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Integrating Non-traditional Data and AI into Central Banking: A Canadian Perspective

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Integrating Non-traditional Data and AI into Central Banking: A Canadian Perspective*

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Abstract

Rapid advances in artificial intelligence (AI)–including machine learning, natural language processing, and generative AI –are expanding the ability to extract meaningful insights from non-traditional data sources such as text, speeches, images, and real-time transactions, thereby strengthening policy analysis and operational decision-making. These tools also enable more sophisticated analytical approaches to the study of economic dynamics while creating opportunities to improve efficiency across institutional processes and operations. This paper documents the growing use of non-traditional data and AI at the Bank of Canada and their contribution to deeper insight and operational effectiveness. The experience highlights critical considerations for accelerating the responsible integration of AI into central banking functions, including evolving ways of working and career paths, fostering a robust ecosystem for innovation, and addressing emerging risks. A successful AI strategy must balance innovation with trust, transparency, security, reproducibility, sound model governance, data residency, and effective operational risk management.

Keywords: Artificial Intelligence, AI Strategy, Granular Data, LLM, Central Bank

JEL Codes: C45, C55, C88, O33, M15, L23

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Introduction

The analysis of data lies at the core of evidence-based decision-making in central banks, underpinning monetary policy decisions as well as the management of financial systems and central bank operations. This has led central banks to develop a suite of increasingly sophisticated analytical tools that draw on a wide range of data sources to inform decisions. In recent years, advanced analytical techniques – including tools that underpin artificial intelligence (AI) – have expanded the set of usable data sources (Macklem, 2024; Varian, 2014; Bok et al., 2018; Brault et al., 2024; Haghighi et al., 2025), with the COVID-19 pandemic accelerating investment in alternative data sources (Chetty et al., 2020; Duprey, 2020; Chapman and Desai, 2020; Foroni et al., 2022). The rapid recent progress in AI – particularly the striking progress in Large Language Models (LLMs) – has the potential to accelerate the development of new analytical tools and reshape ways of working at central banks.

This paper reviews the growing use of non-traditional data and advanced AI techniques in central banking in recent years, with a focus on developments at the Bank of Canada, and provides a strategic framework for integrating AI into central-bank analysis and operations. Although AI is often closely associated with LLMs, the underlying technology is rooted in machine learning (ML) and other statistical models that support a wide range of analytical tools. The recent experience illustrates the potential impact of these new tools for better informing policy decisions and also highlights some of the key adaptation challenges that central banks will face in making effective use of such tools. In doing so, we also discuss how these forces should help frame a strategy for the adoption of artificial intelligence.

Rapid advances in AI build on the ongoing digitization of society. Digitization has enabled central banks to tap into vast and diverse data sources beyond conventional statistical frameworks. The ongoing data revolution – driven by exponential growth in computational capabilities and digital connectivity – has given rise to so-called "big data," characterized by the "three Vs": volume, variety, and velocity. These data are often generated in real time and originate from a broad array of sources, including financial transactions, social media platforms, satellite imagery, videos, and textual content (Gandomi and Haider 2015). Ongoing advancements in AI tools are lowering the costs of constructing and analyzing non-traditional data sources, enabling a further increase in volume, variety, and velocity of data. These ongoing innovations are leading to an increased volume of data which can be generated at significantly higher velocity – often updating in real-time or near-real-time – as opposed to traditional quarterly or monthly cycles.

Collectively, these innovations offer new opportunities to enhance economic monitoring, detect emerging risks, and develop more responsive and nuanced policy interventions (Varian 2014; Einav and Levin 2014b; Bok et al. 2018; Kapetanios and Papailias 2018; Buono et al. 2017). These data sources and the AI tools used to analyze them are enabling a more dynamic and responsive view of economic and financial conditions, and are transforming how central banks analyze, interpret, and use timely data to make informed policy decisions (Varian, 2014; Einav and Levin, 2014a;

Athey, 2017; Mullainathan and Spiess, 2017; Chakraborty and Joseph, 2017; Athey and Imbens, 2019; Desai, 2023). A key advantage of AI tools is their suitability for large and complex datasets, which is enabling the identification of patterns, anomalies, and predictive signals that traditional econometric models may overlook (Coulombe et al. 2021; Bishop 2006). ML-based models are improving the accuracy of nowcasting and forecasting (Richardson et al. 2020; Chapman and Desai 2023), while tools such as natural language processing (NLP) enable central banks to extract economic insights from unstructured text sources, including news articles, earning-call transcripts, executive speeches, and social media content (Duprey et al. 2022; Alexopoulos et al. 2024; Angelico et al. 2022; Gosselin and Taskin 2023). Moreover, AI-driven models are being applied to improve operational efficiency by detecting anomalies in financial transactions, estimating payment-system policy functions, and automating cash-management processes (Desai et al., 2025; Castro et al., 2025; Aldasoro and Desai, 2025).

The integration of advanced analytical techniques with non-traditional data sources that has taken place has helped sharpen analytical insight, increase the timeliness and precision of information, and supported more agile, evidence-based responses. They also enable central banks to better identify emerging structural shifts, such as those driven by digitalization, climate change, or evolving consumption patterns. These tools proved especially useful during the pandemic when timely and granular data was of particular value for policy. These methods enhance risk monitoring and contribute to strengthening the overall resilience of the financial system.

The past investments in analytical tools and non-traditional data by the Bank of Canada point to several key lessons that should help shape the strategic adoption of AI tools at central banks. First, it is essential to build both the infrastructure and the capacity to manage and analyze new data sources. Second, to free up resources for investment in data and analytics, it will be important to use AI tools to find operational efficiencies. Third, bringing new tools and data to inform policy in a timely way requires developing not only the deep expertise to manage and use these tools but also a systematic approach on how to bring the insights from research into the policy process.

The rapid advancements in AI mean that the benefits of further integrating non-traditional data and advanced analytics into central banking are substantial. We outline a broad agenda for the effective adoption and use of AI tools. Commercially available tools to stream line operations — ranging from efficiencies in managing files, meetings, resources, and procurement — should be quickly adopted. Since several aspects of the operations side of central banks is similar to many other corporate operations, this should largely involve a buy and adapt strategy. In contrast, tools for economic analysis are likely to be undersupplied by private firms due to the small and specialized size of the market. This means that central banks will need to develop deep staff expertise in their use. In an era of tight budgets, this means that central banks will face pressure to cooperate to share the development of new tools.

The experience with non-traditional data also highlights that central banks will need to pay close attention to data quality, privacy, and the ethical use of AI. Alternative data sources often

lack the standardized methodologies and definitional consistency of statistics produced by statistical agencies. These challenges are amplified by AI tools, which often feature an evolving training corpus that makes past results hard to replicate and compounds the lack of methodological standardization. The use of complex and opaque AI models introduces additional risks, including diminished transparency, potential algorithmic bias, and overreliance on automated decision-making processes. These risks, if left unaddressed, could undermine the credibility of policy decisions and erode public trust (Varian 2014; Athey and Imbens 2019; Mullainathan and Spiess 2017; Chakraborty and Joseph 2017; Desai 2023).

To mitigate these risks, central banks must establish strong data governance and model risk management frameworks. This includes implementing rigorous validation protocols, ensuring human oversight, and developing ethical guidelines for the use of AI and non-traditional data. Transparent and accountable use of these technologies is essential to maintain legitimacy and institutional integrity (Athey and Imbens 2019; Mullainathan and Spiess 2017; Crisanto et al. 2024).

These tools can enhance the ability of central banks to understand structural economic changes, anticipate emerging risks, and respond with greater agility and effectiveness. By strategically adopting these innovations, grounded in responsible governance and ethical practice, central banks can better navigate the complexities of the modern economy.

