

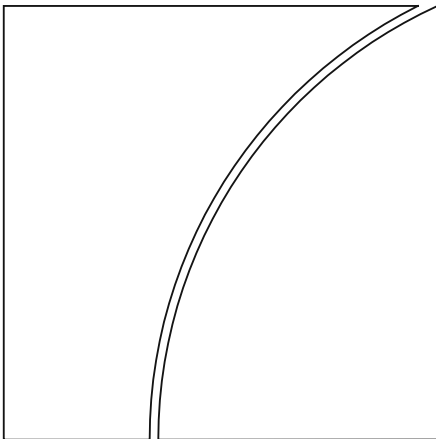
IFC Report

No 19

AI readiness in central banks

2026 survey conducted by the Irving Fisher Committee on
Central Bank Statistics (IFC)

October 2026



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Executive summary

Artificial intelligence (AI) has been gaining significant interest in central banks, reflecting its potential to support a wide range of their activities. This interest was already highlighted in a comprehensive survey conducted in 2024 by the Irving Fisher Committee on Central Bank Statistics (IFC). Back then, many AI applications were still at an early stage, underscoring the need for further efforts on governance, infrastructure and resources to ensure effective deployment (IFC (2025a)).

Two years later, **the focus has broadened beyond experimentation to encompass AI readiness**. This concept refers to the institution's preparedness to adopt, adapt and advance AI in its operations, decision-making and objectives. It is particularly relevant for central banks as they seek to ensure that both their organisation and data are ready to make the most of this technology. At the same time, they also constantly need to review their state of preparation to deal with the implications of AI's fast-paced and uncertain evolution.

Yet, in practice, assessing AI readiness is a complex task. It calls for distinguishing between perceived readiness – ie how an institution considers itself to be prepared – and actual readiness – ie as reflected in the reported actions taken to use AI. To shed light on these issues, **this new IFC survey has been expanded to cover progress in AI readiness in central banks**. The results highlight four main bottom lines.

To start with, **central banks increasingly perceive themselves as being AI-ready**. This is underscored by the growing prioritisation of AI on their agenda as well as the development of organisational and data readiness strategies. Most institutions are indeed actively elaborating plans to strengthen their resources – such as skills and infrastructure – and to manage data in ways that support a secure and responsible use of AI.

The above perception is **confirmed both by the growing number of reported use cases as well as by the steps taken to strengthen AI governance, infrastructure and capabilities in central banks**. Compared to two years ago, more AI applications, supported by rising budgets, are being deployed in production and are already transforming many existing workflows. Moreover, central banks have been making significant advances in terms of governance – eg by issuing guidance on AI use, introducing safeguards to protect sensitive data, setting up dedicated organisational structures – and capabilities – eg by developing skills and comprehensive infrastructure to customise AI solutions to business needs.

Despite progress, several challenges remain. First, expectations about AI's impact across central banking functions remain uneven and show some signs of moderation for specific areas. This arguably suggests cautious optimism vis-à-vis the technology as well as the difficulties of scaling pilot projects and tailoring applications to specialised business needs. Second, risks remain elevated, especially those related to costs and dependence on a smaller number of AI providers. Third, broader organisational challenges persist and continue to emerge, particularly in relation to security, skills and ethics. Lastly, there is awareness that important investments will continue to be needed amid rapid yet uncertain technological evolution.

Looking ahead, **experience suggests that strengthening central banks' AI readiness calls for making progress on two fronts, namely their organisational setups and data**. At the organisational level, main priorities include optimising AI costs, mitigating concentration risks and external dependencies as well as developing oversight mechanisms, especially for agentic AI. At the data level, a key objective is to ensure that AI can adequately tap into the available information, putting a premium on data interoperability, protection, machine-readability and actionability, supported by robust semantic layers that translate raw data into business terms. Fortunately, ongoing international initiatives, such as the standard for Statistical Data and Metadata (SDMx), can already provide a strong foundation for this endeavour.

1. Introduction: the concept of AI readiness

Over recent years, central banks have paid growing attention to AI (BIS (2024); IFC (2025a)).² This technology is commonly understood as a machine-based system that infers, from the inputs it receives, how to generate outputs such as predictions, content or decisions to perform tasks traditionally requiring human intelligence (OECD (2024a); FSB (2026); IFC (2026)). Two transformative strands have in particular emerged: *generative AI*, which produces new textual, audio or visual content based on patterns learned from existing “training” data; and *agentic AI*, which relates to systems designed to autonomously perform complex tasks with limited human oversight.

These rapid developments have reinforced central banks’ interest in leveraging innovation to support the broad range of their activities. At the same time, they have also triggered **greater attention to their readiness, or state of preparedness, to adopt, adapt and advance AI** in their operations, decision-making and objectives. AI readiness is a multifaceted concept that encompasses two main scopes in an institution. The first relates to its *organisational readiness*, that is, the state of preparedness to use, govern and implement AI by having comprehensive and integrated frameworks, resources and capabilities to perform innovative tasks. The second scope is *data readiness*, that is, the state of preparedness to manage its information assets to ensure an effective, secure and responsible use of AI.

Yet **assessing AI readiness is a complex task**. One has in particular to distinguish between *perceived readiness* – reflecting an institution’s assessment of its own preparedness – and *actual readiness* – as reflected in the reported actions, capacities and capabilities to use, govern and implement AI in its operations.

In addition, **the degree of AI readiness aimed for will depend on institutional objectives, the types of tasks considered and the time horizon**. First, as regards objectives, different use cases for deploying AI may demand distinct levels of readiness. For example, the implementation of general-purpose AI tools can require the setup of organisational-wide governance frameworks, while domain-specific applications such as in analysis, statistics or supervision might be conducted on a more ad hoc basis. Turning to the tasks being contemplated, readiness will depend on how AI is used, such as the types of models deployed (eg *large language models*, *computer vision*, speech recognition) and the way they are implemented (eg *retrieval-augmented generation*, agents). A third aspect is the time horizon, as readiness might develop at different speeds. For instance, central banks may identify AI as a strategic priority before using it extensively. Similarly, its adoption in specific business areas can advance ahead of bank-wide efforts in terms of governance, infrastructure or skills.

These considerations underscore **the importance of assessing the various aspects of AI readiness both at a point in time and over time**, not least to capture evolving states within institutions, identify longer-term trends and anticipate the rapidly changing opportunities and challenges brought by this technology. To this end, the IFC conducted a new survey in 2026 with two objectives: first, to document the developments in AI governance, expectations and applications observed in the most recent years; and second, to identify priority areas for improving AI readiness further.³

This report presents the key findings. Section 2 examines how central banks perceive their AI readiness from both an organisational and data perspective. Section 3 documents how they have been reporting on advancing use cases, governance arrangements and capabilities to leverage AI and support their activities. Section 4 sheds light on the current and emerging challenges faced in this endeavour. Finally, section 5 identifies a number of focus areas for further improving organisational and data AI readiness in the context of central banks.

² Terms in *italics* are defined in the Glossary.

³ See Annex 2 for details on the coverage of the new survey conducted in early 2026. Comparisons between the results in 2024 and 2026 simply include all respondent jurisdictions, as composition changes did not significantly affect aggregate results.

2. Assessing readiness: central banks' perceptions

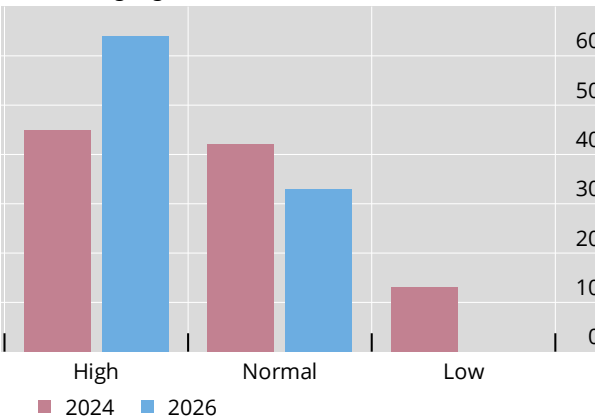
Since 2024, central banks have steadily elevated AI on their strategic agenda, recognising its potential value to support their functions and operations. In 2026, most respondents classify AI as a high priority, up from less than half two years before (Graph 1.A). Reflecting this evolution, AI and *machine learning* (ML) are increasingly being formally discussed within organisations (Graph 1.B).

AI is a key strategic priority for central banks

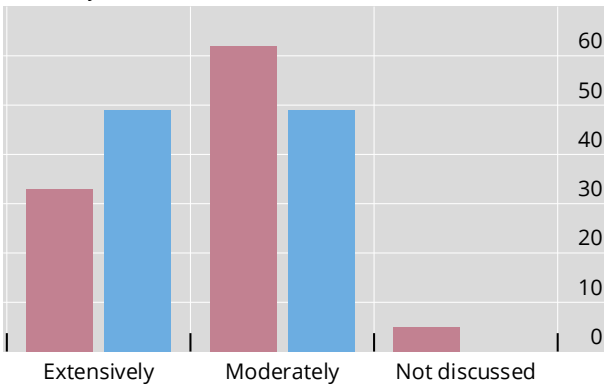
In per cent of respondents

Graph 1

A. Almost two thirds of central banks now prioritise AI in their strategic goals...



B. ...with AI and ML being extensively discussed internally across half of them

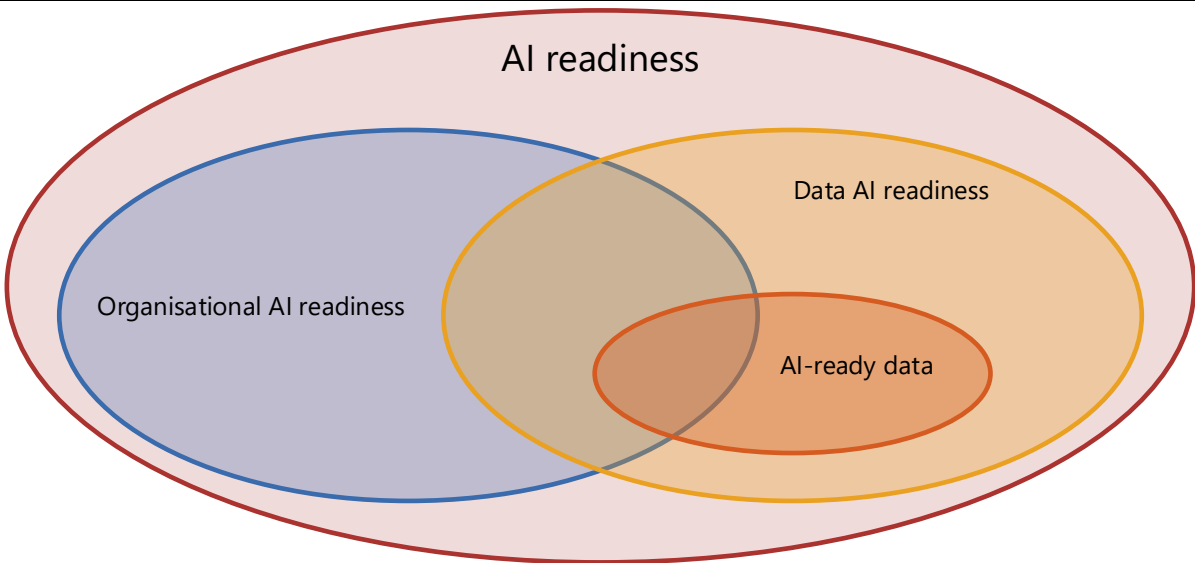


Sources: IFC survey on AI (2024, 2026); authors' calculations.

