensive experience in this endeavour at different levels (IFC (2023c)). Within the organisation, they have set up comprehensive approaches to managing their data assets, for instance through master data management systems, common metadata repositories and data catalogues. They have also facilitated interoperability through statistical standards

[9] For example, the European Union Regulation (EU) 2024/1689 encourages developers of AI models "to implement widely adopted documentation practices, such as model cards and data sheets, as a way to accelerate information-sharing along the AI value chain, allowing the promotion of trustworthy AI systems"; see eur-lex.europa.eu.

[10] For example, see the Fundamental Principles of Official Statistics (UN (2014)).

such as SDMX (IFC (2021b, 2025a)). Within the perimeter of official statistics, they have also promoted adequate data-sharing with key counterparts, including NSOs, financial supervisors, international organisations and academia (IFC (2015a); see Box E). Within the broader data ecosystem, they have implemented various initiatives to make better use of administrative and alternative sources, as was evident during the Covid-19 pandemic (De Beer and Tissot (2021), UNECE (2021)). Further, some countries have started developing national and global data libraries to make public data sets more accessible to all users, both human and machine.[11]

Box E

Collaborating with private actors: data and AI

Forging partnerships with private stakeholders can benefit central banks willing to access new information sources and leverage AI techniques. A first reason for this is that a large share of alternative data – especially unstructured data – are in the hands of private actors.① Their access can complement official statistics or cope with sudden episodes of "statistical darkness" during unforeseen events. It can also help to effectively reduce the reporting burden for data reporters.② Lastly, public authorities have a keen interest in engaging with private providers of AI-based solutions to ensure that their data inputs are of sufficient quality.

In practice, **there are already examples of successful public-private collaboration** to use official data sources and in turn improve the quality of AI systems. In fact, several central banks, such as the US Federal Reserve, have worked on setting up adequate frameworks for using private information sources for their own statistical production.③ Another noteworthy initiative is the Data Commons, a project led by Google to provide a unique platform for accessing official statistics, such as those supporting the UN Sustainable Development Goals. This can help to better link correctly vetted databases publicly available on the internet④ as well as train AI models more accurately, thus reducing hallucination risks.⑤ Another example is the direct collaboration of central banks with financial actors. For instance, the Bank of England has launched an initiative to identify how AI could be used in UK financial services while mitigating risks.⑥ This echoes other initiatives ongoing at the global level, such as the one by the Financial Stability Board.⑦

Yet **partnerships with the private sector may also raise a number of challenges**. One limitation is the volatility of private data sources. When their access is granted for free, this often occurs on a voluntary basis and can be easily interrupted rapidly. Even in the presence of commercial contracts, there is a risk of excessive vendor lock-in, in addition to the potentially high costs involved. Private sources may also have various methodological limitations – such as biases – as they are usually not bound by the strict quality standards of official statistics.

The above suggests that public authorities have a keen interest in **better collaboration with private initiatives in the field of data and AI**. Clearly, official statisticians should have a leading role in this endeavour, as they oversee the enforcement and monitoring of reference data and statistical standards at the national and international levels. Case in point, the UN Committee of Experts on Big Data and Data Science for Official Statistics is working on a global programme on emerging data and technologies such as AI.⑧ Additionally, the UN High-Level Advisory Body on AI is providing guidance on the development of AI governance as well as common data frameworks.⑨

① See BIS (2024). ② See P Gennari, "Data equity and official statistics in the age of private sector data proliferation", *Statistical Journal of the IAOS*, vol 40, no 4, November 2024, pp 757–64 and De Beer and Tissot (2021). ③ See Križman and Tissot (2022). ④ See S Verhulst, "Unlock the hidden value of your data", *Harvard Business Review*, May 2020 and Fraisl et al (2024). ⑤ Cf the DBpedia project (J Lehmann, R Isele, M Jakob, A Jentzsch, D Kontokostas, P Mendes, S Hellmann, M Morsey, P van Kleef, S Auer and C Bizer, "DBpedia – A large-scale, multilingual knowledge base extracted from Wikipedia", *Semantic Web*, vol 6, no 2, January 2015). Since 2024, the Data Commons has been largely used to train LLMs such as DataGemma; cf P Ramaswami and J Manyika, "DataGemma: Using real-world data to address AI hallucinations", *The Keyword*, September 2024. ⑥ See Bank of England (2024). ⑦ See FSB (2024). ⑧ See UNSC, "Revised terms of references of UNCEBD and its task teams", *Background document*, no 3(q), Fifty-sixth session, March 2025. ⑨ See UN HLAB-AI (2024).

[11] An example is the National Data Library initiative in the United Kingdom; see Tobin (2024).