The following sections explore examples of how non-traditional data and AI are being applied in central banking contexts. Through a series of examples and insights from the Bank of Canada, we examine how these tools are being used to enhance research, improve decision-making, and address evolving challenges across the financial system.

The Bank of Canada's Ongoing Engagement with AI and Nontraditional Data

The Bank of Canada has a long-standing engagement with non-traditional data sources and AI tools, reflecting a gradual, yet deliberate, evolution in its analytical and operational capabilities. This section examines the Bank's initial forays into AI and non-traditional data, and how these efforts align with broader trends in the central banking community.

The adoption of AI techniques within central banks has generally served two primary purposes. First, they have been used to deepen analytical insight by enabling more accurate and comprehensive use of both traditional and novel data sources. This is creating new opportunities to enhance economic monitoring, detect emerging risks, and develop more responsive and nuanced policy interventions (Varian 2014; Einav and Levin 2014b; Bok et al. 2018; Kapetanios and Papailias 2018; Buono et al. 2017). Second, AI tools are being adopted to improve efficiency and organizational resilience by automating processes, reducing manual burden, and accelerating decision-support functions.

The combination of AI tools and the ongoing digitalization of economic activity is leading

to new data sources that can enhance economic monitoring. These alternative data sources — highlighted in Figure 1 — can be utilized to provide granular, high-frequency insights into localized economic dynamics, consumer behavior, and evolving market sentiment. For example, payments transaction data can offer timely and disaggregated indicators of consumption trends (Verbaan et al. 2017; Chapman and Desai 2020; Dahlhaus and Welte 2021; Chapman and Desai 2023). Satellite imagery can be used to monitor economic activity in real-time, for example agricultural output, port operations or cement plant production, which can provide early signals of supply-chain disruptions, shifts in trade flows, or changes in overall production activities (Donaldson and Storeygard 2016; d'Aspremont et al. 2025). Likewise, mobile phone location data, internet search trends, or data from social media platforms have been used to infer migration patterns, consumer confidence, or even the geographic spread of health crises (Carrière-Swallow and Labbé 2013; Koop and Onorante 2019; Angelico et al. 2022). Similarly, real-time data from platforms like Google Places can track business closures, reopenings, aiding in monitoring economic trends (Duprey et al. 2022), while online job postings offer real-time insights into emerging job market trends (Bellatin and Galassi 2022). Also, tone of voice and facial expressions in executive speeches, such as central bank communications, can be analyzed to study their real-time influence on financial markets alongside the content of the message (Alexopoulos et al. 2024).

Figure 1: A schematic overview of potential sources of non-traditional datasets valuable for central banking research and policy-making.

Figure 2 presents an overview of increasing AI initiatives at the Bank of Canada, including the

number of Bank of Canada working papers leveraging AI methods since 1995. The marked increase between 2020 and 2024 in published research reflects growing interest in the capabilities of AI, particularly as central banks face increasingly digital, complex, data-rich environments. A similar trend is underway in policy and operational work, where AI techniques are increasingly being used to develop monitoring indicators, create support tools, and streamline routine processes.

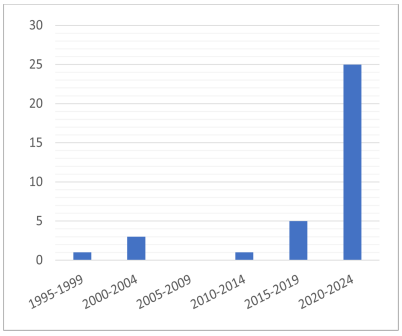
In our economic & financial research	In support of our policy work	To help with our operations
Number of Bank of Canada working papers incorporating non-traditional data, AI /ML methods 	**Customized LLM to analyze text and create sentiment-based indicators:** • Balance of demand and supply sentiment in earnings call transcripts • Oil market news to predict price movements • Financial market sentiment towards Bank announcements **Customized AI assistants:** • LLM engine summarizing views from Bank's speeches, reports, and analysis	**Detect anomalies in regulatory submission data:** • ML identifies anomalies in financial institutions (FI) submissions, fast and reliably **Real-time monitoring of high-frequency data:** • Detect anomalous transactions (e.g., payments, cyber attacks, operational outages) **Cyber operations resiliency:** • ML identifies suspicious internet activity likely to be malware attack on the Bank's network

Figure 2: Increasing trend in AI use

Non-traditional data and AI have been used to provide new and sharper insights to help inform decision making. Table 1 provides a number of examples, many of which have involved the research and data science community. Many of these projects use alternative data – ranging from consumer prices, to credit bureau and regulatory data on credit use, to job posting, and business activity – to offer new insights. To a large extent, this work does not make intensive use of AI tools beyond some machine learning applications in statistical analysis and forecasting and text or sentiment analysis of unstructured data.

In addition to publicly available research, the Bank of Canada has undertaken a number of internal initiatives. These internal projects in support of policy development, economic forecasting, financial system monitoring, and operational modernization generally mirror the trends observed in other central banks, as documented by (Desai 2023). These efforts are supported by the growing availability of cloud-based platforms for AI and broader access to ML, NLP and LLMs. These initiatives have catalyzed deeper collaboration among economists, data scientists, and computer science professionals, strengthening the Bank's capacity for innovation at the intersection of policy, research, and technology. Together, these developments mark a shift from exploratory experimentation to the more purposeful integration of AI as a key tool into our daily work.

Table 1: Applications of AI to Central Bank Research

Central Banking Domain	Example of Publications from the Bank of Canada
Inflation and prices	Cavallo and Kryvtsov (2023) study the dynamics of shortages and prices over the COVID-19 pandemic using high-frequency data on consumer products.
Evaluating policy impact	Allen et al. (2022) examine the effectiveness of debt-relief programs using high-frequency credit data. Bellatin and Galassi (2022) analyze employment demand in relation to the pandemic and technological change using online job posting.
Financial stability	Duprey et al. (2021) identify vulnerable regions in Canada using geospatial data on disasters in conjunction with household financial data. Duprey et al. (2022) build real-time measures of business exit/entry and closures/re-openings using Google Maps data.
Media and CB communications	Alexopoulos et al. (2024) use ML to quantify Fed chair testimony emotions (words, voice, facial expressions) and the real-time market impact. Macaulay and Song (2023) show how engagements with recessionary narratives influence sentiment using Twitter data.
Real-time monitoring	Gosselin and Taskin (2023) analyze earnings call transcripts using NLP tools to produce a real-time measure of economic slack. Chapman and Desai (2020, 2023) conduct macroeconomic nowcasting using payments data and machine learning. Desai et al. (2025) develop a machine learning framework for real-time transaction monitoring for Canada's high-value payment system.

While non-traditional data and AI tools present significant opportunities for central banks, they also introduce new modes of operation, along with associated risks and operational complexities. As highlighted in Figure 3, AI tools span a wide spectrum—from commercially available off-the-shelf products to highly customized, sophisticated models developed for specific use cases. Each tool offers distinct advantages and limitations, and their selection must be carefully aligned with the strategic objectives, risk profile, and technical requirements of a given use case.

The adoption of these tools has brought to the fore the need for robust governance frameworks. The use of (each) new model and data has raised questions about appropriate standards for model validation, transparency, ethical use, and human oversight. Similarly, the uniqueness of AI systems raises questions around strategies in terms of how to account for interoperability, accountability, and vendor transparency. The Bank of Canada has made solid progress in developing a well-structured approach to governance and procurement. There is a recognition that systematic governance structures are needed to ensure that AI applications fulfill operational objectives while also reinforcing institutional integrity and public trust—foundational principles for central banking. A well-designed, risk-based AI governance framework enables an organization to make effective use of the full spectrum of AI options (see Figure 3), while simultaneously mitigating risks and optimizing costs.