In line with the growing relevance of AI, **central banks report that they have been rapidly advancing their readiness to use AI**. One way to account for this progress is to look at how they self-assess their own readiness (perceived readiness) in terms of both their organisation and data (Graph 2).

Organisational and data AI readiness

Graph 2



Source: authors' illustration.

One key insight from the survey is that **central banks report taking active steps to strengthen their organisational preparedness for AI**. This reflects the establishment of strategies within the organisation, for example through comprehensive and integrated frameworks, resources and capabilities to use, govern and implement AI in order to support business objectives and institutional goals. Specifically, over two thirds of the respondents have either already established or are drafting such organisational strategies, with less than 10% not planning to do so (Graph 3.A). This focus on developing organisational readiness reflects two broad motivations (Graph 3.B). A key one, shared by a large group of central banks (approximately two fifths), is to follow a comprehensive approach to address business needs through organisation-wide policies, with a particular focus on strengthening security and governance frameworks. Another motivation, representing around one third of respondents, is to ensure a broader and more forward-looking approach to align AI use with the long-term policy objectives of the central bank.

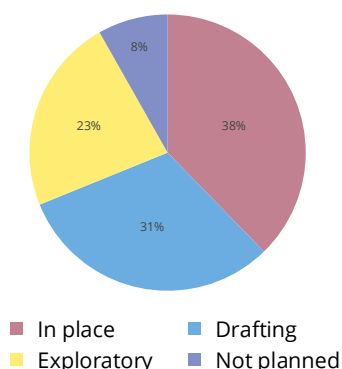
Another insight is that **central banks are also indicating significant progress regarding their data AI readiness**. This concept can be understood as the organisation's state of preparedness to manage its information assets in ways that support the effective, secure and responsible use of AI. In practice, almost two thirds of central banks report that they have already implemented or are planning to implement such strategies, often as part of broader modernisation programmes (Graph 3.C). The aim is to make better use of available information within the organisation, by ensuring that the relevant data are available, accessible, interoperable, secure, machine-readable and, broadly, *AI-ready*. Strategic initiatives often involve establishing information infrastructure, governance and standards, including through harmonised taxonomies, semantic layers, classification policies and inventories. These initiatives can also cover data quality controls, access and sharing protocols, lineage, privacy and confidentiality rules, as well as processes for managing data documentation (or metadata) throughout their entire lifecycle.

Central banks indicate progress in their organisational and data AI readiness

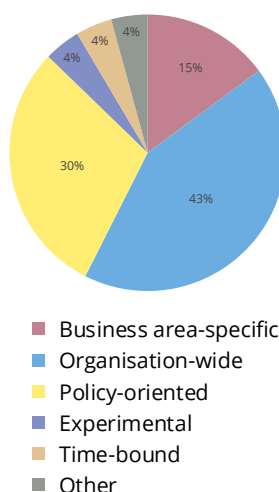
Graph 3

In per cent of respondents

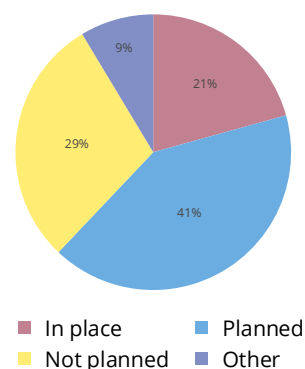
A. Most organisational AI readiness strategies are in place or being explored...



B. ...focusing mostly on organisation-wide and policy aspects



C. Almost two thirds of central banks have, or plan to have, data AI readiness plans



Sources: IFC survey on AI (2026); authors' calculations.

3. Progress in AI readiness: advancing use, governance and implementation

A second angle to assess readiness is to look at how central banks report using, governing and implementing AI to support their functions and operations effectively (actual readiness). In practice, this can be done by analysing the surveyed use cases (i) as well as the steps taken to strengthen governance (ii), infrastructure and related AI capabilities (iii).

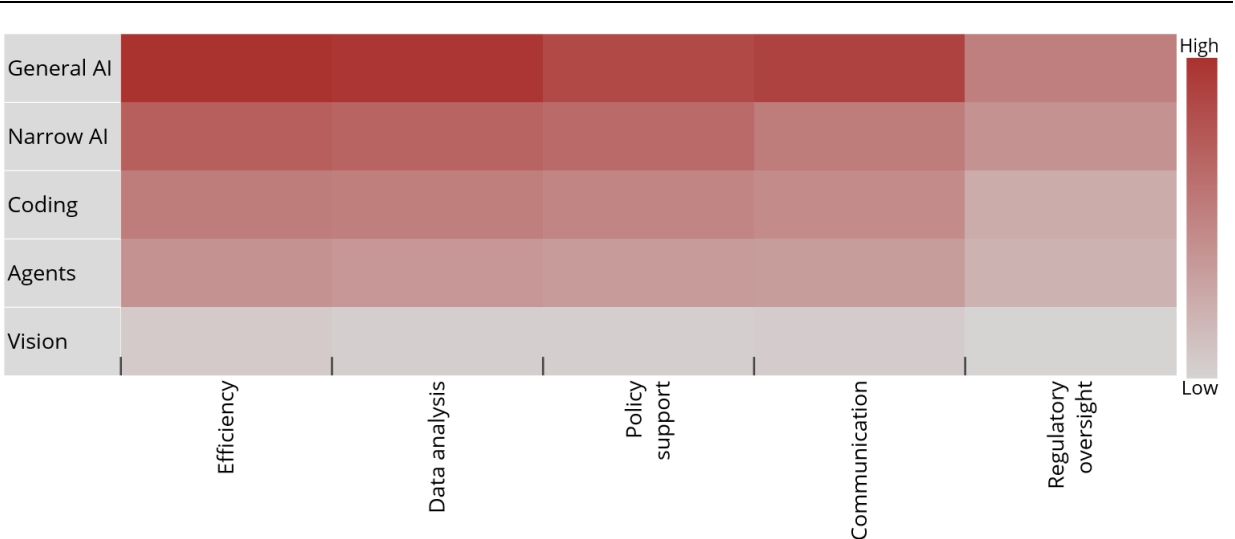
Growing use across central banking functions

The growing adoption of AI by central banks reveals three main patterns. First, AI usage has expanded towards general purpose activities to support efficiency (Graph 4). This contrasts with the initial adoption phase, which was more focused on specific tasks, such as search, coding and translation. A notable development is the deployment of productivity copilots, which are increasingly integrated into routine operations in many organisations (Graph 5). Second, AI is also being employed as a context-specific technology for supporting distinctive central banking functions, such as monetary and financial stability policy, economic analysis and research, statistics as well as their various oversight and supervisory mandates. For instance, most central banks report using AI for activities such as data analysis. Third, advanced tools like agentic AI and computer vision remain relatively less used than general purpose techniques to date, underscoring the trade-offs related to costs, security, integration, fast-paced technological developments and broader governance issues (OECD (2026a)).

Central banks typically use general AI solutions to support efficiency

Mean scores

Graph 4



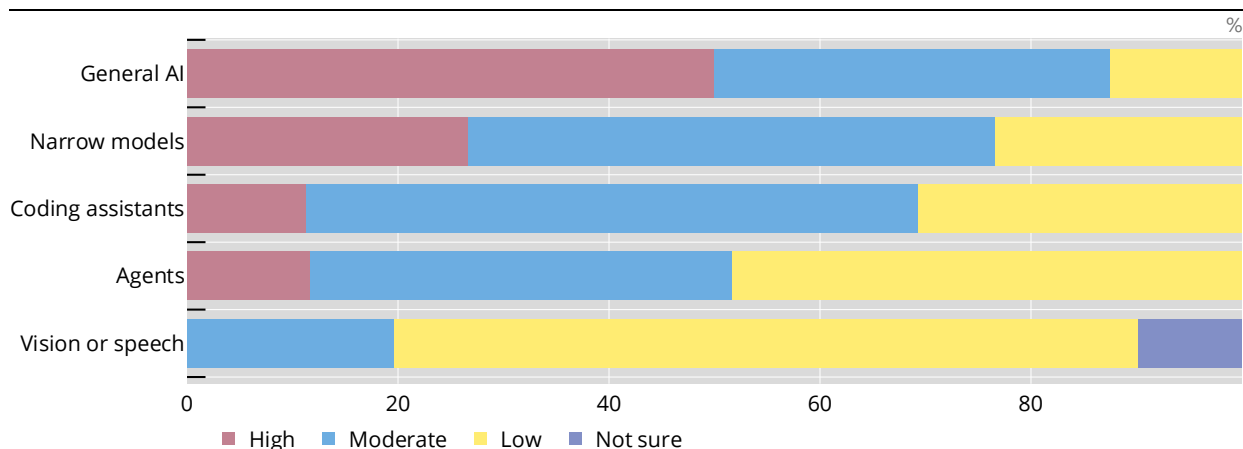
The more intense the colour, the stronger the alignment between the type of AI used (y-axis) and its scope (x-axis). Mean scores are calculated by averaging responses for each category.

Sources: IFC survey on AI (2026); authors' calculations.

Most central banks refer to AI in its general form

In per cent of respondents

Graph 5



High: extensive or widespread usage across the institution (eg critical and integral to operations and can be accessed on a large and/or regular basis); moderate: medium usage, mostly by specific teams and/or for tailored purposes (eg important but not critical to operations and can be accessed in specific scenarios); low: limited usage, mostly confined to limited users (eg not important, experimental or auxiliary).

General purpose AI includes solutions such as productivity copilots (excluding for coding). Narrow models cover tailored use cases, such as forecasting or sentiment analysis applications. Agents support applications and workflows.

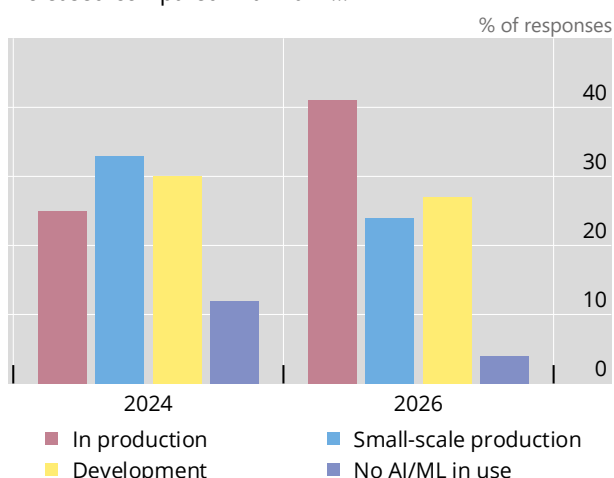
Sources: IFC survey on AI (2026); authors' calculations.

Reflecting the above, **there has been a notable increase in the share of production-grade initiatives deployed over the past years.** Specifically, the proportion of AI projects in production (including on a small-scale basis) is over two thirds in 2026, compared with about half two years earlier (Graph 6.A). Meanwhile, the fraction of use cases under development has remained relatively unchanged between these two periods, at less than one third of the total. Finally, the number of respondents not using AI/ML has fallen to almost zero, confirming the reported widespread AI adoption by central banks.