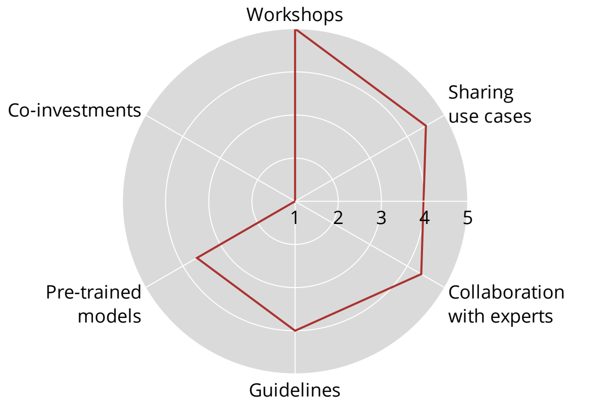
There are also important **international initiatives aim to deliver guidance and practical solutions to facilitate cross-border exchanges of data.** One is the OECD Recommendation on Enhancing Access to and Sharing of Data, which introduces the concept of a "data openness continuum" to cover a broad range of access and sharing arrangements for both data and AI/ML models (OECD (2021, 2025)). Another is the G20 Data Gaps Initiative (DGI), which promotes best practices on data-sharing and access to private and administrative sources, while also balancing legal requirements such as privacy and confidentiality rights.[12] Finally, ongoing work could help to set up the foundations of an international data governance framework, in particular to harmonise terminologies, facilitate the exchange of knowledge and promote data commons (UN-CEB (2024), MacFeely et al (2025)).

Beyond data, the survey highlights central banks' interest in **sharing use cases, models, tools and software** (Graph 16.A). One option is to adopt open AI models, allowing central banks to leverage peer solutions, reduce costs, minimise environmental impact and maintain better control over the data.[13] Another solution is to use and produce OSS. One example is the BIS Open Tech platform, whose primary goal is to share statistical and financial software (UNSC (2025)). However, despite central banks' interest in and demand for OSS, the survey shows limited progress, with around one third of the respondents sharing code or models privately – ie within the organisation and/or with peer institutions – or publicly (Graph 16.B).

Collaboration, cooperation and sharing are key priorities — Graph 16

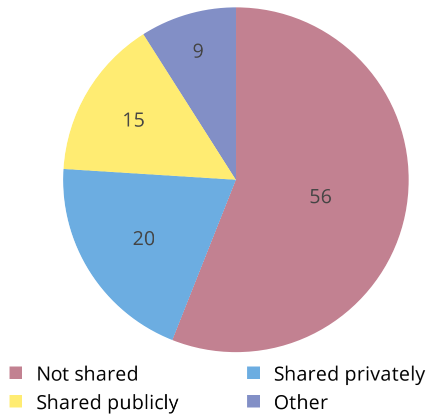
A. Sharing knowledge, code and use cases is a priority…[1]

Normalised scores, 1–5



B. …yet most central banks do not share AI/ML code or models[2]

% of responses



[1] Normalised scores from 1 to 5 (1 = not sure; 2 = not impactful at all; 3 = slightly impactful; 4 = moderately impactful; 5 = highly impactful). [2] Respondents could indicate more than one answer ("Not shared" = no code is shared outside or within the central bank; "Shared privately" = code is shared within the central bank only or with similar national authorities; "Shared publicly" = code is shared with the public, including through the institution's website).

Sources: IFC survey on AI and ML (2024); authors' calculations.

[12] See Recommendations 13 and 14 of the third phase of the G20 DGI; see IMF et al (2023, 2024) and imf.org.

[13] For instance, open AI systems are typically free to use, inspectable, editable and shareable; see opensource.org.

Modernising data processes and systems

Making the most of AI opportunities calls for further modernising current data management processes, not least to facilitate the use of novel data types and the linking of multiple information sources.

For central banks, this first implies further efforts to **adapt their existing data and IT infrastructures to store, integrate and protect diverse information types**, for instance in dedicated data lakes and hubs (Graph 17.A).[14] Such platforms, combined with metadata-driven solutions such as common metadata registries and data inventories, can facilitate data access for both internal and external users, including researchers. They can also ensure greater automation, adequate cyber security and protection of sensitive information (Graph 17.B). Additionally, the establishment of single access points and common data spaces offers another avenue to improve data access, reuse and sharing, as shown by the European data strategy (European Commission (2024a,b)).