	Off-the-shelf Products	Middle Ground AI Development	Highly Sophisticated AI
Examples	• ChatGPT • Microsoft Copilot • GitHub Copilot	• Customized AI assistants • AI trained for limited Proof-of-Concept • Sector-specific AI tools	• Machine learning models specifically developed from the ground up for economic analysis • End-to-end in-house AI platforms
Advantages	• Fastest to adopt • Lowest upfront cost • Well-tested and stable for common use cases	• Higher potential in efficiency gains relative to off-the-shelf tools • Lower development cost compared to sophisticated AI • Better alignment to organizational needs • Customization and guardrails possible	• Can bring in the most insight • Internal ownership of model evolution and capability • Full rights to intellectual property • Maximum customisation and control • Tailored explanation, governance, security, and guardrails possible
Challenges	• Vendor dependence • Access management needed • Limited control over behaviour • Weak alignment with specific use cases	• Needs technical skillset to deploy • Ongoing monitoring and lifecycle management • Some customization and maintenance needed • Cost uncertainty as usage grows	• Substantial technical expertise required • Long deployment and integration timelines • High development and operational cost • Expensive lifecycle management • Greater responsibility for safety, compliance, and controls

Figure 3: Spectrum of AI tools and techniques

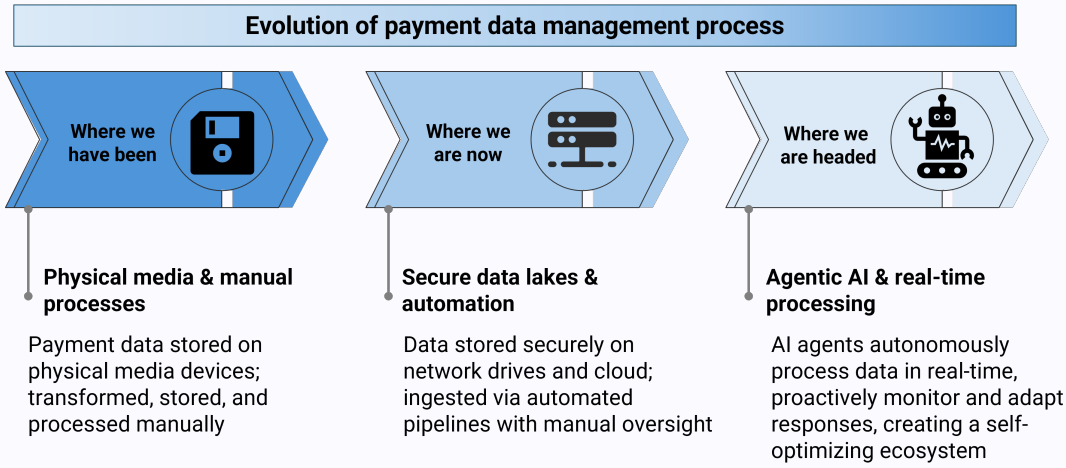
The Bank of Canada has been active in adopting new technologies to support its operations and analysis. In Box 1, we outline two examples of how new technologies are transforming operation at the Bank of Canada.[1] The first examines payments data management, a critical area that en-

[1] Another example is the shift to a digital Monetary Policy Report (MPR), which improves the user experience

capsulates both the operational complexity and the strategic importance of data-driven innovation within central banks. The evolution of payments system data over recent years illustrates the gradual evolution from manual-intensive data collection and analysis towards a more automated and efficient process. The second example highlights how an AI-enabled robotic process automation (RPA) bot to automate digital filing in payment and settlement operations has replaced paper-based workflows, improved accuracy, and freed significant staff capacity for higher-value work.

Box 1: The Adoption of Digital Tools at the Bank of Canada: Payments Data and Operational Automation

The Management of Payments Data: In Canada, historically, payments data collected by Payments Canada was transferred to the Bank of Canada through manual processes. Early workflows relied on hard drives for data storage, with the physical transfer of these drives often taking one to two weeks due to the manual nature of the process. With the advent of secure network drives and increased need for real-time access as well as new ways of working following the COVID-19 pandemic, the data transfer process was streamlined to enhance security and speed, but remained largely dependent on human intervention for data ingestion, verification, and validation.



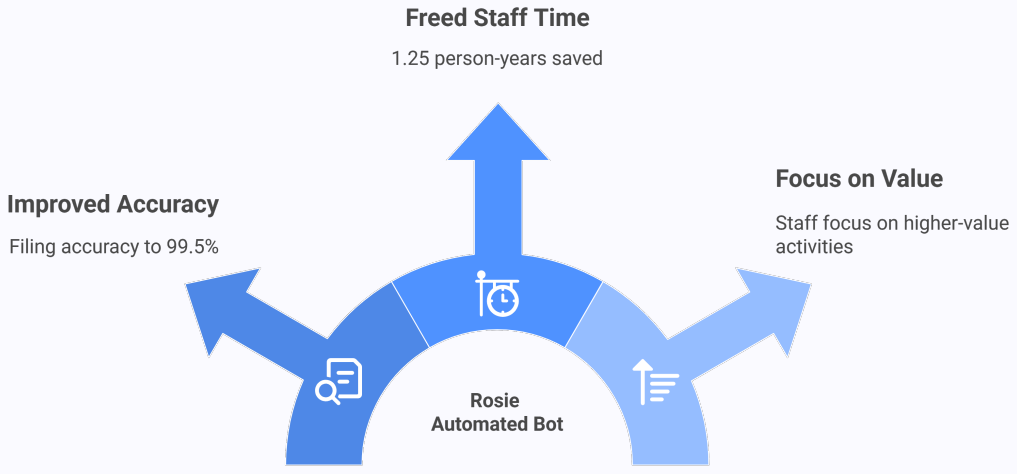
Since then, modern data lake and cloud-based architectures have improved payment data management by automating most of the ingestion process. Automated pipelines now allow rapid, scalable, and efficient data handling, integrating advanced analytics, machine learning algorithms, and near real-time processing into the data workflow. Current processes continue to require manual oversight, particularly when it comes to verifying and validating incoming data to ensure its integrity and accuracy.

and accessibility, while also enabling the use of NLP and LLM tools for analysis. Another example is efforts over several years which have led to a fully operational AI-based pipeline to detect anomalies in financial institutions regulatory submission data (Jones et al., 2026).

Looking forward, the integration of AI agents—a system capable of autonomously planning and executing multi-step processes—promises to further transform these processes (Aldasoro and Desai, 2025). Future data management systems may leverage intelligent agents capable of autonomously ingesting data, performing comprehensive validation, and verifying data integrity with minimal human intervention. These AI agents would continuously monitor incoming data streams, using ML models to detect anomalies and automatically adjust processing parameters in real-time. By taking over routine verification and validation, they could substantially reduce manual work, streamline operations, and enhance data accuracy and reliability. However, human oversight would remain important. At first, humans would handle complex or ambiguous cases, and later help the agents learn how to deal with new types of anomalies. This ensures that automation is supported by proper governance and control.

This journey—from manual, hard-drive-based processes to automated data-lake solutions and now toward an ecosystem enhanced by AI—illustrates how each stage of digital adoption improves existing processes. It also opens the door to more transformative advances in how data is managed, analyzed, and used.

Automate Filing in Payment and Settlement Operations: Another notable example undertaken internally at the bank is Project Rosie—named informally after the robot housekeeper from The Jetsons. The COVID-19 crisis fundamentally reshaped banking operations, shifting activity from relatively low-volume processes to sustained periods of high-volume, high-value transactions under exceptional time pressure. To meet these rising demands, the bank launched a project using RPA, leveraging software that automates repetitive, rule-based tasks.