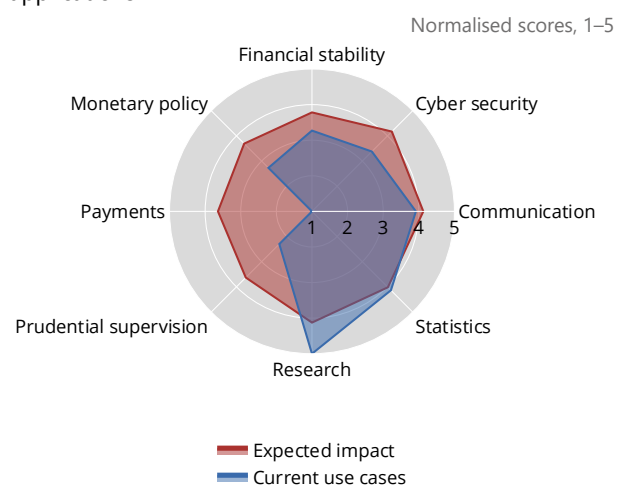
AI adoption in central banks is reported to have increased since 2024

Graph 6

A. AI projects declared in production in 2026 have increased compared with 2024...



B. ...with statistics and research still featuring the most applications¹



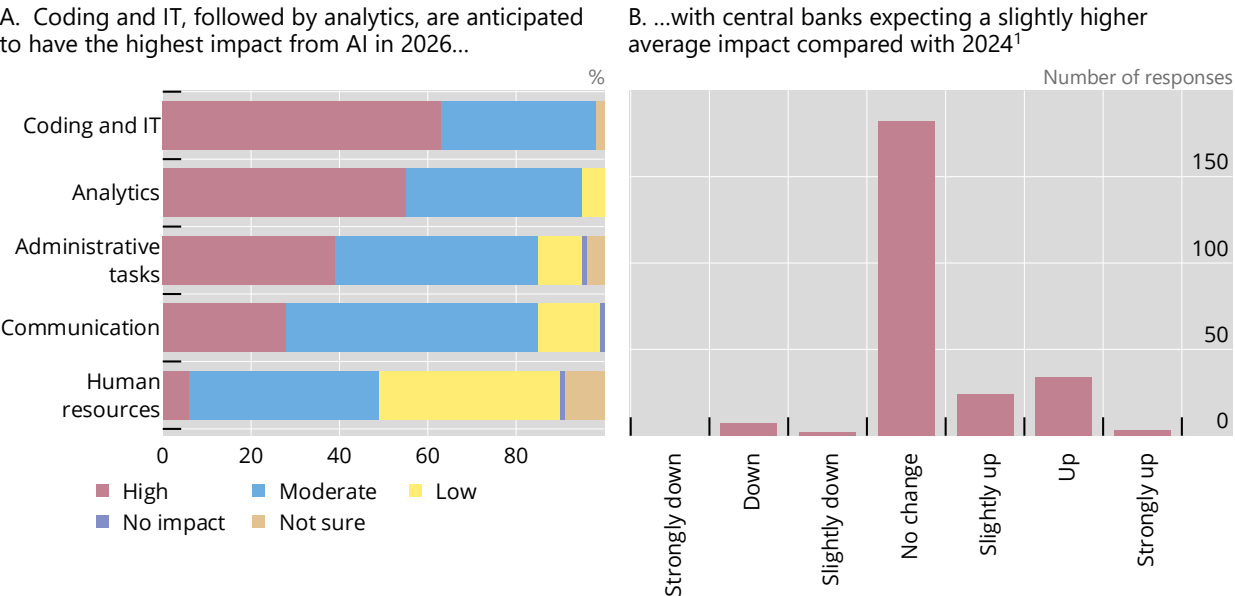
¹ Expected impact is calculated as the average of the responses rated on a scale from 1 to 5. The number of current use cases is normalised on a scale from 1 (min) to 5 (max); pilot or ongoing use cases are included.

Sources: IFC survey on AI (2024, 2026); authors' calculations.

Turning to the functional areas where AI is being used, research and statistics remain in the lead, accounting for most deployed applications (for both current and expected ones; Graph 6.B). Additionally, the communication area has attracted a substantial and increasing proportion of the projects actually implemented, surpassing monetary policy, financial stability and cyber security. As regards prudential supervision, the number of use cases appears still relatively limited but is reported to have been growing notably in recent years, especially for summarisation and data analysis tasks (Chow et al (2026)).

Looking forward, **central banks keep expecting AI to transform many of their existing workflows**, particularly those related to cross-cutting activities such as coding, IT as well as data analytics. By contrast, tasks related to human resources are anticipated to be the least affected (Graph 7.A). Compared to two years ago, most central banks report anticipating a broadly similar impact of AI on their activities overall, although the distribution of responses has shifted towards more positive expectations (Graph 7.B).

AI is still expected to deliver the greatest impact on coding and IT functions Graph 7



¹ Bars show the number of responses by change in expectations (eg “strongly up” indicates a significant increase between 2024 and 2026).
Sources: IFC survey on AI (2024, 2026); authors’ calculations.

Marking progress on AI governance

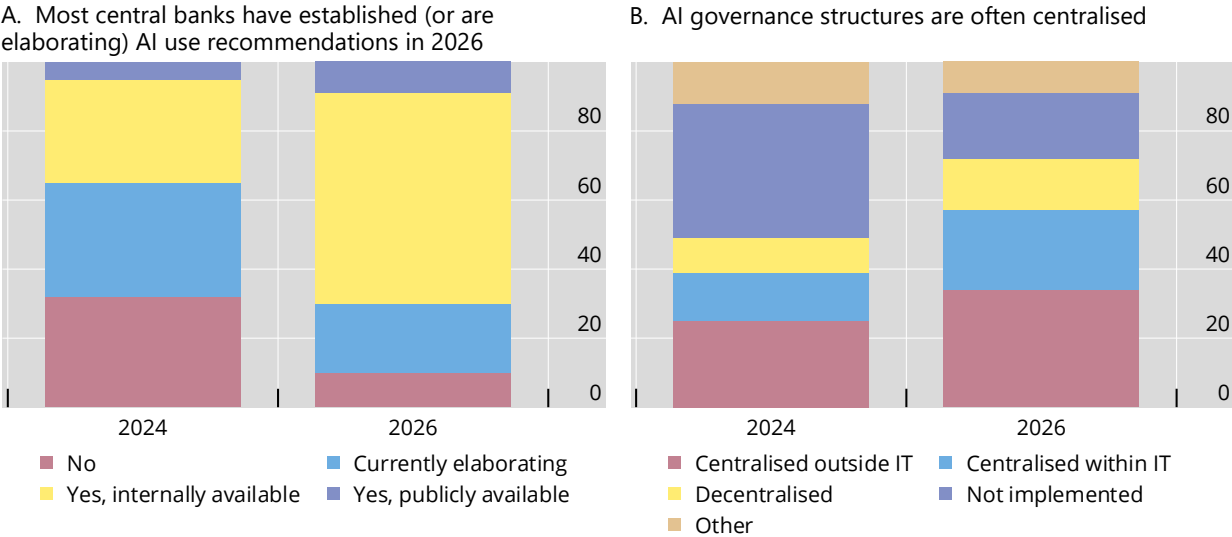
Over the past few years, there has been a noticeable improvement in central banks’ ability to manage AI developments, reflecting the need to make the most of the opportunities offered by this technology as well as to mitigate the associated risks.

First, **central banks have made significant headway in AI governance**, a complex concept which can be understood as the broad rules and policies, functions, structures and frameworks enabling the effective use of the technology while aligning it with organisational goals and compliance standards (IFC (2025a)). Indeed, reported evidence shows that internal rules or recommendations for AI use are broadly in place for the majority of surveyed institutions. The proportion of those that have not developed such guidance has fallen to less than one tenth, down from about one third two years ago (Graph 8.A). Interestingly, most central banks have centralised AI governance in units outside (around one third of the jurisdictions) or inside (around one fifth) their IT department (Graph 8.B).

Central banks have taken significant steps to develop AI governance

In per cent of respondents

Graph 8



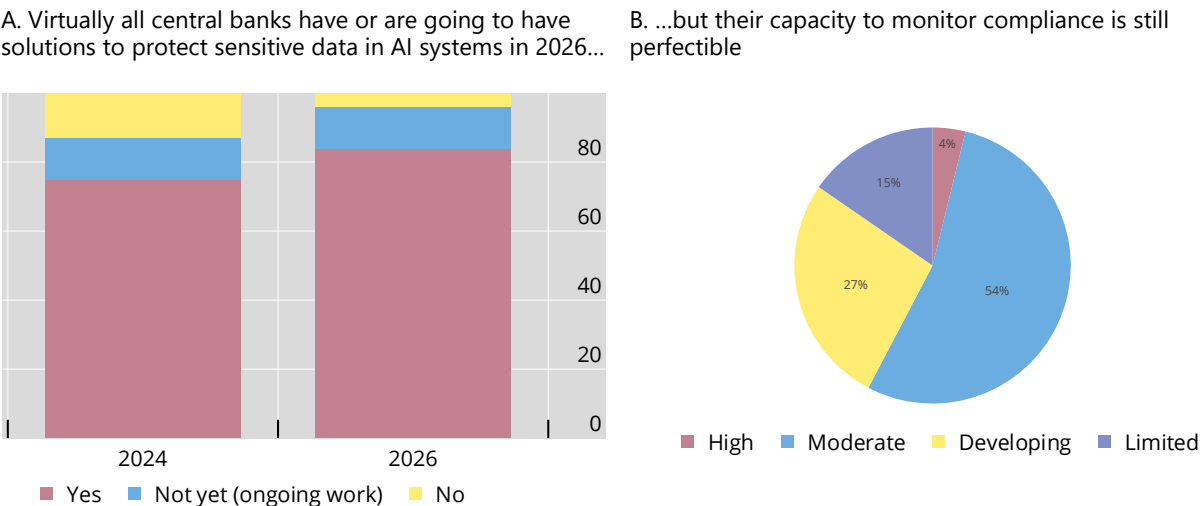
Sources: IFC survey on AI (2024, 2026); authors' calculations.

Meanwhile, virtually all of the **respondents have or are going to have solutions to strengthen their capacity to monitor and, to the extent possible, mitigate AI-related risks**, especially to protect sensitive information (Graph 9.A). Yet, about half indicate that their capacity to monitor compliance remains moderate, while a large minority report that it is still under development or limited (Graph 9.B).

Central banks have set up a framework for protecting sensitive data in the AI era

In per cent of respondents

Graph 9



Sources: IFC survey on AI (2024, 2026); authors' calculations.

Advancing AI implementation through enhanced IT and human capabilities

Central banks have expanded their capabilities to harness AI along three dimensions.