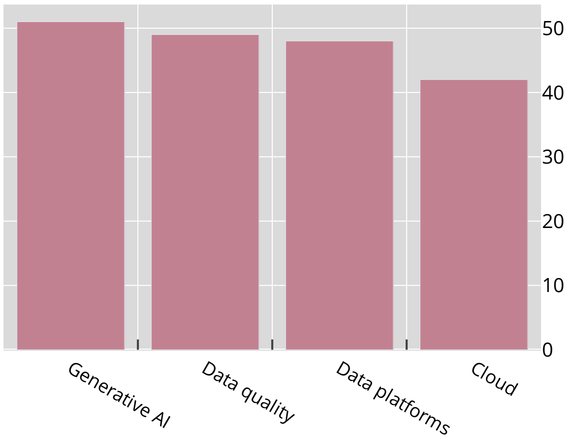
Second, the demand for pooling large and complex data sets may accelerate central banks' **move towards cloud-based services** (IFC (2020), OMFIF (2023)). These can be a cost-effective solution to meet and tailor computational needs to the requirements of AI projects. Yet, they also present some important trade-offs, especially in terms of security, dependency and development of internal knowledge, which central banks must carefully weigh against their specific constraints (see Box C above).

Third, managing vast amounts of data also calls for enhanced **interoperability of data processes and systems**. In practice, this implies adopting statistical standards and data formats such as SDMX across the data life cycle, including for micro and geospatial information (IFC (2025a)). Relatedly, promoting unique identifiers and linking registers at the national and global levels can further support interoperability. Lastly, implementing application programming interfaces (APIs) may also facilitate the automation of processes and enable seamless integration, communication and exchange across various information systems.

Generative AI, data quality, platforms and cloud are the top priorities ahead

Number of responses Graph 17

A. Generative AI, data platforms, data quality and cloud as priorities in the near future



B. Other priorities also include quantum computing and cyber security

Sources: IFC AI/ML survey (2024); authors' calculations.

[14] Case in point, the IMF Big Data Center launched in 2024 to consolidate available data sets and fully leverage them for AI (Georgieva (2024)).

Advancing user literacy in data science and AI

Supporting the development of data science innovations such as AI calls for building adequate in-house expertise. Certainly, central banks can already draw on their experience in analysing, managing and producing data. They are also able to leverage their multidisciplinary teams, which are typically proficient in IT tools and statistical and data techniques (Araujo et al (2023)). They also plan to further pursue their efforts to recruit adequate profiles such as cyber security specialists, data scientists and engineers (Antonucci et al (2023)). Yet, **attracting and retaining AI- and data-savvy talent may pose several challenges**. These may include the global shortage of adequate skills and related fierce competition in the labour market as well as a reported lack of attractiveness and limited career prospects in central banks (see Graph 9.A above).

Fortunately, there are many options. One is to increase the **flexibility of sourcing and working arrangements**. Relying on contractors can be a worthwhile solution given that AI-related work is often time-bound and skill-specific. Indeed, the survey shows that most central banks' projects involve external consultants, especially in larger teams (see Graph 12 above). Another solution is to offer specialised career tracks and promote internal knowledge by setting up AI-specific training curricula for staff.[15] Moreover, establishing communities of practice can be helpful to share knowledge within the organisation, among central banks and with external stakeholders, such as academic institutions. Initiatives at the international level include, for example, IFC data science activities (IFC (2025b)) and the newly set up BIS Innovation hubs (BIS (2024)).

More broadly, the increased ability of wider audiences to use innovative techniques underscores **the need to educate users and ensure adequate AI literacy**. Generative AI applications in particular have empowered almost everyone to use complex analytical techniques, for instance through simple chatbots. While beneficial, this trend may present a number of challenging developments, including algorithmic opacity, a poor understanding of AI systems and, ultimately, a gradual erosion of knowledge due to overreliance on AI (Garrett (2024), UNECE (forthcoming)). Against this setting, options could include developing programmes to support adequate skills as well as offering methodological guidance and tailored communication to users to advance AI awareness and literacy for the public good.

[15] Cf the ECB action plan to foster AI skills and ensure that the technology is used safely (Cipollone (2024)). Along the same lines, the Bank of England offers AI fluency programmes for its data experts on top of basic AI literacy courses (Benford (2024)).

References

Aldasoro, I, S Doerr, L Gambacorta, S Notra, T Oliviero and D Whyte (2024): "Generative artificial intelligence and cyber security in central banking", *BIS Papers*, no 145, May.

Ali, S, T Abuhmed, S El-Sappagh, K Muhammad, J Alonso-Moral, R Confalonieri, R Guidotti, J Del Ser, N Díaz-Rodríguez and F Herrera (2023): "Explainable artificial intelligence (XAI): What we know and what is left to attain trustworthy artificial intelligence", *Information Fusion*, vol 99, no 101805, November.

Antonucci, L, A Balzanella, E Bruno, C Crocetta, S Di Zio, L Fontanella, M Sanarico, B Scarpa, R Verde and G Vittadini (2023): "Data science skills for the next generation of statisticians", *Statistical Journal of the IAOS*, vol 39, no 4, November, pp 773–82.