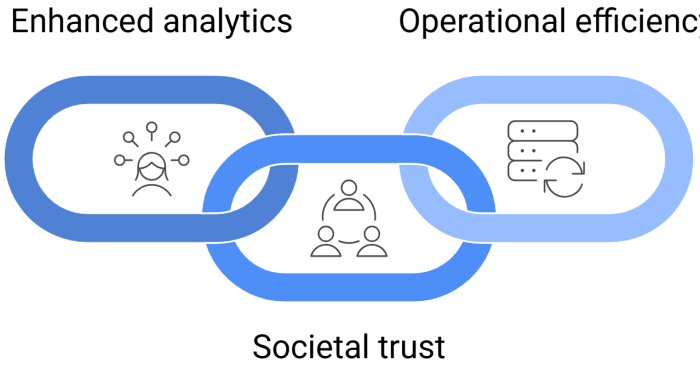
The project introduced a bot to fully automate digital filing in payment and settlement

operations. By replacing paper-based workflows and taking over repetitive, low-value tasks, the bot improved filing accuracy to 99.5 per cent and freed approximately 1.25 person-years of staff time, allowing greater focus on higher-value activities. The initiative required governance comparable to that of a new core IT system, including cyber-security, audit, privacy, and business-continuity reviews, and highlighted the importance of early cross-departmental collaboration and sustained support models. While this initiative was not AI-enabled, building on this success, the bank is now expanding automation and introducing additional AI-enabled tools to further modernize other core operational processes.

Why does AI matter to central banks?

Central banks have been adopting and integrating the use of AI tools and alternative data in their work. This may suggests that there is no need for central banks to develop a strategic approach to AI, but instead to continue with past practices. This view fails to take on board the implications of the rapid acceleration of progress over the past few years. The large investments in both compute and models suggest that AI will continue to progress rapidly and will open new opportunities and challenges for central-bank analysis and operations. To fully take advantage of these changes, central banks will have to make deliberate and thoughtful choices.

The integration of AI into central banking represents both a strategic opportunity and a complex challenge. As stewards of monetary and financial stability, central banks must understand, adopt and shape the responsible use of AI to fulfill their mandates effectively. The combination of AI and alternative data opens up three key dimensions that will shape central banks investment in AI:



1. **Enhancing Analytical Capabilities for Policy and Research:** Timely data and the tools to extract insight from it is essential for evidence-based economic policy. AI has the potential to enhance economic analysis both by lowering the cost of analyzing data and enabling the computation of more complicated models. AI is enabling more nuanced and real-time economic analysis by leveraging large and heterogeneous datasets, including unstructured

sources such as text, audio, and images. Techniques such as natural language processing and machine learning can extract insights from previously untapped information, improving the timeliness and granularity of economic forecasts, inflation monitoring, and labour market assessments. These capabilities augment the analytical foundation for policy decisions in an increasingly complex economic environment. AI tools are also supporting the development of predictive models as well as relaxing the computational limits on decision theoretic models. The impact of these new tools is already visible, as evidenced by predictive models that can detect early warning signals in credit, market, and liquidity risks to support stress testing frameworks and macroprudential surveillance. By uncovering nonlinear relationships and rare-event risks that traditional models might miss, these models can strengthen the capacity of central banks to identify emerging vulnerabilities in the financial system.

2. **Maintaining Societal Trust and Institutional Legitimacy:** Central banks play a critical role in maintaining public trust in the payments and financial systems. As AI is deployed in policy analysis and supervisory oversight, maintaining transparency in how these tools are used—and ensuring that decisions remain aligned with public mandates—is essential. Misuse or misinterpretation of AI outcomes could erode confidence in central banks' independence and judgment. Establishing clear governance principles for AI use, including human oversight, explainability, and equity, is central to sustaining societal legitimacy.

   The integration of AI into financial services challenges existing regulatory approaches in several ways. First, it has highlighted the governance challenges surrounding the ethical use of data and algorithms for decision making. Next, issues of explainability, accountability, and fairness in algorithmic decision-making raise concerns about compliance with existing norms and the adequacy of current oversight mechanisms. For example, if AI tools were used to support supervisory risk assessments by regulators, opaque models could inadvertently prioritize or penalize certain institutions based on patterns that cannot be explained or justified. Central banks therefore need to adapt regulatory frameworks to ensure that AI applications are transparent, mitigate bias, and align with the public interest.

   While AI offers clear benefits, it also introduces new forms of systemic risk. For instance, the widespread use of similar "off-the-shelf" AI models could reduce diversification and lead institutions to react in increasingly correlated ways (herding behaviours) to market signals, potentially amplifying volatility. Furthermore, opaque decision-making processes and increased reliance on external AI providers could weaken resilience and increase cybersecurity risks. The ability of AI tools to allow for "deep fakes" also threatens to make it harder for citizens to identify reliable data and information. Central banks must incorporate these novel risks into their oversight frameworks.

3. **Improving Operational Efficiency and Automation within Central Banks:** AI has the potential to improve productivity in many sectors of the economy. For central banks,

AI-driven tools could streamline internal processes, from document analysis and regulatory reporting to forecasting budget and human resources to meeting management to communication. Machine learning algorithms can recognize subtle patterns indicative of illicit activity, improving the effectiveness of transaction monitoring and cybersecurity. AI systems can be used to enhance supervision and regulatory compliance by analyzing transactional data at scale to detect anomalies and potential fraud. Other areas for operational efficiency gains include internal audit preparations, document classification, briefings, document translations and coding assistance. In all these examples, AI systems can help automate initial drafts for further human reviews, thereby speeding up tedious processes and also lowering barriers to entry in tasks such as coding.

The potential for recent advances in AI to have significant impacts on operations at central banks is increasingly recognized. The 2024 BIS Irving Fisher Committee (IFC) on Central Bank Statistics conducted a survey of 60 jurisdictions on the use of AI within central banks. The results of the survey show that over 90 % of the responding central banks are moderately or extensively discussing AI in their internal discussions (Brault et al., 2024). As well, Figure 4 shows there is agreement that AI will have broad impacts on both central banks operations and policy machinery.