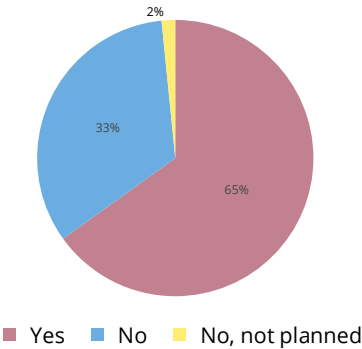
First, **as regards IT solutions, almost two thirds of surveyed central banks report having established a dedicated infrastructure** (Graph 10.A). This covers the computing hardware, data platforms and tooling needed to safely deploy and operate AI models within the organisation. A key insight from central banks is that such investment is linked to the need to customise models, fully or in part (Graph 10.B), which is consistent with previous findings (IFC (2025a)). This demand for customisation appears to be primarily explained by the development and deployment of tailored applications associated with ML and natural language processing (Graph 10.C).

Most central banks have dedicated AI infrastructure, including to customise models

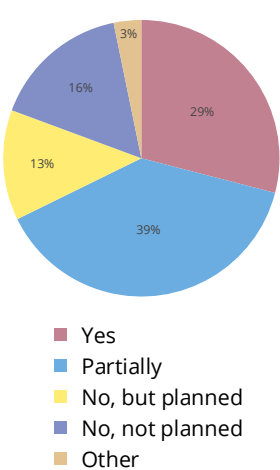
In per cent of respondents

Graph 10

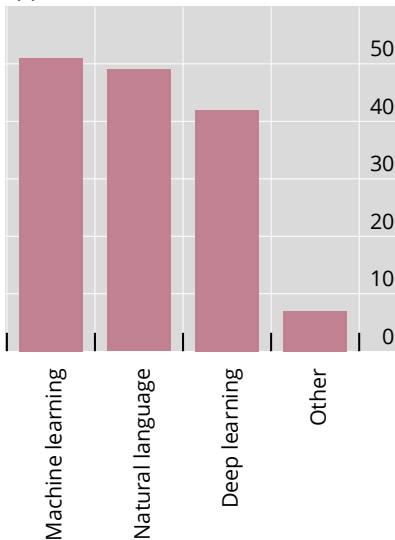
A. Most central banks have set up dedicated infrastructure for AI...



B. ...including to customise models...



C. ...especially for supporting ML and natural language processing applications



Sources: IFC survey on AI (2026); authors' calculations.

Second, and relatedly, **central banks are mainly using external, or “off-the-shelf”, AI models**, with about a fifth opting for self-hosting or deploying models in-house only (Graph 11.A). This result, which is shared across jurisdictions in advanced and emerging market economies, suggests a preference for deploying commercial tools within central banks' own environments and to adapt them to specific contexts (Graph 11.B). Indeed, this approach likely reduces the immediate need for significant upfront investments in computing infrastructure and specialised skills, arguably making it a cost-effective, faster and more practical choice. At the same time, it raises questions ranging from customisation difficulties to privacy protection, strategic autonomy and, broadly, sovereignty – issues that are of increased relevance to public authorities globally (OECD (2024b)).

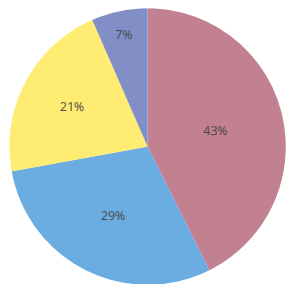
Finally, **central banks are building capabilities through targeted hiring and upskilling**. Specifically, almost three fourths of respondents report employing AI experts, with only a small minority not yet planning to do so (Graph 12.A). Nonetheless, these experts still represent only a tiny fraction of staff, often accounting for less than 2.5% of the total workforce (Graph 12.B). Looking ahead, concerns about attracting AI-savvy talent appear relatively moderate (Graph 12.C), suggesting that central banks have been able to adapt their workforce to harness AI in line with broader developments in the labour market (Bell et al (2025); OECD (2026c)).

External AI models are mostly used in central banks worldwide

In per cent of respondents

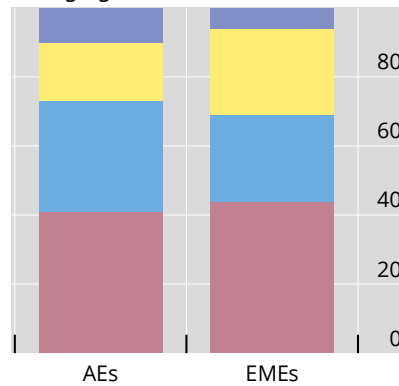
Graph 11

A. Central banks mostly use external or off-the-shelf AI models...

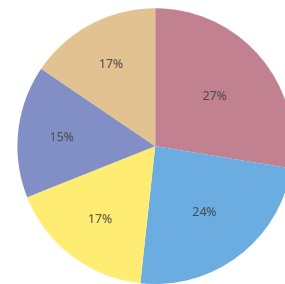


■ External
■ External but customised
■ Internal
■ Other

B. ...across both advanced and emerging market economies...



C. ...with high reliance on a few providers for frontier models



■ OpenAI
■ AzureAI
■ Anthropic
■ Meta
■ Gemini and others

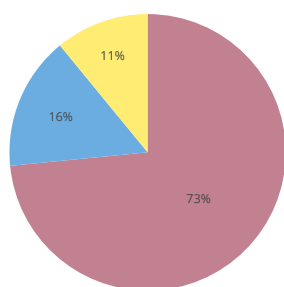
Sources: IFC survey on AI (2026); authors' calculations.

While a large majority of central banks employ specialised AI professionals, their share relative to the total headcount is reported to be small

In per cent of respondents

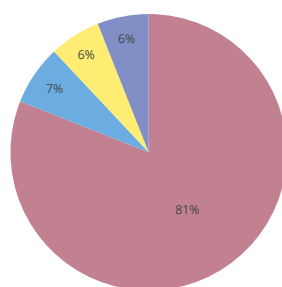
Graph 12

A. Central banks typically employ data scientists, ML and AI experts...



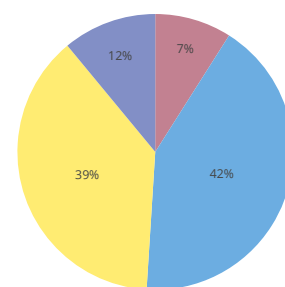
■ Yes
■ No, but planned
■ No, not planned

B. ...but their share in total staff is relatively limited...¹



■ 0-2.5
■ 2.5-5
■ 5-10
■ Do not know

C. ...and concerns about the ability to attract AI-savvy profiles appear moderate



■ Extremely
■ Moderately
■ Slightly
■ Not concerned

¹ Categories indicate the reported share of specialised AI professionals relative to overall full-time equivalents (FTEs) in the organisation.

Sources: IFC survey on AI (2026); authors' calculations.

4. Significant challenges amid rising risks

Despite reported progress in AI readiness, central banks' experience to date highlights a combination of challenges. These include uneven expectations regarding AI's impact across key central banking functions (i); risks related to AI usage that remain and in some cases are intensifying, alongside newly emerging ones (ii); as well as broader governance and ethical issues (iii).

Uneven and somewhat tempered expectations about AI impact

Reported expectations regarding AI's impact in central banks remain high but also point to a more prudent and variable assessment in selected domains, reflected in at least two developments.

First, **the expected impact of AI stays elevated overall but features notable differences across domains**. Areas such as cyber security and, to a lesser extent, research and statistics, continue to be the ones expected to be most impacted by AI in 2026 in line with the 2024 results (Graph 13.A). Meanwhile, expectations about AI impact remain more modest in core aspects of central banking, such as monetary policy, financial stability as well as payments. Moreover, the survey also points to some moderation in specific areas compared to two years ago, in particular related to financial stability, monetary policy, statistics and research, for which a larger share of respondents now expect a moderate impact (Graph 13.B, blue bars).

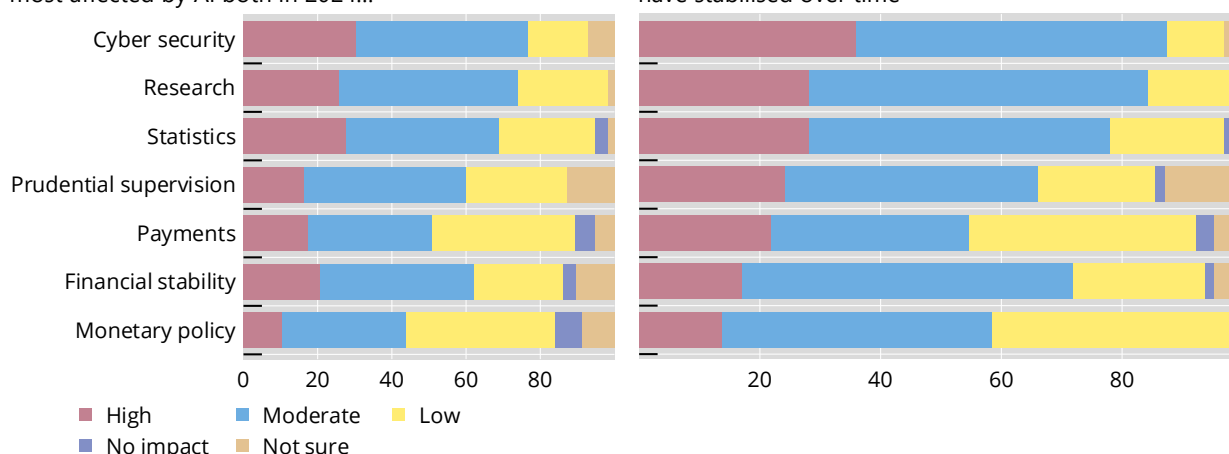
Cyber security is still expected to be most impacted by AI

In per cent of respondents

Graph 13

A. Cyber security remains the domain expected to be most affected by AI both in 2024...

B. ...and 2026 with the projected AI impact appearing to have stabilised over time



Sources: IFC survey on AI (2024, 2026); authors' calculations.

The insights above seem to align with broader developments in the AI sphere, possibly reflecting the uncertainty of the technology as well as the complexity of moving from pilot to full-scale projects (Bains et al (2025); OECD (2025a)). Additionally, challenges in terms of data availability, quality and security can hinder progress in the absence of robust governance frameworks and IT infrastructure, which require significant investment in data, skills and tools (Araujo et al (2026); Crisanto et al (2026)). Finally, revised expectations regarding AI impact may reflect a growing organisational focus on general purpose projects supporting IT operations, including coding and workflow automation (Graph 7.A above). By contrast, addressing specific use cases tailored to business needs can be more difficult to develop.

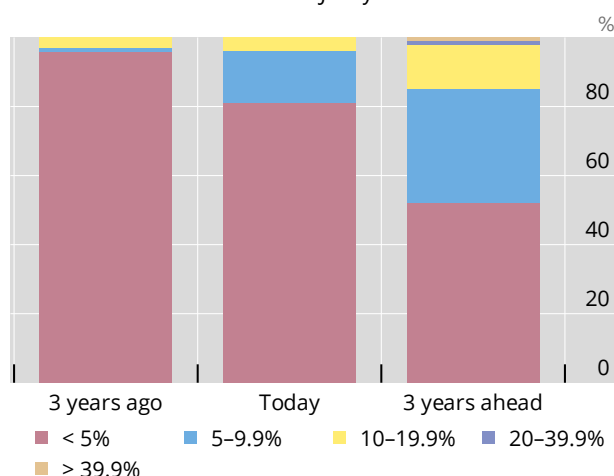
A second element from the survey is that, **while central banks continue to anticipate significant budget increases for AI, their reported actual spending has fallen short of the projections made two years ago.** Most of the surveyed jurisdictions declare allocating currently less than 5% of their overall budget to AI, with only a small share spending more (Graph 14.A). In fact, and relative to 2024 plans, many organisations appear to have spent less than expected. Looking ahead, nevertheless, expenditures are still anticipated to rise further, as illustrated by the projected share of larger budget envelopes devoted to AI (ie those representing 10–19.9% of the overall budget; Graph 14.B).