Aquilina, M, D Araujo, G Gelos, T Park and F Pérez-Cruz (forthcoming): "Harnessing artificial intelligence for financial market monitoring", *BIS Working Papers*.

Araujo, D, G Bruno, J Marcucci, R Schmidt and B Tissot (2023): "Data science in central banking: applications and tools", *IFC Bulletin*, no 59, October.

Araujo, D, S Doerr, L Gambacorta and B Tissot (2024): "Artificial intelligence in central banking", *BIS Bulletin*, no 84, January.

Araujo, D, S Nikoloutsos, R Schmidt and O Sirello (forthcoming): "Open sourcing central banks", *IFC Guidance Note*.

Bank for International Settlements (BIS) (2024): "Artificial intelligence and the economy: implications for central banks", *Annual Economic Report 2024*, Chapter 3, June, pp 91–127.

BIS Innovation Hub (BISIH) (2024): "Project Aurora: the power of data, technology and collaboration to combat money laundering across institutions and borders", press release, 27 March.

Bank of England (2024): *Artificial Intelligence Consortium – Terms of reference*.

Benford, J (2024): "TRUSTED AI: Ethical, safe, and effective application of artificial intelligence at the Bank of England", speech given at the Central Bank AI Conference, London, 25 September.

Brault, J, M Haghighi and B Tissot (2024): "Granular data: new horizons and challenges for central banks", *IFC Bulletin*, no 61, July, pp 1–24.

Chui, M, E Hazan, R Roberts, A Singla, K Smaje, A Sukharevsky, L Yee and R Zemmel (2023): *The economic potential of generative AI: the next productivity frontier*, June.

Cipollone, P (2024): "Artificial intelligence: a central bank's view", speech at the National Conference of Statistics on official statistics at the time of artificial intelligence, Rome, 4 July.

Consultative Group on Risk Management (CGRM) of the BIS Representative Office for the Americas (2025): *Governance of AI adoption in central banks*, January.

Crane, L, M Green and P Soto (2025): "Measuring AI uptake in the workplace", *FEDS Notes*, February.

Crisanto, J, C Benson Leuterio, J Prenio and J Yong (2024): "Regulating AI in the financial sector: recent developments and main challenges", *FSI Insights on policy implementation*, no 63, December.

De Beer, B and B Tissot (2021): "Official statistics in the wake of the Covid-19 pandemic: a central banking perspective", *Theoretical Economics Letters*, vol 11, no 4, August.

Desai, A, A Kosse and J Sharples (2024): "Finding a needle in a haystack: a machine learning framework for anomaly detection in payment systems", *Bank of Canada Staff Working Paper*, no 2024-15, May.

Dohotaru, M, M Prisacaru, J H Shin and Y Palta (2025): "AI for risk-based supervision: another nice to have tool or a game-changer", World Bank Group, *Prosperity Insight Series*, January.

Drechsler, J and A-C Haensch (2023): *30 years of synthetic data*, April.

Dunn, W, E Meade, N Sinha and R Kabir (2024): "Using generative AI models to understand FOMC monetary policy discussions", *FEDS Notes*, December.

European Commission (2024a): *Commission staff working document on common European data spaces*, SWD (2024) 21, January.

——— (2024b): *The role of artificial intelligence in processing and generative new data: an exploration of legal and policy challenges in open data ecosystems*, July.

Financial Stability Board (FSB) (2017): *Artificial intelligence and machine learning in financial services – market developments and financial stability implications*, November.

——— (2024): *The financial stability implications of artificial intelligence*, November.

Fraisl, D, L See, S Fritz, M Haklay and I McCallum (2024): "Leveraging the collaborative power of AI and citizen science for sustainable development", *Nature Sustainability*, vol 8, no 2, December, pp 125–32.

Gambacorta, L, H Qiu, S Shan and D Rees (2024): "Generative AI and labour productivity: a field experiment on coding", *BIS Working Papers*, no 1208, September.

Garg, A, I Kitsara and S Bérubé (2025): "The hidden cost of AI: unpacking its energy and water footprint", *The AI Wonk*, 26 February.

Garrett, A (2024): "The devil, the detail, and the data", *Journal of the Royal Statistical Society Series A: Statistics in Society*, vol 187, no 4, October, pp 857–78.

Georgieva, K (2024): "Measuring the implications of AI on the economy", opening remarks at the 12th IMF Statistical Forum, 20 November.

Gottron, T and D Suranyi (2025): "Metadata integration as a key enabling technique for AI and ML", presentation at the 4th IFC Workshop on Data Science in Central Banking, Rome, 20 February.

Handa, K, A Tamkin, M McCain, S Huang, E Durmus, S Heck, J Mueller, J Hong, S Ritchie, T Belonax, K Troy, D Amodei, J Kaplan, J Clark and D Ganguli (2025): "Which economic tasks are performed with AI? Evidence from millions of Claude conversations", mimeo.