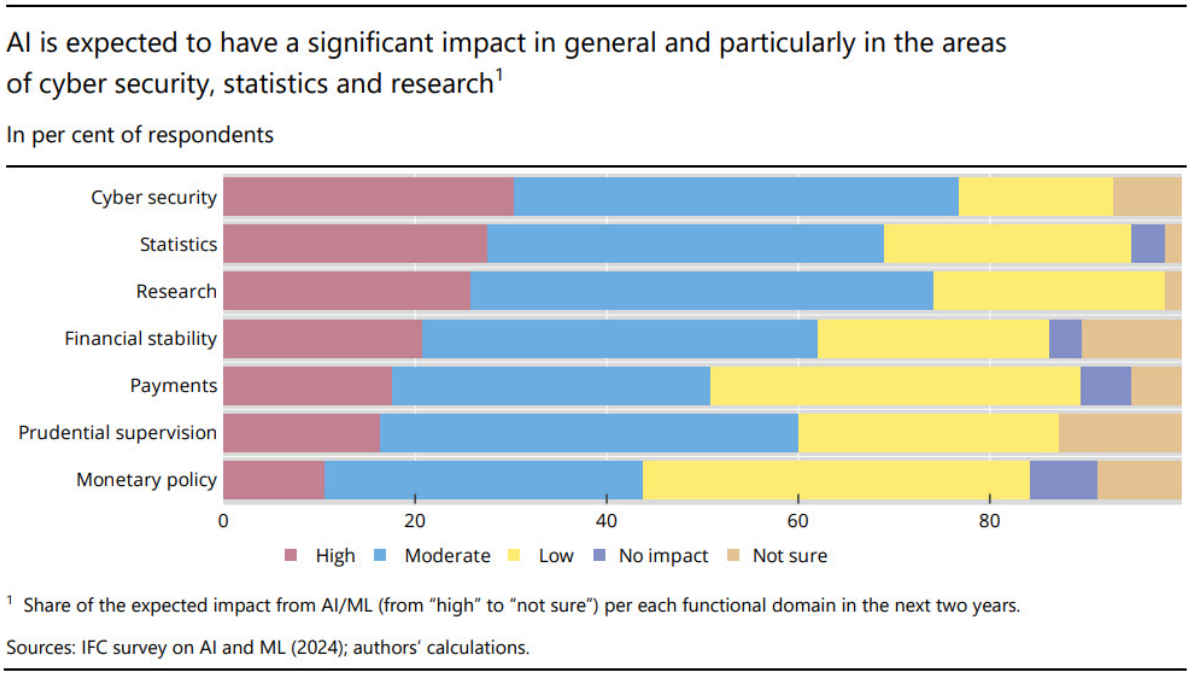


Figure 4: IFC Survey of Central Banks on AI

Charting the path forward: integrating AI into our work

While AI promises to be a transformative technology that will have far-reaching impacts on how work takes place across the economy, much of this impact is yet to be realized. Learning how to effectively use AI will require deliberate experimentation on how to restructure work practices and develop new ways of working. These processes are underway, with several large firms moving to develop new AI-based software products for adoption. Similarly, Kazinnik and Brynjolfsson (2025) argue that LLMs (one form of AI) have the potential to reshape the daily workflow of many jobs at the US Federal Reserve. This seemingly suggests that central banks' AI strategies should focus on how to redesign internal processes for back-office tasks and economic analysis so as to best use commercial software and AI tools.

The breadth of the looming AI revolution means that central banks will be able to adopt commercially developed systems to modernize internal processes. Yet central banks should not be content with remaining passive adopters (see Box 2). Central banks are a major producer and consumer of economic and financial research and analysis. Since specialized economic and financial research applications are a small share of the market for AI related tools, the needs of this community are unlikely to be prioritized by private firms. By coordinating their investments, central banks could accelerate the build-out and adoption of AI tools (OECD, 2024; BIS-IFC, 2025). In addition, as institutions charged with promoting monetary and financial stability, they can play an important role in shaping standards for the safe and effective use of AI in payments and financial markets—provided this is done in close coordination with other financial regulators, supervisors, and relevant authorities (CGRM-BIS, 2025; OSFI, 2023; OSFI-FCA, 2024). This is particularly important since the incentives for private market participants to take into account systemic risks differ from those of a regulator.

Box 2: Why Central Banks Should Strategically Invest in Shaping AI

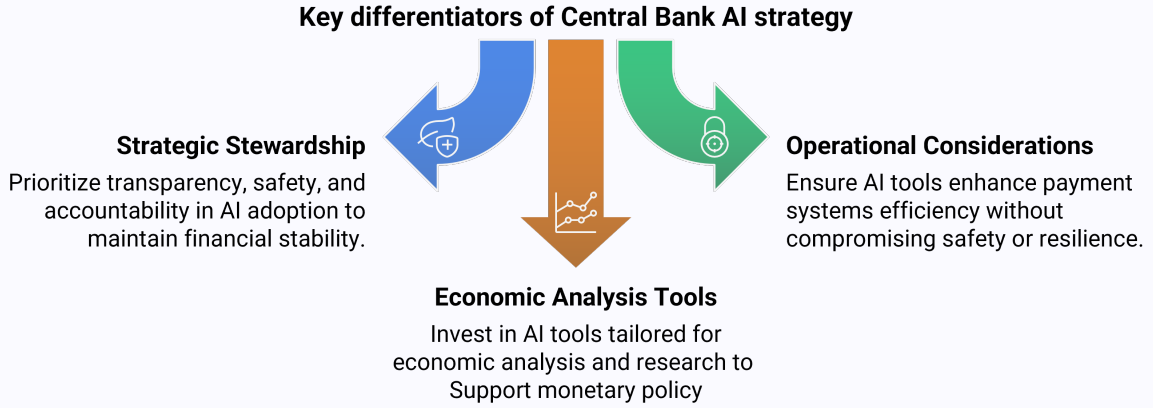
Central banks' AI strategies should internalize the ways in which AI systems differ from private market participants. In particular, three factors can uniquely shape a central bank's approach.

1. **AI Tools that support the unique work of central bank**: Much of the innovation in AI will target larger (profitable) market segments. However, the market for AI tools tailored to economic research and analysis most relevant to monetary policy is relatively small and specialized. In this smaller domain, central banks are relatively large players (i.e., **Big Fish in a Small Pond**). With modest but targeted investments through internal innovation or external collaborations, central banks can shape the standards and development of AI tools suited to support their objectives.

2. **Operational Considerations: Efficiencies, Payments and Security**: Central

banks play a key role in ensuring that the payment system – the essential plumbing of the economy – functions smoothly and reliably. While the adoption of appropriately designed AI tools could improve the efficiency of payments, this cannot come at the cost of increased cybersecurity vulnerabilities or worsened operational resilience. Central banks support innovations in payment and settlement systems that deliver the highest standards for reliability and robustness.

3. **Strategic Stewardship and System-Wide Responsibility**: Central banks are stewards of financial and macroeconomic stability. Although their direct regulatory role varies across countries, central Banks are leaders in identifying best practices for financial markets and payments. As leaders, central banks should model a thoughtful and deliberate approach to AI adoption in terms of transparency, safety, and accountability. In particular, central banks should push for AI tools that are robust, explainable, and reliable, even if this comes at the cost of speed or cost.



A Differentiated Approach from Industry

The three factors outlined in Box 2 above give rise to niches in the AI ecosystem where central banks objectives differ from those of the mainstream private financial and technology sectors. This points to a scope for a strategic approach to AI by central banks that focuses on developing AI tools to support better decisions by monetary policy makers while at the same time increasing the transparency of central bank analysis and encouraging the long-term systemic resilience of financial and payment systems.

Central to this strategy is a recognition of both how the needs of central banks may diverge from more commercially focused developers of AI and where central banks can leverage their strategic investments to have a large impact on development and application in economic analysis, financial stability, and policy design. Unlike industries where decisions must be made in milliseconds (e.g., self-driving cars), central banking policy decisions operate on a lower-frequency but with

potentially high-stakes. For monetary policy decisions, what matters is not marginal milliseconds gains in speed, but rather transparency about how a result was obtained. This means that central banks need to be able to trace model outputs, unpack reasoning steps, and articulate these to stakeholders. To achieve these objectives, a central bank's AI strategy will need to be deliberate in **building human capital and deep expertise** as well in effectively **supporting an innovation ecosystem** that delivers the specialized tools and data needed for its objectives.

Building Human Capital and Deep Expertise

The restructuring of internal workflows to take advantage of AI to automate tasks needs to be accompanied by a plan for central bank staff to build deep expertise in this domain (Bell et al., 2025). Current career paths in central banks often see junior roles learn about the workings of policy models and economic data (and how it is constructed) as a byproduct of routine data analysis and the running of models. However tasks such as preparing regular data updates, basic statistical analysis, literature surveys and running multiple model simulations are well suited for AI to automate (e.g., see (Korinek, 2024; Baily et al., 2025)). While these tasks contribute to building expertise, the efficacy is less clear since much of the time involves repetitive tasks which do not contribute to deeper understanding of data and model. Perhaps even more importantly from the perspective of recruiting and retaining talented staff, a thoughtful approach to building expertise could help close the gap between what workers would like AI to do and what tasks are currently prioritized for automation (Shao et al., 2025).

A promising strategy is to use the opportunity created by automating routine tasks to reallocate staff time toward in-depth analysis- and cognitive-intensive work. This realignment would increase the share of time devoted to longer-term projects that deepen understanding and enable rigorous evaluation of AI model performance in relation to their use by central banks. Because this approach builds expertise through longer-term work, it would also require careful consideration of how to maintain sufficient breadth of experience to develop future policymakers. In practice, this would imply a shift in people management toward more active, multi-year planning of project portfolios.