Central banks report having spent less on AI than anticipated in 2024 but expect future allocations to increase

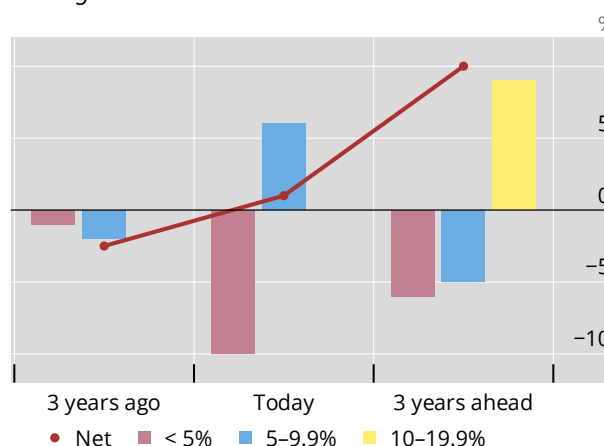
In per cent of respondents

Graph 14

A. While reported current AI budget remains less than 5% of the total in the vast majority of central banks...



B. ...they are still expecting to allocate a larger budget looking ahead¹



¹ A negative (positive) value indicates that the percentage allocated to AI/ML projects decreased (increased) from 2024 to 2026. Percentage changes are calculated on an aggregate basis, by spending bracket and period. The net dot is calculated as the (linearly) weighted sum of the percentage differences for each budget bracket: a positive (negative) value corresponds to a net increase (decrease) in overall budget allocation.

Sources: IFC survey on AI (2024, 2026); authors' calculations.

Risks associated with AI usage remain high and increase, especially related to technology and dependence

A second issue relates to the increasing risks associated with AI usage in central banks, with three main sources of concern.

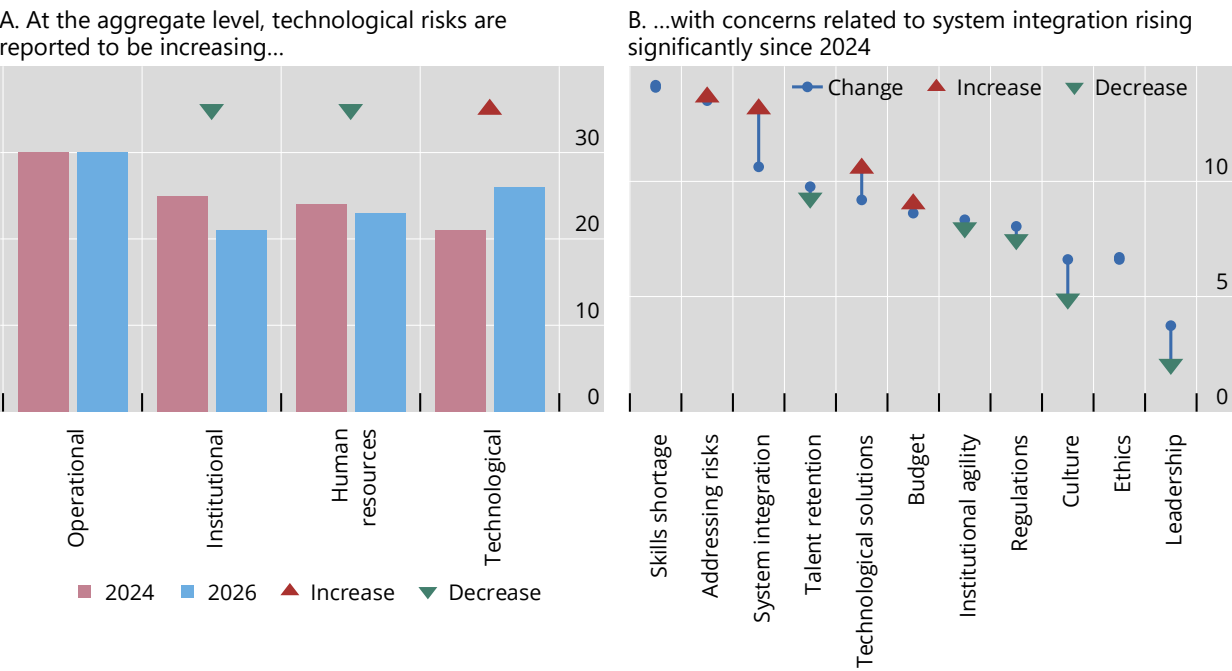
Firstly, at the aggregate level, **a significantly greater proportion of respondents than in 2024 now expect technological risks to rise further** (Graph 15.A). These mostly reflect concerns about system integration and, to a lesser extent, IT solutions (Graph 15.B). In particular, the share of central banks flagging the cost of IT expenditure as a risk has jumped to almost 80%, broadly reflecting questions about the need to finance areas such as computing, storage, cloud usage, integration with legacy systems, vendor and licensing fees, security hardening and compliance tooling. Relatedly, operational risks remain elevated, being cited by the highest number of respondents in 2026 as well as in 2024.

Secondly, and relatedly, **cyber security and privacy protection continue to be critical concerns for central banks.** This pattern, already noticeable in 2024, is even more evident today, suggesting that the introduction of algorithmic biases into decision-making is becoming a growing issue

(Graph 16). Perhaps more striking is the shift observed over the past two years for the other related risks associated with AI usage, with IT costs and dependence moving sharply up the ranking.

Technological risks rise as operational risks remain elevated

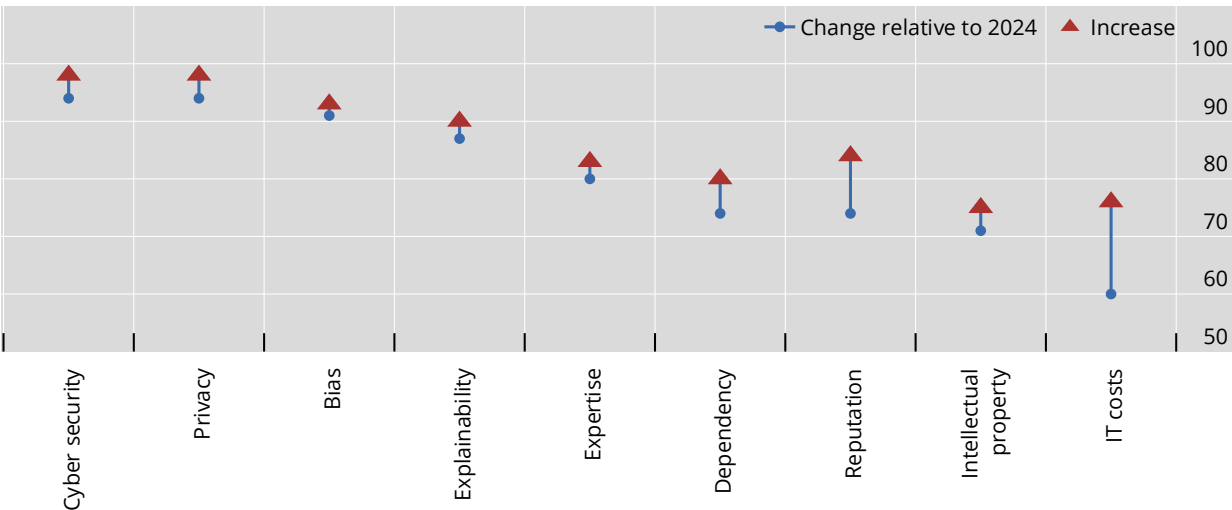
In per cent of respondents Graph 15



The categories are operational (addressing resiliency risks, budget and regulatory issues); institutional (institutional agility, culture, ethics and leadership); human resources (skills shortage and talent retention); and technological (system integration and technological solutions).
Sources: IFC survey on AI (2024, 2026); authors' calculations.

Cyber security and privacy remain the top risks related to AI usage in central banks, while concerns about IT costs and reputation have been rising markedly

In per cent of respondents Graph 16



Sources: IFC survey on AI (2024, 2026); authors' calculations.

Thirdly, **central banks' reliance on external AI providers appears to have been expanding, resulting in increased reported risks related to excessive and concentrated third-party dependence.** Two main patterns have indeed emerged. On the one hand, reliance on a few providers for general purpose AI applications looks high, presumably reflecting the ease of integrating their products in existing internal systems. On the other hand, while the use of frontier AI models for task-specific applications appears more diversified, the supply of the related products seems to be limited to a few firms (cf Graph 11.C above). These two features arguably put a premium on adopting more open, interoperable solutions and common protocols to avoid lock-in, especially in emerging market economies (OECD (2026b); World Bank (2026)).

Finally, **concerns related to human resources remain high** (Graph 15.A), though they appear to be broadly stabilising or even easing over time as regards certain aspects. Most respondents continue to rank skills shortage as the highest risk, reflecting the need to build adequate expertise to keep pace with technological developments. However, compared with 2024, concerns about talent retention and, even more, leadership appear to ease, consistent with earlier findings that central banks are adapting their workforces to leverage AI (Graph 15.B).

Broader governance and ethical challenges

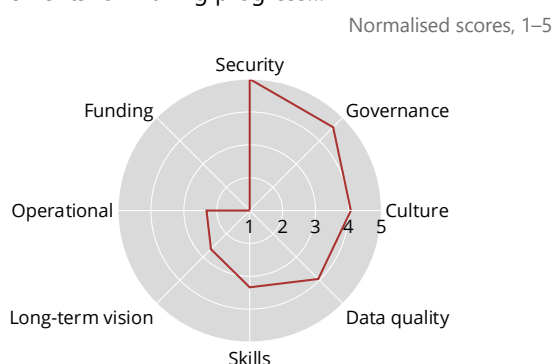
Perhaps more fundamentally, central banks identify two main challenges related to governance and ethics.

The first one is governing increasingly autonomous AI while securing effective human oversight, proper data quality frameworks and adequate security measures (Graph 17.A). These considerations are even more relevant as agentic AI – which can perform complex tasks with limited human oversight – becomes more widely adopted. Mitigating the associated risks requires controls such as human-in-the-loop mechanisms and “kill switches” to halt autonomous processes (FSB (2026)). Moreover, it calls for fostering an appropriate organisational culture supported by effective leadership and literacy, particularly to develop skills required to critically assess and question AI-generated outputs, not least to reduce hallucination risks. Perhaps even more significant is the necessity to adapt information classification to enforce compliance, including by AI agents (CGRM (2025)). While the need for these mitigation factors is clearly recognised, the survey shows that nearly half of central banks are still in the early stages of implementing them, with fewer than 10% approaching completion (Graph 17.B).