International Monetary Fund (IMF), Inter-Agency Group on Economic and Financial Statistics and FSB Secretariat (2023): *G20 Data Gaps Initiative 3 workplan – People, planet, economy*, March.

——— (2024): *Third phase of the G20 Data Gaps Initiative (DGI-3) second progress report*, October.

Irving Fisher Committee on Central Bank Statistics (IFC) (2015a): "Data-sharing: issues and good practices", *IFC Report*, no 1, January.

——— (2015b): "Central banks' use of and interest in 'big data'", *IFC Report*, no 3, October.

——— (2020): "Computing platforms for big data analytics and artificial intelligence", *IFC Report*, no 11, April.

——— (2021a): "Use of big data sources and applications at central banks", *IFC Report*, no 13, February.

——— (2021b): "Issues in data governance", *IFC Bulletin*, no 54, July.

——— (2022): "Machine learning in central banking", *IFC Bulletin*, no 57, November.

——— (2023a): "Data science in central banking: applications and tools", *IFC Bulletin*, no 59, October.

——— (2023b): "How central banks communicate on official statistics", *IFC Report*, no 15, February.

——— (2023c): "Data-sharing practices", *IFC Guidance Note*, no 3, March.

——— (2025a): "SDMX adoption and use of open source tools", *IFC Report*, no 17, February.

——— (2025b): *2024 IFC Annual Report*, January.

Jones, N (2024): "The AI revolution is running out of data. What can researchers do?", *Nature*, vol 636, no 8042, December.

Kase, H, L Melosi and M Rottner (2025): "Estimating nonlinear heterogeneous agent models with neural networks", *BIS Working Papers*, no 1241, January.

Korinek, A (2024): "LLMs learn to collaborate and reason: December 2024 update to 'Generative AI for economic research: use cases and implications for economists'", *Journal of Economic Literature*, vol 61, no 4.

Križman, I and B Tissot (2022): "Data governance frameworks for official statistics and the integration of alternative sources", *Statistical Journal of the IAOS*, vol 38, no 3, August, pp 947–55.

Kroese, B (2024): "Exploring official statistics using generative AI and SDMX", presentation at the 72nd plenary session of the Conference of European Statisticians, Geneva, 20–21 June.

Kuhail, M, S Mathew, A Khalil, J Berengueres and S Shah (2024): "'Will I be replaced?' Assessing ChatGPT's effect on software development and programmer perceptions of AI tools", *Science of Computer Programming*, vol 235, no 103111, July.

Kwon, B, T Park, F Perez-Cruz and P Rungcharoenkitkul (2024): "Large language models: a primer for economists", *BIS Quarterly Review*, December.

Longpre, S (2025): "AI crawler wars threaten to make the web more closed for everyone", *MIT Technology Review*, February.

MacFeely, S, A Me, F Schueuer, J Costanzo, D Passarelli, M Veerappan and S Verhulst (2025): "Towards a set of universal data principles", *Statistical Journal of the IAOS*, vol 41, no 1, March, pp 150–5.

Mäntymäki, M, M Minkkinen, T Birkstedt and M Viljanen (2022): "Defining organizational AI governance", *AI and Ethics*, vol 2, February, pp 603–9.

McMillan-Major, A, E Bender and B Friedman (2024): "Data statements: from technical concept to community practice", *ACM Journal on Responsible Computing*, vol 1, no 1, March, pp 1–17.

Mitchell, M, S Wu, A Zaldivar, P Barnes, L Vasserman, B Hutchinson, E Spitzer, I Raji and T Gebru (2019): "Model cards for model reporting", proceedings of the Conference on Fairness, Accountability and Transparency, Atlanta, 29–31 January, pp 220–9.

Moradi Dakhel, A, V Majdinasab, A Nikanjam, F Khomh, M Desmarais and Z M Jiang (2023): "GitHub Copilot AI pair programmer: asset or liability?", *Journal of Systems and Software*, vol 203, September.

National Institute of Standards and Technology (2024): *Artificial intelligence risk management framework: generative artificial intelligence profile*, July.

Official Monetary and Financial Institutions Forum (OMFIF) (2023): *Central banking and cloud services: the new frontier*, June.

Organisation for Economic Co-operation and Development (OECD) (2021): *Recommendation of the Council on Enhancing Access to and Sharing of Data*, October.

——— (2024a): "Explanatory memorandum on the updated OECD definition of an AI system", *OECD Artificial Intelligence Papers*, no 8, March.

——— (2024b): "Defining AI incidents and related terms", *OECD Artificial Intelligence Papers*, no 16, May.