This reallocation of staff time would also contribute to building the deep expertise needed to unpack the predictions of policy models (i.e., explainability) as well as their suitability for public-sector mandates. The development of new tools and data have facilitated the development of richer models and analysis. While these models deliver important insights, they also require upskilling of users who can unpack what drives the results. Although not all AI models are inherently "black boxes", the intuition behind AI model predictions can often be challenging to parse out for non-experts. In addition, policy decisions need to be based both on the predictions of models as well as the judgment of (expert) policy makers (Agrawal et al., 2022). Investing in building staff expertise on understanding and assessing AI models will both meet the demands for explainability – which is essential to be transparent about the rationale of policy decisions – and provide a structure for the development of early to mid career human capital.

In their publication on AI for risk-based supervision (Dohotaru et al., 2025), the World Bank Group discusses the importance of explainability. Based on their assessment, to build trust, supervisory authorities should prioritize transparency and explainability in AI systems by adopting explainable AI models that offer insight into how decisions are made. They emphasize that regular audits of AI systems for bias, fairness and accuracy should be conducted, with clear accountability structures in place. Adversarial testing is also a useful practice to ensure the robustness of developed AI models, for instance, feeding slightly manipulated inputs to a fraud-detection model to see if it can still flag suspicious activity (Vassilev et al., 2025) . All of these evaluations and tests would require deep technical expertise within central banks (BIS, 2024; Kazinnik and Brynjolfsson, 2025).

Since building in-house expertise is costly, public sector budget pressures are likely to constrain central banks investment in building human expertise while at the same time investing in developing new tools. One option to mitigate these financial pressures is closer collaboration across central banks in the development of new tools and how to unpack the drivers of AI tools and models. For instance, initiatives such as ECONDAT and the BIS Innovation Hub are providing platforms for shared experimentation, knowledge exchange, and joint capability-building in precisely these areas. More broadly, central banks should look to systematically share lessons learned on how to effectively redesign workflow to incorporate AI to increase productivity while developing deep expertise. Finally, by engaging with universities, central banks can help speed up the updating of curriculum to better prepare future graduates for the new work world which would lower the training required for new hires.[2]

Supporting Innovation Ecosystems

Strategic investments and leadership by central banks could accelerate the development of academic and open-source AI research tailored to economics and finance. Korinek (2024) and Eisfeldt and Schubert (2024) outline several ways in which AI tools could be used to support economic analysis and a substantial take-up of LLMs to assist in economic research, including editing and synthesis (Feyzollahi and Rafizadeh, 2025) is in progress.

Although commercially available AI tools should continue to be used, some research suggests that the full power of large language models (LLMs) like GPT can only be realized through domain-specific adaptations and system-level integration (Agrawal et al., 2022). Although experiments like BloombergGPT has shown mixed gains in finance applications, the healthcare field is seeing a surge in tailored LLMs (Meng, 2024). A challenge in the development of LLMs tailored to specific subject domains is access to a large database of subject matter training documents. This suggests that central banks could accelerate the development of tailored LLMs by forming a consortium to share internal economic papers and analytical notes which could be used as a database to train an

[2] ECONDAT community and BIS Innovation Hub are exploring in this direction

economic LLM.[3] To avoid confidentiality concerns, such a tailored LLM could be restricted to use by participating central banks. More generally, central banks may also support projects that seek to develop AI agents to aid in analytical work that is common across central banks. This could help lower the cost of training specialized AI agents.

A second priority area for investment is the development of AI-based tools for economic analysis to enable richer models for policy analysis. One promising direction outlined by Fernández-Villaverde et al. (2024) is using AI tools to relax the computational constraints on economic model related to the curse of dimensionality. Central banks could similarly benefit from domain-specific models—whether to assist in enhancing forecasting or supporting policy simulations through AI agents. The revolution in deep learning (Dell, 2025) has opened up new options for the analysis of unstructured data using LLMs. Central banks should support more research into how to rigorously use these new tools for economic analysis.[4]

There are also two more specific elements that should be included in the strategic plan for central banks. These complementary objectives focus on how central banks can contribute to the important general challenges around **building trust and confidence in the use of AI in economic analysis and monetary policy decisions** and **measuring the impact of AI**.

Building trust and confidence in the use of AI in economic analysis and monetary policy decisions: There is growing concern around the potential misuse of AI to promote false information. As custodians of currency, central banks have long worked to proactively limit counterfeits by designing hard to copy banknotes. A similar role of providing a robust source for reliable economic analysis could become even more important to deal with the risk of "counterfeit economic analysis". This points to scope for central banks to engage with other public bodies on developing a combination of trusted websites for the dissemination of economic data and analysis and their underlying AI models, as well as whether unique watermarks can be added to files for verification and trust. Although central banks will naturally focus their efforts on economic data related to their policy mandates, many of the technical solutions will likely have broader applications.

There has already been AI-based attacks on several central banks via generating deepfake video messages. By increasing their capabilities in detecting deepfakes and increasing their resiliency, central banks can further build trust via a *proactive stance to avoid fake policy announcements or speeches*. Given the rapid pace of developments on this front, the main way to increase this form of resilience for central banks is to start by developing their in-house expertise to remain abreast of the advances.

Measuring the impact of AI: The potential for large impacts on productivity have been suggested by a number of authors (Kazinnik and Brynjolfsson, 2025). Measuring productivity is not easy, particularly when technology leads to new ways of working and new products (Syverson, 2017). Recent advances in AI have revived expectations of transformative productivity gains and

[3] This could also lower the cost of training domain specific LLM, which could be of growing importance of recent decline in the costs of training continue to hold (Baily et al., 2025).

[4] For example, Ludwig et al. (2025) outline some (stringent) conditions for using LLMs in empirical research.

large-scale labour-market disruption. Yet despite rapid improvements in AI capabilities, aggregate productivity growth in advanced economies remains subdued, and widespread job displacement has not yet materialized. This divergence between technological promise and measured outcomes—the "AI productivity paradox"—poses important challenges for policy (Brault et al., 2026).

By thoughtfully developing internal metrics on the impact of AI tools, central banks can both develop the data needed to better manage the use of AI tools and also contribute to better understanding the impact on the broader economy.

From strategy to execution

The combination of large costs associated with developing and applying AI tools and non-traditional data needs means that central banks could accelerate adoption by working together on multiple fronts. Given the diversity of central banks, this will likely see different combinations of central banks cooperating on different initiatives. By working together, central banks can amplify their investments and speed up their learning about how best to use AI tools. In addition, central banks will need to make internal changes in how they work as they experiment with AI tools. A challenge in coordinated projects is that not all central banks will be interested in all topics or projects. This points to a project based approach where the "coalition of the willing" joins different projects.

Central banks should also look to coordinate on developing better tools for economic analysis and model development. Much of this coordination may simply involve being more systematic in sharing AI tools and experiences with new ways of working. This sharing can be done via a combination of a shared repository of tools/software as well as ongoing workshops. However, there is also scope for sharing staff resources for the development of models and tools.

Perhaps most importantly, central banks will need to encourage innovation and adaption of new tools. This will require building (and training) staff with the in-depth **subject matter expertise** required to build and use AI tools. This will require increased use of cross-disciplinary expertise that integrate staff with a deep technical knowledge of AI tools with staff with expertise in economics and the policy mandates. Making these teams work effectively will require investment in targeted training programs for team members to equip them to work together to adapt the evolving capabilities of AI and data science to support central banking priorities.