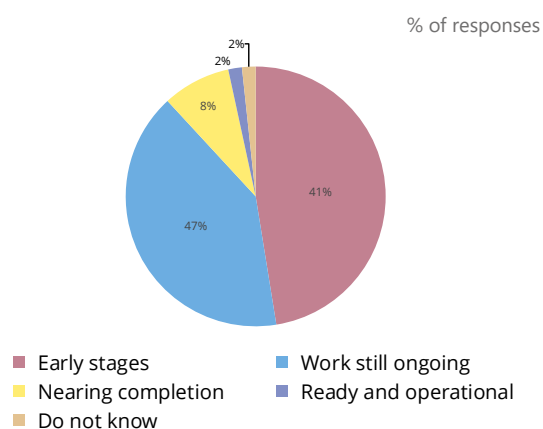
Security, governance, culture and data quality are key dimensions to advance AI readiness

Graph 17

A. Security, governance, culture and data quality are key requirements for making progress...¹



B. ...yet work to attain full AI readiness is mostly at early stages

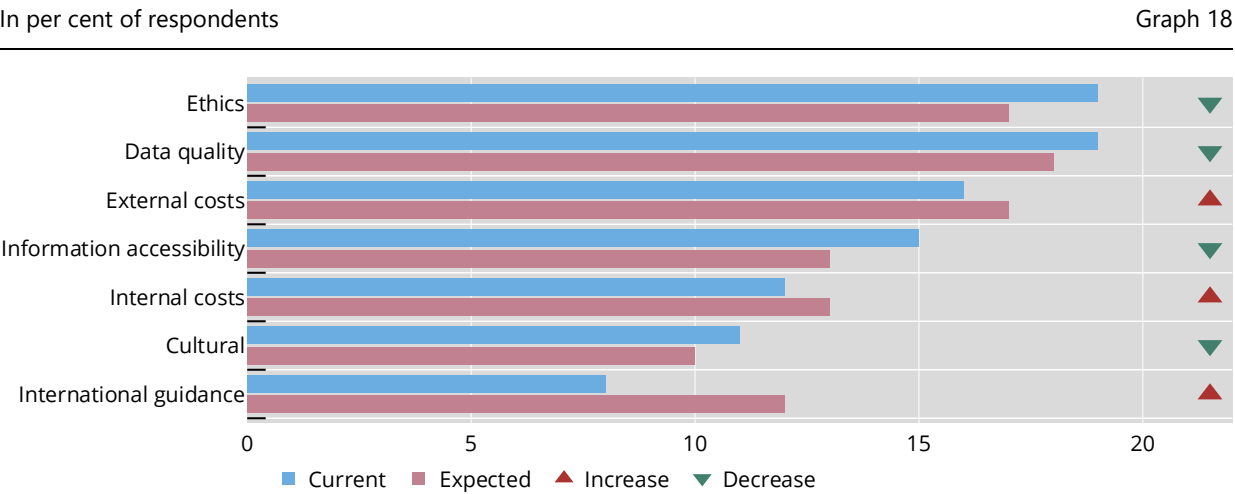


¹ Normalised scores from 1 to 5 (1 = not sure; 2 = not impactful at all; 3 = slightly impactful; 4 = moderately impactful; 5 = highly impactful).

Sources: IFC survey on AI (2026); authors' calculations.

The second challenge is managing the ethical and information reliability issues associated with AI use, which are identified by central banks as the most significant hurdles (Graph 18). Ethical concerns, in particular, revolve around potential biases introduced or amplified by AI models, calling for guardrails to mitigate the associated (reputational) risks and ensure the responsible and ethical use of AI tools across the institution. More broadly, these concerns also reflect the need to preserve those human-centred principles, such as autonomy, accountability and judgment, that are key elements underpinning central banks’ policy-making (Koroye and Alaekwe (2025); Brunnermeier (2026); MacFeely and Ward (2026)). Fortunately, central banks anticipate that most of these challenges may ease as relevant standards and frameworks are progressively developed, including at the international level.

The primary challenges for organisational AI readiness are ethics and information quality, although concerns over costs are expected to grow



An increase (decrease) indicates that the challenge is expected to become more (less) of a concern in the future.
 Sources: IFC survey on AI (2026); authors’ calculations.

5. Advancing AI readiness in central banks: focus areas

Key organisational priorities for an effective and responsible use of AI

As AI use becomes widespread, central banks increasingly recognise the need for further efforts to strengthen the frameworks developed for its effective adoption, prevent the excessive burden posed by rising IT costs as well as deepen international cooperation on standards and knowledge-sharing.

A key priority is to **continue advancing frameworks allowing for responsible AI use, with three main areas to consider**. Firstly, there is merit in establishing clear decision boundaries to identify areas where AI may be used, where it remains unsuitable and where human control is essential. For example, AI could assist with coding or information retrieval, while human approval would remain mandatory for policy work. Secondly, continued efforts could be devoted to strengthening human capabilities, for instance by investing in interdisciplinary expertise across areas such as data science, statistics, analysis and cybersecurity, as well as by preserving staff’s critical thinking and verification skills (OECD (2026e)). Thirdly, more resilient, interoperable and independent technology infrastructures can be achieved by diversifying reliance on model developers, cloud providers and other technology suppliers; adopting open standards, interoperability measures and contingency arrangements; assessing the

implications of deploying and maintaining AI models internally; and regularly reviewing technological developments to ensure that investments remain aligned with organisational needs (IFC (2026)).

Another related priority is to **alleviate the burden posed by AI-related costs**, which are expected to rise further as central banks expand their capabilities and invest in advanced technologies. A number of solutions could help in this regard. First, *AI tokenomics* – an emerging framework to analyse model consumption – can optimise the allocation of AI resources, in turn reducing costs (Bergemann et al (2025)). Furthermore, the development and adoption of *open source* and/or *open weight* models could, in addition to improving operational resilience, dampen costs, for instance by providing accessible and scalable solutions that reduce dependence on exclusive or proprietary systems (Box A). Finally, faster AI development will arguably unlock new productivity gains, with potential savings for adopting institutions

Box A

AI openness: benefits for central banks

AI openness has become an increasingly important topic as new technologies become more integrated with central banks' operations and policy functions.

AI openness is a broad concept encompassing different degrees and forms of access. On the one hand, it can refer to "*open source* AI", that is, an AI system whose code, data and model parameters can be used, studied, modified or shared freely.^① On the other hand, AI openness is also – and increasingly – associated with AI models whose trained parameters (called "weights") and, to some extent, training data, are made available for download and local deployment, although the underlying data and code may not be fully accessible. These "*open weight* AI models" have proliferated in recent years, reportedly representing over half of commercially available AI models as of 2025.^②

For central banks, greater openness in AI can offer several potential benefits. First, these models are often cost-effective, featuring a better quality-to-price ratio compared with proprietary ones.^③ However, this cost advantage ultimately depends on the scale of use and the availability of technical expertise and infrastructure needed for deployment. Second, open weight models can enhance reproducibility, interoperability and integration with existing systems, in turn allowing central banks to adapt their projects to specific institutional needs and use cases. Third, access to model components can facilitate greater scrutiny, testing and customisation of safeguards, even though it may also raise specific risks, such as malicious use, model weaknesses, data leakage or other security vulnerabilities. Finally, a wide range of AI models and providers can contribute to supply diversification – enhancing operational resilience, improving competition and reducing dependencies on a few providers, including for sovereignty purposes. However, it must be noted that the supply of open weight models and of the underlying AI infrastructure has so far remained concentrated in a few countries and firms. Moreover, deploying such models securely may require complex and costly infrastructure and technical expertise. These considerations are particularly important for central banks, which handle highly sensitive information and perform critical policy functions.

Beyond AI models, the concept of openness also encompasses data. In particular, the availability of high-quality data – including in terms of sufficient volume, uniqueness, variety, granularity and reliable metadata – is essential for developing effective AI applications. But there are increasing restrictions on data availability, for example due to stricter information protection regulations, a general push to reduce reporting burden, as well as growing sovereignty concerns that hinder (cross-border) data-sharing. While these restrictions can be legitimate, they also risk creating barriers to innovation and collaboration, possibly leading to higher costs. This puts a premium on striking an adequate balance between protecting sensitive information and effectively enabling the advancement of AI systems.

The challenge is therefore not to maximise openness irrespective of the risks, but to establish appropriate frameworks that enable secure and responsible access to data, AI models and tools. Greater use of common standards, privacy-preserving techniques, trusted data-sharing arrangements and cooperation could help in this endeavour. Such measures would strengthen the central banking community's capacity to develop AI while limiting unnecessary duplication, costs and dependence on individual providers.

^① For example, see OSI (2025). It should be noted that the definition of open source AI remains a topic of debate, not least because AI systems are much more complex than traditional software (to which the term "open source" is typically applied). The classification of open source AI also involves various licensing considerations, which have not been fully standardised at the international level thus far. ^② OECD (2025b). ^③ OECD (2026b).

as well as a decline in the quality-adjusted prices of AI models (André et al (2025)) – though this will also depend on the degree of actual competition in the global AI supply chain, especially in terms of diversification and access to critical resources, such as computing power, data and cloud infrastructure (Gambacorta and Shreeti (2025); Frost et al (2026)).

A third priority is to strengthen international cooperation, **reflecting the fact that AI is a global phenomenon deserving coordinated efforts**. This is particularly important to tackle issues related to cross-border data sharing, the implementation of common information standards and interoperable systems, as well as the exchange of best practices to optimise resources. It would also enable central banks to use AI more effectively, by promoting the exchange of concrete use cases and tools, as suggested by the BIS Open Tech initiative. Collaboration through international fora, such as the BIS and the IFC, can also support the sharing of knowledge and facilitate responses to emerging AI-related risks among central banks, supervisors, international organisations, statistical offices, academia and the private sector.

Making data AI-ready: establishing a robust information infrastructure

The second key aspect identified by central banks for advancing AI readiness relates to data, with at least two priorities.

The first one is to **ensure that organisations' data, particularly unstructured types such as documents, can be effectively and securely accessed by AI systems**. Achieving this requires the establishment of robust data quality frameworks as well as the adoption of interoperable information standards to facilitate machine-readability and actionability. A key focus point highlighted by the survey is to enhance the information about the data (ie metadata). These should be clearly defined with adequate taxonomies, context knowledge and classification policies, including to mitigate hallucinations by models and, more broadly, safeguard data protection (Graph 19.A). Another important action point is to ensure that available data sets are accessible, discoverable and findable by AI machines, for example through *model context protocol* (MCP) and robust semantic layers, such as knowledge graphs or ontologies (OECD (2026d)).⁴ Solutions can also include securing appropriate data lineage, provenance and traceability, for example through adequate data version control techniques.

Fortunately, **ongoing international initiatives and the long-standing expertise of official statisticians (including in central banks) in general data management issues can provide valuable support**. For example, the well-established SDMX standard already offers a solid framework for ensuring interoperability of statistical information (IFC (2025b)). Additionally, AI itself can assist in producing and classifying data (including their associated metadata), potentially creating a virtuous cycle of continuous improvement (Sirello et al (2025)). For most surveyed central banks, however, initiatives to prepare data to be AI-ready are still ongoing or at an early stage, and progress will require substantial work and resources to establish the necessary data infrastructure, standards and frameworks (Graph 19.B).