——— (2024c): "Assessing potential future artificial intelligence risks, benefits and policy imperatives", *OECD Artificial Intelligence Papers*, no 27, November.

——— (2025): *Enhancing access to and sharing of data in the age of artificial intelligence: Companion Document to the OECD Council Recommendation on Enhancing Access to and Sharing of Data*, February.

Petropoulos, A, V Siakoulis, K Panousis, L Papadoulas and S Chatzis (2022): "A deep learning approach for dynamic balance sheet stress testing", at the 3rd ACM International Conference on AI in Finance (ICAIF '22), New York, 2–4 November.

Ribarsky, J (2025): "Compilers Hub: an overview", presentation at the UNECE Meeting of the Group of Experts on National Accounts, Geneva, 8–10 April.

Sirello, O, B Bogdanova and M Erdem (forthcoming): "Metadata in the age of AI: the role of official statistics in securing a virtuous circle", *Statistical Journal of the IAOS*.

Spencer, D (2024): "AI, automation and the lightening of work", *AI & Society*, vol 40, May, pp 1237–47.

Tobin, J (2024): "King's Speech 2024: Science, technology and innovation", *House of Lords Research Briefing*, July.

United Nations (UN) (2014): *Resolution adopted by the General Assembly on 29 January 2014: 68/261 – Fundamental Principles of Official Statistics*, January.

United Nations Economic Commission for Europe (UNECE) (2021): *Guide to sharing economic data in official statistics*, April.

——— (2023): *Large language models for official statistics*, High-Level Group on the Modernisation of Official Statistics white paper, December.

——— (2024a): *Data stewardship and the role of national statistical offices in the new data ecosystem*, April.

——— (2024b): "Working together to advance artificial intelligence for official statistics: an overview of the High-Level Group for the Modernisation of Official Statistics initiatives and output", at the 72nd plenary session of the Conference of European Statisticians, Geneva, 20–21 June.

——— (2025a): *Use of generative AI for communication in statistical organization*, High-Level Group on the Modernisation of Official Statistics, January.

——— (2025b): *The future of national statistical offices*, High-Level Group on the Modernisation of Official Statistics, March.

——— (forthcoming): *Generative artificial intelligence in official statistics*.

United Nations Educational, Scientific and Cultural Organization (UNESCO) (2023): *Open data for AI: what now?*, July.

United Nations High-Level Advisory Body on Artificial Intelligence (UN HLAB-AI) (2024): *Governing AI for humanity – final report*, September.

United Nations Statistical Commission (UNSC) (2025): "Report of the Statistical Data and Metadata Exchange sponsors", *Item for information*, no 5(h), Fifty-sixth session, March.

United Nations System Chief Executives Board for Coordination (UN-CEB) (2024): *Proposed normative foundations for international data governance: goals and principles*, CEB/2024/2/Add.1, November.

United States Department of Commerce (US DoC) (2025): *Generative artificial intelligence and open data: guidelines and best practices*, January.

Verhulst, S (2024): "Are we entering a Data Winter? On the urgent need to preserve data access for the public interest", *Frontiers Policy Labs*, 19 February.

Villalobos, P, A Ho, J Sevilla, T Besiroglu, L Heim and M Hobbhahn (2022): "Will we run out of data? Limits of LLM scaling based on human-generated data", *arXiv*, October.

Wang, Q, Y Li and R Li (2024): "Ecological footprints, carbon emissions, and energy transitions: the impact of artificial intelligence (AI)", *Humanities and Social Sciences Communications*, vol 11, August.

Wilkinson, M et al (2016): "The FAIR Guiding Principles for scientific data management and stewardship", *Scientific Data*, vol 3, March.

Willis-Núñez, F and M Ćwiek (2022): "Thirty years on, the Fundamental Principles of Official Statistics remain the shared foundation of an informed society", *Statistical Journal of the IAOS*, vol 38, no 3, August, pp 711–23.

List of abbreviations

AI	Artificial intelligence
API	Application programming interface
BERT	Bidirectional Encoder Representations from Transformers
BIS	Bank for International Settlements
BISIH	BIS Innovation Hub
CDO	Chief data officer
CGRM	Consultative Group on Risk Management
DGI	Data Gaps Initiative
EU	European Union
FSB	Financial Stability Board
G20	Group of Twenty
Gen AI	Generative artificial intelligence
GPT	Generative pre-trained transformer
GPU	Graphics processing unit
GSBPM	Generic Statistical Business Process Model
IFC	Irving Fisher Committee on Central Bank Statistics
IMF	International Monetary Fund
IT	Information technology
LLM	Large language model
ML	Machine learning
NIST	National Institute of Standards and Technology
NLP	Natural language processing
NSO	National statistical office
OECD	Organisation for Economic Co-operation and Development
SDMX	Statistical Data and Metadata eXchange
TPU	Tensor processing unit
UN FPOS	United Nations Fundamental Principles of Official Statistics
UN HLAB-AI	United Nations High-Level Advisory Board on Artificial Intelligence
UNECE	United Nations Economic Commission for Europe