Central banks will also need to evolve internal processes and ways of working so as to manage the implications of a rapidly evolving AI field. To take advantage of this evolving technology frontier will require a shift to a more agile way of working. This agility will be much needed in both the operational side in IT, procurement and vendor management functions and in the development of policy tools. Below we outline 6 key strategic enablers or "accelerators" that support innovation while safeguarding institutional integrity that central banks should adopt to effectively realize the opportunities presented by AI and non-traditional data.

Accelerator 1: Sandbox Environments for Safe Experimentation Experimentation is essential for unlocking value from novel data sources and AI techniques. Given the sensitivity of

Figure 5: AI Accelerators – steps for driving AI adoption in central banking

central bank operations, establishing a dedicated cloud-based sandbox environment separate from operations is a prudent approach. Such environments allow teams to safely test algorithms on non-sensitive datasets, fostering innovation without introducing operational risk. Sandboxes provide a controlled setting for iterative learning, algorithm development, and feasibility testing.

Accelerator 2: Technology Readiness and Maturity Assessment An essential step in operationalizing AI is evaluating whether a solution is sufficiently mature. Technology Readiness Levels (TRLs), originally developed by NASA, offer a structured framework for assessing technological maturity. Central banks can adapt TRLs to evaluate whether an AI solution is robust, validated, and reliable enough for integration into mission-critical systems. This approach supports informed decision-making and reduces the risk of premature or ill-suited deployment.

Accelerator 3: Access to High-Quality Data As AI systems mature, the quality of input data becomes a critical determinant of performance. Access to high-quality, well-documented, and ethically sourced data is essential for building reliable and trustworthy models. Investments in data infrastructure, metadata standards, and data governance frameworks are foundational to ensuring that AI applications are both effective and sustainable over time.

Accelerator 4: Pattern-Based Reusable Development Given the resource constraints many central banks face, efficiency can be improved through the development of reusable analytical patterns or modular toolkits. These patterns—such as sentiment analysis frameworks or anomaly detection modules—can be applied across a range of use cases, including market monitoring, policy communication analysis, and public sentiment tracking. By standardizing and reusing proven tools, central banks can reduce duplication, accelerate deployment, and achieve broader impact.

Accelerator 5: Scalability from Prototype to Production Moving from experimentation to implementation requires deliberate planning for scalability. While prototypes may yield promising insights in a sandbox, operational deployment demands robust software engineering, secure and scalable data pipelines, and strong cybersecurity practices. This transition is often complicated by what Scully et al. (2015) describe as "technical debt"—the growing complexity and maintenance burden of real-world machine learning systems. Early investment in scalable infrastructure and design principles helps mitigate long-term operational challenges.

Accelerator 6: Develop Appropriate Risk Management and Governance Frameworks AI introduces novel risks that must be addressed through adapted governance structures. While some traditional risk mitigation mechanisms remain applicable, others must evolve to account for new challenges, such as privacy, model opacity, explainability, data bias, data residency, hallucinations, model drift and dynamic behavior. Central banks should review and expand their risk frameworks to explicitly address the unique characteristics of AI. Recent guidance from the Bank for International Settlements offers a valuable reference point for shaping AI-specific risk management practices. It is important to do this up front since failing to manage these risks could lead to resistance to the development of new tools.

One approach to amplifying the impact of investments in these 6 accelerators is more systematic sharing of information across central banks. Given the shared desire of central banks to further enhance their work by leveraging modern data and AI, and the limited resources and knowledge in this area, it is advantageous for central banks to share information, models and best practices among each other. While this desire is broadly shared, there are several challenges for sharing information across the central banking community. Generally speaking, these challenges can be divided into 3 groups of technical, administrative, and willingness. Platform challenges, cybersecurity concerns and incompatible systems are some of the top technical challenges for sharing information, data and models. Contractual, legal and other administrative barriers play an important role in impacting the abilities to share information. The risk tolerance levels among central banks becomes a factor in their willingness to engage with other central banks in a more open and frequent manner.

Putting these 6 accelerators into practice will not be easy. Fortunately, there are a number of practical solutions and experiences to build on. From a technical perspective, organizations can leverage methods such as synthetic data generation, privacy enhancement techniques and various encryption capabilities to address some of the technical as well as administrative challenges. New data acquisition contracts can be drafted with information sharing in mind that leverage non-disclosure agreements between informed parties.

These initiatives can also build upon ongoing communities of practice among central banks such as the ECONDAT program. The ECONDAT Program consolidates efforts by multiple central banks, which currently includes the Bank of Canada, the Bank of England, Banca d'Italia, the European Central Bank, the Federal Reserve Board, Sveriges Riksbank and the Bank of Japan, to create a community of researchers across diverse fields (including economics, data science, statistics

and computer science) and institutions (academic and non-academic). The program organizes regular conferences on non-traditional data and advanced analytical methods to foster an environment that will spur cutting-edge research for the development of tools which are ultimately used for better decision making in central banking. Some examples of the recent workshops demonstrate the connections between these topics and the mandates of central banks. Bank of Canada (2025), Bank of England (2025), Bank of Italy (2024), US Federal Reserve Board (2023) and Sveriges Riksbank (2022). The central banking community benefits from a systematic program in support of such efforts.

International organizations such as the Bank for International Settlements (BIS) have also recognized the importance of fostering collaboration in this domain and have formed various innovation networks. For example, the BIS Innovation Hub aims to foster international collaboration on innovative financial technology within the central banking community. They focus on key technological trends that impact central banks and projects of exploratory nature to test technologies, as well as building a community of practice for sharing experiences through digital collaboration platforms.

Regulatory and supervisory authorities are also actively developing revised **regulatory standards** for the use of AI in payments and financial markets. In Canada, for instance, through the Financial Industry Forum on Artificial Intelligence (FIFAI), co-hosted by OSFI and the Global Risk Institute (OSFI, 2023; OSFI-FCA, 2024). Globally, several efforts are underway. Notably, the Consultative Group on Risk Management (CGRM) established at the BIS published a report on the governance of AI adoption in central banks. This report provides guidance on the AI implementation and proposes a governance and risk management framework that leverages existing risk management models and processes (CGRM-BIS, 2025; OSFI-FCA, 2024). Likewise, the Irving Fisher Committee on Central Bank Statistics published a 2025 survey-based report on how central banks are implementing and governing AI. It reviews current practices, governance arrangements, and how AI is being integrated into statistical production, data processing, and other core central bank functions (BIS-IFC, 2025; OECD, 2024).

Managing the Risks of AI in Central Banking

While the use of AI offers compelling benefits, it also introduces complex trade-offs and new types of risk. A fundamental question for central banks is: *When is a result "good enough"?* Striking the right balance between productivity and accuracy is critical, particularly in high-stakes policy contexts. Additionally, ensuring the reproducibility of AI-generated insights continues to remain a challenge, especially with rapidly evolving algorithmic techniques. Establishing rigorous validation and documentation standards is essential to safeguard model integrity and transparency.

An effective risk management strategy will require more than adopting best practice in documentation and validation of models. Moving forward, central banks will need to remain mindful about several key risks.

Understand the Limitations of AI Tools for Prediction and Policy Analysis: The Lucas Critique and AI

In a seminal paper, Lucas argued that economic analysis based on historical data could give misleading guidance on the impact of a change in economic policy (Lucas Jr, 1976). This insight — termed the *Lucas Critique* — was based on the observation that when people make decisions, they try to take into account new information. This means that when the world changes, some people are likely to change their decisions (rules).

The Lucas critique that historical data can sometimes be a poor guide to the impact of changing economic policy will not be eliminated by more complex AI tools. Although machine learning techniques are unlocking new insights from data, the quality of the predictions depend intrinsically on the quality and relevance of past data. As a result, both sophisticated simulation models – such as the DSGE and agent based simulation models – and human expertise and judgment will need to remain as part of the central bank policy and research toolkit.[5] In fact, human expertise and judgment will likely become even more important during the transition to more use of AI across the economy as many AI-based models are likely to place too much weight on pre-AI historical data.