The second priority centres on **making data AI-ready for use and reuse by (third-party) AI systems**, which increasingly act as conduits of information in the public discourse. Central banks, along with statistical offices and international organisations, have a keen interest in ensuring that their publicly disseminated data can be accurately (re)interpreted, (re)distributed and (inter)mediated by machines (Araujo et al (2026)). If not, there could be a risk of misinterpretation or even misinformation, which may not only undermine trust in their ability to pursue their public mandates, but also blur general economic analysis, threaten global financial and monetary stability and, in turn, lead to broader societal challenges (Hernández de Cos (2026); Nahmias (2026)). These risks call for rapidly and actively enhancing the data function in central banks to better adapt to the increasing role of AI as producer, mediator and user of reference information in society for the public good.⁵ Additionally, further strengthening central banks'

⁴ In the context of information science, ontology refers to a system of representations, concepts, properties and relations between data, concepts or, broadly, entities.

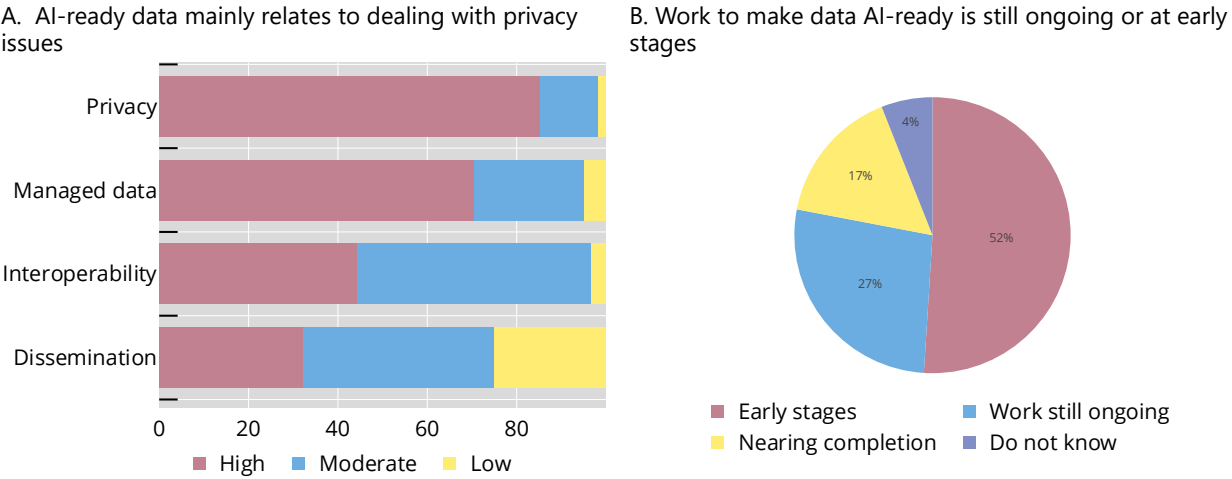
⁵ On the concept of reference information or semantic capital, see Floridi (2018).

quality frameworks is warranted to ensure that, even when mediated by AI, the information they produce continues to conform to well established – including international – principles (UNECE (2025); Rusev et al (2026)). This requires clear traceability, terms of use, versioning and integrity rules for the managed data.

Making data AI-ready, especially by addressing their protection, is a priority

In per cent of respondents

Graph 19

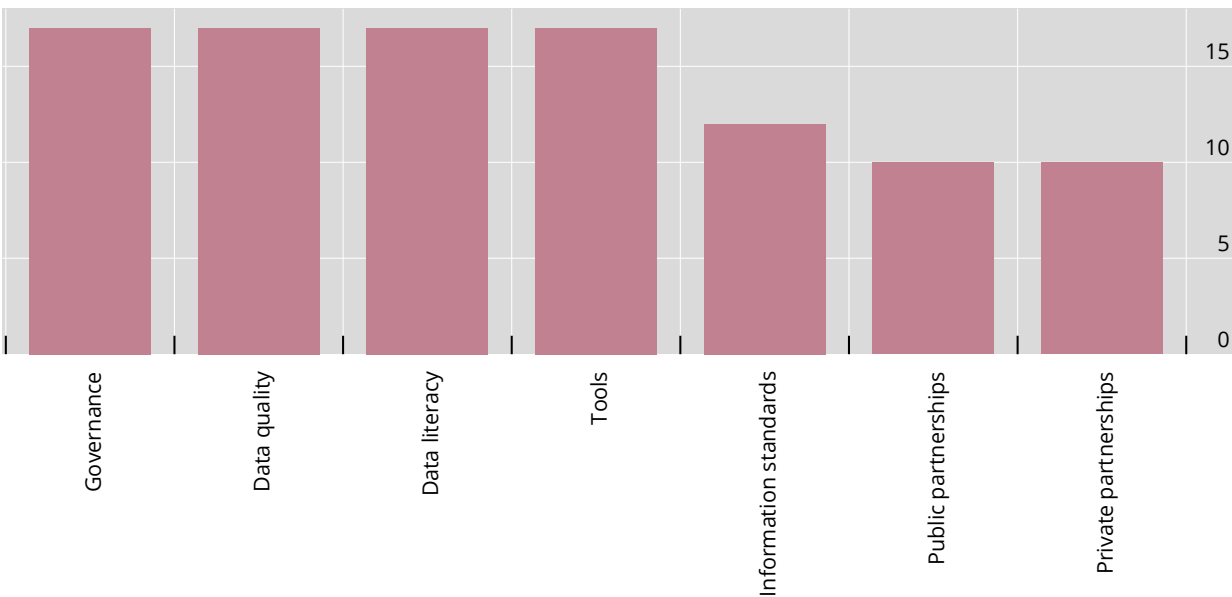


Taken together, the above considerations highlight the importance of further advancing data governance, quality and literacy. Strengthening these areas will ensure that the information curated by central banks can be used by AI effectively (Graph 20). Perhaps more importantly, it will also enable them to fully harness AI potential in a secure, ethical and responsible manner.

Governance, data quality, literacy and IT tools are needed for making data AI-ready

In per cent of respondents

Graph 20



Glossary

This glossary defines the key terms used in this report, with the recognition of the need for ensuring coherence and consistency with previous IFC publications⁶ as well as other authoritative international sources.⁷

Agentic AI: systems designed to act autonomously to perform complex tasks, often making decisions based on their programming and objectives with limited human oversight.

AI-ready data: data that are suitable for consumption by AI systems and models, such as LLMs. Key dimensions for readiness include quality, interoperability, accessibility and compliance (both ethical and legal).

AI capabilities: resources of an organisation to effectively use AI in its operations, decision-making and strategic objectives. Capabilities typically include data, technological and human resources.

AI readiness: state of preparedness of an institution to adopt, adapt and advance AI in its operations, decision-making and objectives.

AI readiness (actual): reported state reflecting the actions, capacities and capabilities to use, govern and implement AI. It contrasts with perceived readiness.

AI readiness (data): state of preparedness of an institution to manage its information assets to ensure the effective, secure and responsible use of AI.

AI readiness (organisational): state of preparedness of an institution to use, govern and implement AI by having integrated frameworks, capacity (ie sufficient resources) and capabilities.

AI readiness (perceived): state reflecting an institution's assessment of its own preparedness. It contrasts with actual readiness.

AI tokenomics: framework to manage and optimise the consumption of tokens by generative AI models.

Artificial intelligence (AI): computer systems capable of performing tasks that normally require human intelligence, for instance by inferring how to generate outputs from the inputs they receive. It includes applications such as machine learning (ML) and generative AI.

Computer vision: systems able to process and interpret visual inputs such as images. Common applications include image understanding, visual search and mapping, often relying on tasks such as object or event detection and image classification.

Generative AI: subset of AI that produces new content, such as text, images, audio or video, based on patterns learned from existing data (or "training data"), usually in response to a user's prompt.

Large language models (LLMs): AI models trained on vast amounts of text data with the goal of generating human-like language. These models are designed to perform a wide range of natural language processing tasks, including summarising, translating, answering questions and interacting with users.

⁶ For example, IFC (2022, 2025a, 2026).

⁷ For example, FSB (2017, 2026); OECD (2024a, 2025c).

Machine learning (ML): method of designing algorithms – sequences of actions to solve a problem – that improve automatically through experience, with limited or no human intervention.

Model Context Protocol (MCP): open framework and standard that enables the integration of AI systems with selected external software and data sources.

Open source AI models: AI models whose components, such as the training code, data or architecture, are made publicly available for use and/or modification.

Open weight AI models: AI models whose trained parameters, or “weights”, and, to some extent, training data, are made available for download and local deployment. The underlying data used for training as well as the code may not be fully accessible.

Retrieval-augmented generation (RAG): technique aimed at improving the quality of LLM responses by integrating relevant context from specific knowledge sources for each user prompt, offering the possibility to select only reliable and well defined information sources for the generation of responses.

Small language models (SLMs): AI models similar to LLMs, but with significantly fewer parameters and trained on less data. While their smaller size reduces their capabilities compared with LLMs, SLMs are less computationally intensive and can often serve more specialised roles in specific domains.

Taxonomy: classification process to arrange information into groups or categories, for example following a hierarchical order. Taxonomies are often used in social sciences, including economics and statistics, to classify domains or activities.

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

Scope

- 1. AI is a broad concept that can take various forms. Please select the option(s) that most apply to your institution and quantify its usage. (*)** (Please leave empty if not applicable):

	High	Moderate	Low	Not sure
General purpose AI solutions	☐	☐	☐	☐
Narrow AI/ML models for tailored applications (eg forecasting, sentiment analysis)	☐	☐	☐	☐
AI coding assistants	☐	☐	☐	☐
AI agents supporting applications (eg search)	☐	☐	☐	☐
Computer vision or speech models	☐	☐	☐	☐
Other (please specify)	☐	☐	☐	☐

(*) Note:

- High: extensive or widespread usage across the institution (eg critical and integral to operations and can be accessed on a large and/or regular basis).
- Moderate: medium usage, mostly by specific teams and/or for tailored purposes (eg important but not critical to operations and can be accessed in specific scenarios).
- Low: limited usage, mostly confined to limited users (eg not important, experimental or auxiliary).

- 2. How does your institution typically access and/or use AI systems (including models/platforms)?** (Please select all that apply)

- ☐ Operational efficiency (eg automating routine tasks such as email drafting, scheduling or document summarisation)
- ☐ Data analysis and visualisation (eg predictive analytics, anomaly detection, statistical applications)
- ☐ Policy support (eg assisting in economic modelling, forecasting and stress testing)
- ☐ Regulatory oversight (eg monitoring compliance, detecting fraud and overseeing financial institutions)
- ☐ Communication (eg drafting public documents, speeches and reports)
- ☐ Other

Interest, expectations and applications

- 3. 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?**

- ☐ 1 (low)
- ☐ 2 (normal)
- ☐ 3 (high)

4. 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?