Annex 1: Survey on the use of AI and ML in central banks

A. Scope and interest

1. **On a scale from 1 (low priority) to 3 (high priority), how important is AI/ML to your institution's strategic goals over the next two years?**

☐ Low
☐ Normal
☐ High

2. **On a scale from 1 (not discussed) to 3 (extensively), how much does your institution formally discuss the topic of AI/ML for internal usage?**

☐ Not discussed
☐ Moderately
☐ Extensively

3. **What percentage of the total budget of your institution is intended to finance AI/ML projects?** (Optional)

	Less than 5%	5–9.9%	10–19.9%	20–39.9%	More than 39.9%
3 years ago	☐	☐	☐	☐	☐
Today	☐	☐	☐	☐	☐
3 years ahead	☐	☐	☐	☐	☐

B. Expectations

4. **Please rate the impact you expect from AI/ML in the following functional domains in the next two years**: (please select one option per row among the following: highly impactful; moderately impactful; slightly impactful; not impactful at all; not sure)

☐ Monetary policy
☐ Statistics
☐ Research
☐ Financial stability (except prudential supervision)
☐ Prudential supervision
☐ Oversight of payments systems
☐ Cyber security
☐ Other

5. **Please rate the impact you expect from AI/ML for the following work areas in the next two years:** (please select one option per row among the following: highly impactful; moderately impactful; slightly impactful; not impactful at all; not sure)

☐ Coding and IT development
☐ Analytics
☐ Administrative tasks
☐ Communication
☐ HR-related tasks
☐ Other

6. **Please rate the impact you expect from AI/ML in the following aspects in your institution in the next two years:** (please select one option per row among the following: highly impactful; moderately impactful; slightly impactful; not impactful at all; not sure)

☐ Operational efficiency and productivity
☐ Collaboration and knowledge-sharing
☐ Automation
☐ Creativity and innovation
☐ Cost efficiency
☐ Engagement with external users
☐ Other

C. Applications and use cases

7. **What is the state of AI/ML adoption in your institution?**

☐ No AI/ML in use
☐ Few pilot projects
☐ Limited production
☐ A number of projects in production
☐ Widespread use in production

8. **In which functional domains does your institution use AI/ML?** (Please select all that apply)

☐ Monetary policy
☐ Statistics
☐ Economic research
☐ Financial stability (except microprudential supervision)
☐ Prudential supervision
☐ Oversight of payments systems
☐ Cyber security
☐ Communication
☐ Other

9. **If "statistics" is selected in the previous question, in which of the following statistical phases does your institution use AI/ML?** (Please select all that apply)

☐ Collection

☐ Processing (including editing, classification, validation)

☐ Analysis (including disclosure controls)

☐ Dissemination

☐ Evaluation

☐ Other

10. **Please describe (i) the main projects currently under way in your institution using AI/ML (including pilot projects); (ii) the main data sources used; (iii) the purpose of the projects; (iv) the platform and application used; (v) time invested; and (vi) team involved (eg fully external, mix of internal/external, 100% dedication, mixed with regular business)**

(i) Project name	(ii) Data sources	(iii) Purpose	(iv) Type of activity	(v) Platforms/applications	(vi) Time	(vii) Team

11. **Please describe the same elements for the future projects planned for the next two years** (Optional)

(i) Project name	(ii) Data sources	(iii) Purpose	(iv) Type of activity	(v) Platforms/applications	(vi) Time	(vii) Team

12. **Are you currently using generative AI in your institution?**

☐ Yes

☐ No (not yet)

☐ No (not planned)

13. **If yes, please select the applicable use cases** (Please select all that apply)

☐ Text generation (using ChatGPT; Copilot; others)

☐ AI transcript services (used in meetings)

☐ Generative AI interface to community (chatbots; search tools)

☐ Code generation, debugging and documentation

☐ Non-textual content generation (images, audio, video)

☐ Other

D. Organisational policies

14. Does your institution currently have recommendations/guidelines for the use of AI?

☐ Yes, publicly available
☐ Yes, internally available
☐ Currently elaborating
☐ No

15. How is the work on AI/ML projects organised in your institution?

☐ Centralised by a specific unit
☐ Developed by cells within the different business areas
☐ Coordinated by the chief data officer (CDO)
☐ Other

16. How is the AI governance role implemented in your institution? (Optional)

☐ Centralised by a specific unit outside from the IT department
☐ Centralised within the IT department
☐ Developed by cells within the different business areas
☐ Not implemented
☐ Other