This points to a complicated balancing act for central banks: the adoption of new AI tools will take considerable investments but at the same time central banks will need to continue to maintain and invest in other models and building deep expertise among staff. This will require careful management and sequencing of new ways of analysis, and a recognition that AI-based tools are only complements to human expertise and knowledge in policy making.

Developing Skills and Fostering a Collaborative Culture

The rise of AI will necessitate a parallel investment in human capital. Central banks must design and implement tailored training programs to build the right AI capabilities across different staff profiles. This includes upskilling data scientists into AI specialists, and ensuring economists and analysts acquire foundational programming and AI skills. The sophistication of emerging technologies, particularly generative AI, further amplifies this skills challenge, requiring continuous updates to training curricula to stay aligned with rapid technological advances. Additionally, central banks would require deep technical expertise in software engineering and IT practices to support tools and platforms that are foundational to AI models.

Equally important is the need to foster a culture of interdisciplinary collaboration. Successful AI adoption requires close cooperation between economists, data scientists, policy practitioners, and information technologists. Creating space for experimentation and integrating cross-functional workflows will be essential to unlock the full potential of AI in central banking.

[5] An additional factor is the risk that the design of Generative AI tools will mean that the risk of hallucinations may not be fully eliminated. This will also require human expertise to identify and correct.

Building Technological Infrastructure and Managing Platform Risks

Central banks must also make strategic decisions regarding the technological platforms and infrastructure that underpin AI capabilities. Many will rely on a small number of large technology providers, raising concerns about concentration risk, operational resilience, and potential exposure to external cyber incidents or service outages. Moreover, these relationships pose reputational risks should disruptions occur.

Another critical consideration is **privacy and data residency**, particularly with commercial generative AI systems and LLMs, which often require high-performance GPUs located in specific jurisdictions. Cross-border data transfer, legal compliance, and national sovereignty concerns must be addressed proactively. At the same time, central banks must ensure their computing environments are both current and flexible to accommodate evolving tools, while managing the high costs associated with model acquisition, licensing, and long-term maintenance.

From Experimentation to Operationalization

To move from isolated experimentation to sustained and scalable operational integration, central banks must adopt a structured approach to the **AI lifecycle**. As outlined in Figure 6, this lifecycle encompasses data collection, understanding, preparation, modeling, evaluation, deployment, and ongoing monitoring of model performance. Attention must be paid to risks such as model drift, hallucinations, or performance degradation over time. Embedding oversight, governance, and quality assurance at each phase is essential for scalable and trustworthy AI deployment.

Finally, to close the gap between research and implementation, central banks should formalize mechanisms for transitioning successful and valuable proofs of concept and pilot projects into production environments. Establishing dedicated pathways from pilot evaluation to policy integration will ensure that innovative research informs practice and enhances policy effectiveness in a timely and responsible manner.

Sustaining in the face of rapid innovation

Some of the most technically demanding yet often overlooked aspects of effective AI use and integration occur in steps 12, 13, and 14 of the AI lifecycle in Figure 6. Modern AI systems, particularly the large foundational models that underpin generative AI and LLMs, are typically developed outside of central banks by major technology firms or research organizations. Because these models are external and frequently updated, central banks have little to no control over their evolution, deprecation, or background modifications, which can occur with minimal notice. Consequently, applications built on such models may produce erroneous results or even fail entirely when upstream changes occur. This reality compels central banks to establish mechanisms for continuous verification and validation of outputs and, in some cases, to restart entire projects when model updates cause inconsistencies or breakdowns.

Addressing this challenge requires central bank teams to deepen their technical expertise, stay closely connected to emerging AI research and industry, and plan for the capacity needed to manage complex maintenance cycles. They should also design contingency approaches, such as maintaining non-AI-based methods, to ensure continuity of operations and reliability. While such safeguards already exist to some degree, their importance grows sharply in the AI era, where rapid model evolution amplifies the need for resilience and preparedness.

If central banks aim to realize their AI ambitions efficiently and responsibly, they must also recognize the interim costs of transition. Two factors are particularly relevant. First, this is a period of active learning and experimentation as institutions explore the most effective applications of AI. Second, rapid technological shifts in the external environment will likely require reinvestment in updating internal tools that depend on third-party software. Together, these factors imply that in the near term, central banks may face increased costs before the efficiency and productivity gains from AI automation fully materialize.

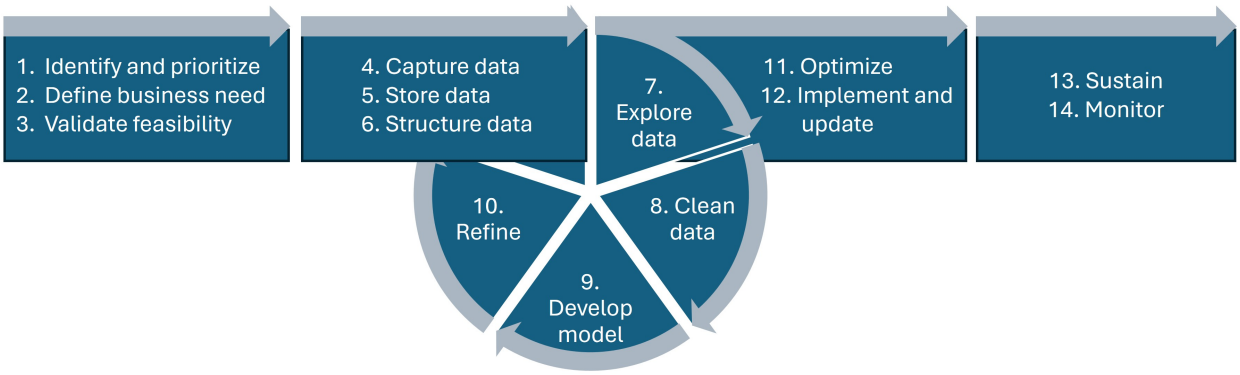


Figure 6: AI lifecycle- building, deploying, and monitoring models.

Conclusions

Artificial intelligence and non-traditional data sources are rapidly reshaping the global financial and policy landscape. For central banks, the adoption of AI presents a unique convergence of opportunity and responsibility. AI can significantly enhance the analytical depth, operational efficiency, and risk management capabilities that underpin core central banking functions—from monetary policy and financial stability to supervision and public engagement. Yet, realizing these benefits requires more than technological adoption; it demands institutional transformation.

This paper outlined the evolving role of AI within central banks through three lenses: where we have been, where we are, and where we should go. We have seen that early experimentation has matured into a more structured exploration of AI's potential, supported by cloud-based sandboxes, interdisciplinary teams, and modern data infrastructure. Real-world innovations, such as

the digitization of policy reports, show how AI and automation can enhance transparency and accessibility.

However, operationalizing AI also introduces complex governance, ethical, and infrastructure challenges. Central banks must navigate issues such as reproducibility, explainability, and data residency, while also managing vendor concentration risks and the rising costs of computational resources. To do so effectively, they must invest in skills development, institutional readiness, and new frameworks for risk and accountability.

Looking ahead, central banks must build organizational capabilities that bridge research, policy and operations, securely integrate advanced experimental tools into production systems, and foster a culture of responsible innovation. By doing so, they will not only strengthen their resilience and relevance in an AI-driven economy, but also uphold the trust and legitimacy that are central to their public mandate.

In sum, the integration of AI in central banking is not a question of if, but how. The path forward lies in a deliberate, values-driven approach, one that pairs technological capability with institutional prudence. As AI integration accelerates, this invites an additional policy question of the future: which central-bank functions should remain primarily human-led, and how should accountability be defined when AI systems increasingly inform—or, in some cases, perhaps execute—important decisions?

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