- ☐ 1 (not discussed)
☐ 2 (moderately)
☐ 3 (extensively)

5. What percentage of the total budget of your institution is intended to finance AI/ML projects?

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

6. 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):

	Highly impactful	Moderately impactful	Slightly impactful	Not impactful at all	Not sure
Monetary policy	☐	☐	☐	☐	☐
Statistics	☐	☐	☐	☐	☐
Research	☐	☐	☐	☐	☐
Financial stability (except prudential supervision)	☐	☐	☐	☐	☐
Oversight of payment systems	☐	☐	☐	☐	☐
Cyber security	☐	☐	☐	☐	☐
Other (please specify)	☐	☐	☐	☐	☐

7. 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):

	Highly impactful	Moderately impactful	Slightly impactful	Not impactful at all	Not sure
Coding and IT development	☐	☐	☐	☐	☐
Analytics	☐	☐	☐	☐	☐
Administrative tasks	☐	☐	☐	☐	☐
Communication	☐	☐	☐	☐	☐
HR-related tasks	☐	☐	☐	☐	☐
Other (please specify)	☐	☐	☐	☐	☐

8. 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

9. 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

Governance and risks

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

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

11. What is your capacity to monitor compliance with the guidelines? Please give examples in the comments.

- ☐ High (ie dedicated teams and robust monitoring frameworks are in place)
- ☐ Moderate (ie some monitoring mechanisms exist, but there are resource or expertise constraints)
- ☐ Low (ie monitoring is limited and shadow use or unapproved tools are difficult to track)
- ☐ Developing (eg monitoring capacity and frameworks are being established)
- ☐ None (ie no capacity currently exists to monitor compliance)
- ☐ Other

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

- ☐ Yes
- ☐ Not yet (ongoing work)
- ☐ No

13. How is the AI governance role implemented in your institution?

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

14. 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

15. 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

Capabilities

16. Which of the following advanced and large-scale (“frontier”) AI models does your institution currently use or plan to use over the next two to three years? Please describe the breadth of their use in the comments. (Please select all that apply)

- ☐ Anthropic Claude
- ☐ Azure AI services
- ☐ Google Gemini
- ☐ Meta Llama models (self-hosted or accessed via a provider)
- ☐ OpenAI
- ☐ Other

17. How does your institution primarily access AI models?

- ☐ External or off-the-shelf
- ☐ External but customised for internal use
- ☐ In-house deployed, self-hosted
- ☐ None of the above
- ☐ Other

18. Does your institution develop and/or customise AI models in-house?

- ☐ Yes (eg fine-tuning, training)

- ☐ Partially (including through RAG systems)
- ☐ No, but planned
- ☐ No, not planned
- ☐ Other

19. If yes or planned, what types of AI models are developed and/or customised by your institution? (Please select all that apply)

- ☐ Machine learning (supervised, unsupervised, reinforcement learning etc)
- ☐ Deep learning (neural networks, generative models etc)
- ☐ Natural language processing (large and small language models etc)
- ☐ Other

20. Which of the following AI platforms does your institution typically use or plan to use (excluding experimental/pilot purposes)? (Please select all that apply)

- ☐ Amazon Bedrock
- ☐ Anthropic platform (including access to Claude models)
- ☐ Application programming interfaces
- ☐ Google Workspace AI
- ☐ Microsoft 365 Copilot
- ☐ None of the above
- ☐ Other

21. Does your institution have dedicated infrastructure for the deployment of AI models and/or development (eg high-performance computing resources, cloud platforms)?

- ☐ Yes
- ☐ No

22. If yes, please briefly describe the infrastructure and its capacity.

23. Does your institution employ specialised AI professionals (eg data scientists, machine learning/AI experts)? Please also comment on the functions they are primarily focused on.

- ☐ Yes
- ☐ No, but planned
- ☐ No, not planned
- ☐ Other

24. What is the share of specialised AI professionals (eg data scientists, machine learning/AI experts) relative to the overall FTEs in your institution (%)?

- ☐ [0, 2.5)
- ☐ [2.5, 5)
- ☐ [5, 10)
- ☐ [10, 20]
- ☐ > 20
- ☐ Do not know

Readiness

25. How important are the following dimensions for your institution to adapt its business, organisation and workforce to leverage AI or be “AI-ready”? (*) (Leave empty if not applicable)

	High	Moderate	Low
Culture, including change management and user adoption	☐	☐	☐
Data quality	☐	☐	☐
Funding and capital availability	☐	☐	☐
Governance frameworks (ethical, legal, risks)	☐	☐	☐
Long-term vision	☐	☐	☐
Operational capacity and staff allocation	☐	☐	☐
Security and privacy	☐	☐	☐
Skills	☐	☐	☐

(*) Note:

- High: the dimension is critical and requires prioritisation as it is essential for achieving organisational objectives.
- Moderate: the dimension is important but not urgent. It requires resources, but its impact on AI readiness is less immediate compared with high-priority dimensions.
- Low: the dimension is not currently a priority or has minimal impact on AI readiness. It may be addressed in the future or requires fewer resources and attention compared with other areas.

26. Based on the definition above, please estimate what percentage of work is complete for your organisation to be “AI-ready” (%).

- ☐ [0, 25) (initial stages or foundational work almost complete)
- ☐ [25, 50) (foundational work fully complete with work still ongoing)
- ☐ [50, 75) (nearing completion, but final adjustments needed)
- ☐ [75, 100] (fully ready and operational)
- ☐ Do not know

27. Does your institution have a strategy (eg including through a dedicated roadmap) to become “AI-ready”?

- ☐ Yes: in place, approved, communicated and funded
- ☐ Yes: drafted but not yet approved and/or funded
- ☐ Maybe: exploratory stage
- ☐ No: not planned

28. If yes, what is the scope of the strategy?

- ☐ Business area-specific (eg tailored to the needs of specific units or functions)
- ☐ Organisation-wide (eg covering all business areas in a top-down approach)
- ☐ Policy-oriented (eg long-term vision, high-level decision-making and strategic direction)
- ☐ Experimental (eg limited in scope to test and evaluate before wider implementation)
- ☐ Time-bound (eg designed for a specific period or milestone)
- ☐ Other

29. If applicable, please comment on your organisation-related strategy versus policy-related strategy goals.

Note: organisation-related strategy focuses on elements such as team collaboration, resource optimisation, day-to-day execution and achieving measurable outcomes. By contrast, policy-related strategy goals emphasise long-term vision, governance, high-level decision-making and strategic direction.

30. What are the main objectives for making your organisation AI-ready? (Please select all that apply)

- ☐ Improve operational efficiency and reduce costs
- ☐ Better support decision-making (eg higher accuracy, timeliness)
- ☐ Enhance information accessibility for users
- ☐ Strengthen regulatory and/or risk compliance
- ☐ Drive innovation
- ☐ Attract and retain talent
- ☐ Other

31. What are the current challenges in making your organisation AI-ready? (Please select all that apply)

- ☐ Cultural and/or organisational resistance
- ☐ Data quality management
- ☐ Ethical and/or regulatory concerns
- ☐ External costs (eg data models, services, platforms etc)
- ☐ Information accessibility
- ☐ Internal costs
- ☐ International guidance
- ☐ IT infrastructure
- ☐ Lack of skilled workforce
- ☐ Security, including cyber security and data leakages
- ☐ Other

32. What are the future challenges in making your organisation AI-ready? (Please select all that apply)

- ☐ Cultural and/or organisational resistance
- ☐ Data quality management
- ☐ Ethical and/or regulatory concerns
- ☐ External costs (eg data models, services, platforms etc)
- ☐ Information accessibility
- ☐ Internal costs
- ☐ International guidance
- ☐ IT infrastructure
- ☐ Lack of skilled workforce
- ☐ Security, including cyber security and data leakages
- ☐ Other

33. To what extent is your institution concerned about talent loss or inability to attract talent due to limitations on access to frontier tools more readily available at private institutions?

- ☐ Extremely concerned (this is a critical issue that could significantly impact the ability of the institution to fulfil its mandate)
- ☐ Moderately concerned (there is a clear risk but not an immediate critical threat requiring urgent action)
- ☐ Slightly concerned (there is awareness but existing measures are sufficient to mitigate this risk in the near future)

- ☐ Not concerned (it is not a significant issue)
- ☐ Other (please specify)

34. Which definition(s) best encompass the concept of “AI-ready data” within your organisation? (Please leave empty if not applicable)

	High	Moderate	Low
Dissemination (eg data optimised for consumption by external AI systems)	☐	☐	☐
Interoperability (eg data that can be used and reused seamlessly across systems)	☐	☐	☐
Privacy-preserving data (eg sensitive information is adequately protected through access controls, encryption, minimisation)	☐	☐	☐
Well documented and managed data (eg metadata, lineage, data catalogue)	☐	☐	☐
Other (please specify)	☐	☐	☐

Note:

- *High: the dimension is critical and requires prioritisation as it is essential for achieving organisational objectives.*
- *Moderate: the dimension is important but not urgent. It requires resources, but its impact on AI readiness is less immediate compared with high-priority dimensions.*
- *Low: the dimension is not currently a priority or has minimal impact on AI readiness. It may be addressed in the future or requires fewer resources and attention compared with other areas.*

35. Based on the definition above, does your organisation have a strategy for “AI-ready data”?

- ☐ Yes: in place
- ☐ Yes: planned
- ☐ No: not planned
- ☐ Other

36. Based on the definition above, please estimate what percentage of work is complete for your data to be “AI-ready” (%).

- ☐ [0, 25) (initial stages or foundational work almost complete)
- ☐ [25, 50) (foundational work fully complete with work still ongoing)
- ☐ [50, 75) (nearing completion, but final adjustments needed)
- ☐ [75, 100] (fully ready and operational)
- ☐ Do not know

37. Which are the core capabilities your organisation finds relevant to make data “AI-ready”?

(Please select all that apply)

- ☐ Data governance
- ☐ Data quality assurance frameworks and processes
- ☐ Data and AI literacy within the organisation
- ☐ Information standards (eg SDMX)
- ☐ Partnerships with official stakeholders (eg statistical offices, international organisations)
- ☐ Partnerships with private stakeholders (eg technology companies)
- ☐ Tools and platforms (eg data catalogues, metadata registries, chatbots)
- ☐ None of the above

Annex 2: List of IFC jurisdictions responding to the survey

- | | |
|---------------------------------------|---------------------|
| 1. Angola | 34. Lebanon |
| 2. Argentina | 35. Lithuania |
| 3. Australia | 36. Luxembourg |
| 4. Austria | 37. Malaysia |
| 5. Bahrain | 38. Malta |
| 6. Bank for International Settlements | 39. Mexico |
| 7. Belgium | 40. Mongolia |
| 8. Brazil | 41. Netherlands |
| 9. Canada | 42. New Zealand |
| 10. Chile | 43. Nigeria |
| 11. Costa Rica | 44. North Macedonia |
| 12. Croatia | 45. Norway |
| 13. Czechia | 46. Peru |
| 14. Denmark | 47. Philippines |
| 15. Dominican Republic | 48. Poland |
| 16. Estonia | 49. Portugal |
| 17. European Union | 50. Romania |
| 18. Finland | 51. Serbia |
| 19. France | 52. Singapore |
| 20. Georgia | 53. Slovakia |
| 21. Germany | 54. Slovenia |
| 22. Greece | 55. South Africa |
| 23. Hong Kong SAR | 56. Spain |
| 24. Hungary | 57. Sweden |
| 25. India | 58. Switzerland |
| 26. Indonesia | 59. Thailand |
| 27. Ireland | 60. Tunisia |
| 28. Israel | 61. Türkiye |
| 29. Italy | 62. Ukraine |
| 30. Japan | 63. United Kingdom |
| 31. Kazakhstan | 64. United States |
| 32. Korea | 65. Viet Nam |
| 33. Latvia | |