17. If your institution has a CDO, what is the primary focus of his or her function? (Optional)

☐ Offence/growth/innovation
☐ Defence/regulatory/efficiency
☐ Other

18. What is the state of data and AI responsibility and ethics in your institution? (Please select all that apply)

☐ Board of directors well versed in data and AI issues and responsibilities
☐ Well established policies and practices in place
☐ Industry has done enough to address data and AI ethics
☐ Other

19. What are the biggest challenges to business adoption of AI/ML? (Please select all that apply)

☐ Lack of institutional alignment/agility
☐ Cultural resistance
☐ Lack of staff with adequate skills
☐ Difficulty retaining talent
☐ Executive leadership

☐ Technology solutions
☐ Addressing risks
☐ Ethical issues
☐ Regulatory uncertainty
☐ Limited budget
☐ Integration with existing systems
☐ Other

20. Which AI/ML risk does your institution consider relevant? (Please select all that apply)

☐ Confidentiality and privacy
☐ Intellectual property infringement
☐ Inaccurate output (bias)
☐ Cyber security
☐ Lack of explainability
☐ Lack of workforce expertise
☐ Regulatory compliance
☐ Institutional reputation
☐ Dependency on external providers
☐ Increase in IT-related costs
☐ Other

21. Please describe measures taken or planned to mitigate those risks (Optional)

E. IT stack

22. Which infrastructure is being used for AI/ML purposes?

☐ Self-deployment / on-premises servers
☐ Managed services / IaaS (infrastructure as a service)
☐ Not sure
☐ Other

23. Do you have access to any cloud infrastructure for AI/ML purposes? (if yes, please specify below which technologies you are using) (Optional)

☐ In regular business
☐ For testing only
☐ Not allowed
☐ Other

24. **What purposes, if any, does open source software for AI/ML serve for your institution** (Please select all that apply) (Optional)

☐ Lower dependency on external providers
☐ Better data security
☐ High customisation
☐ Cost-effectiveness
☐ Not relevant
☐ Other

25. **When using generative AI and large language models (LLMs), what is the strategy for choosing between closed models (eg OpenAI's ChatGPT) vs open models (eg Meta's Llama3)** (Optional)

☐ Usually explore both closed and open models and use the model that performs best
☐ Usually use closed models only
☐ Usually use open models only
☐ Generative AI and LLMs are not currently used

26. **Do you have any restriction on internal, confidential or sensitive data in AI tools? (eg separated environments for AI tools)**

☐ Yes
☐ Not yet (ongoing work)
☐ No

27. **If yes, how are those restrictions carried out?** (Please describe)

F. <u>Collaborative strategies</u>

28. **What are the main avenues for central bank collaboration to address the challenges of AI going forward?** (Please select all that apply)

☐ Workshops
☐ Consolidated guidelines for the use of AI and best practices
☐ Sharing user cases and code
☐ Co-investment opportunities
☐ Collaboration with AI/ML experts from other institutions
☐ Access to pre-trained models (eg LLMs, Hugging Face)
☐ Other

29. Does your institution share AI/ML code or models, or plan to? (Please select all that apply)

- ☐ No internally developed code or model is shared
- ☐ With other similar authorities in the same country
- ☐ Publicly sharing codes (eg open source) on the institution's website
- ☐ Publicly sharing codes (eg open source) on dedicated repository websites (eg GitHub, GitLab)
- ☐ Other

30. In your opinion, what will be the emerging technologies topics that will concentrate interest and resources in the upcoming future? (Please select all that apply)

- ☐ Generative AI
- ☐ Data platform/data lake
- ☐ Data quality/data health
- ☐ Cloud migration
- ☐ Other

Annex 2: List of IFC jurisdictions responding to the survey

1. Angola
2. Argentina
3. Armenia
4. Australia
5. Austria
6. Bank for International Settlements
7. Bolivia
8. Brazil
9. Canada
10. Chile
11. Costa Rica
12. Croatia
13. Denmark
14. Dominican Republic
15. Ecuador
16. Egypt
17. Estonia
18. European Union
19. Finland
20. France
21. Germany
22. Greece
23. Hong Kong SAR
24. India
25. Indonesia
26. Ireland
27. Israel
28. Italy
29. Japan
30. Kazakhstan
31. Korea
32. Latvia
33. Lebanon
34. Lithuania
35. Luxembourg
36. Malaysia
37. Malta
38. Mexico
39. Mongolia
40. Netherlands
41. North Macedonia
42. Norway
43. Peru
44. Philippines
45. Poland
46. Portugal
47. Romania
48. Serbia
49. Singapore
50. Slovakia
51. Slovenia
52. South Africa
53. Spain
54. Sweden
55. Switzerland
56. Thailand
57. Türkiye
58. Ukraine
59. United States
60. Vietnam