GLOBAL EXPERIENCE OF STATE INSTITUTIONS USING ARTIFICIAL INTELLIGENCE TECHNOLOGIES FOR PRUDENTIAL SUPERVISION OF CREDIT INSTITUTIONS' ACTIVITIES

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DOI: https://doi.org/10.30525/978-9934-26-715-4-19

Abstract. *Relevance.* Prudential supervision of credit institutions has traditionally relied on balance-sheet checks, financial-statement analysis, and on-site/off-site inspections. In an era of digital transformation and exponentially growing volumes of financial data, these conventional methods are increasingly insufficient for the timely detection of threats to financial stability. Central banks and supervisory authorities worldwide are therefore adopting supervisory technology (SupTech) solutions built on artificial intelligence (AI) and machine learning (ML) to process data in real time, detect atypical behavioral patterns among credit institutions, and forecast the probability of distress well before it materializes. *Purpose.* The chapter aims to systematize and critically compare the international experience of applying AI technologies in prudential banking supervision across leading jurisdictions, and to identify common patterns, jurisdiction-specific priorities, and outstanding challenges that condition the further diffusion of SupTech tools. *Methodology.* The study draws on official publications and primary regulatory sources (including the Bank for International Settlements, the Financial Stability Board, European Central Bank, Bank of England, UK Prudential Regulation Authority and Financial Conduct Authority, U.S. Office of the Comptroller of the Currency, Federal Reserve System, Monetary Authority of Singapore, Hong Kong Monetary Authority, and U.S. Government Accountability Office) supplemented by

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academic literature and industry reports. *Results.* The comparative analysis of five jurisdictions reveals that, despite structural differences, supervisors converge on two guiding principles: technological neutrality (AI-related risks are assessed under the same risk-management frameworks as any other technology) and human-in-the-loop oversight (AI systems generate proposals and flag anomalies, but final decisions remain with supervisors). The chapter identifies five persistent challenges to further AI adoption in supervision: "black-box" problem of explainability and transparency, including the emerging concern of "misaligned" AI systems; data quality and confidentiality constraints; third-party dependencies and service-provider concentration risk in the AI supply chain; algorithmic herding and procyclicality risk arising from correlated model behavior across institutions; shortage of supervisory staff combining financial-sector expertise with AI/ML competence. *Conclusions.* AI adoption in prudential supervision has moved from conceptual debate to concrete, operational implementation among leading regulators. Its sustainable development requires strategic digital-transformation planning, secure IT infrastructure, systematic staff training, international SupTech cooperation, and adherence to the human-in-the-loop principle as a precondition for trust in AI-assisted supervision. A balanced, technology-neutral regulatory approach combined with robust safeguards for data quality and confidentiality, is essential to realizing AI's supervisory potential while managing its systemic risks.

INTRODUCTION

Prudential supervision of credit institutions' activities is one of the most important instruments for ensuring the financial stability of any state. Traditionally, it is based on checking balance sheet indicators, analyzing financial statements, conducting on-site and off-site inspections, as well as assessing credit institutions' compliance with capital adequacy, liquidity, and asset quality standards. In the era of digital transformation, these methods prove insufficient for the timely identification of threats to financial stability.

Artificial intelligence (AI) and machine learning (ML) technologies are fundamentally changing approaches to prudential supervision worldwide. Central banks and supervisory authorities in most developed countries are implementing so-called supervisory technologies (SupTech – Supervisory

Technology), which make it possible to process data arrays in real time, identify atypical patterns of behavior of credit institutions, forecast the probability of distress long before it occurs, and significantly increase the efficiency of the supervisory process as a whole.

The concept of "prudential supervision" (from Lat. prudentia – prudence, foresight) covers a system of measures applied by regulators to guarantee the safety and soundness of credit institutions, protect depositors and creditors, and maintain the stability of the financial system as a whole. Given the rapid growth in the volume of financial data, the Bank for International Settlements (BIS), in its Bulletin No. 84 of 2024, stated that central banks and supervisory authorities became among the first institutions to master machine learning methods in order to obtain valuable analytical information for statistics, research, and policy formation [1].

The transformations in supervisory practice outlined above are driven by several factors. First, the volume of data generated by the financial system is growing at an unprecedented rate, since each credit institution generates a large number of transactions daily, submits dozens of reporting forms, and interacts with hundreds of counterparties – processing this data by traditional methods is becoming practically impossible. Second, the systemic nature of banking activity means that problems at one institution can quickly spread to the entire financial sector. Third, the financial crises of 2007-2009 and 2023 showed that traditional supervisory instruments are not always able to timely identify hidden risks.

According to the FSB report "The Financial Stability Implications of Artificial Intelligence" (2024), AI technologies in the SupTech field are applied mainly in the following areas: on-site inspections and analysis of reporting data using NLP and generative AI to extract key paragraphs from large volumes of documents and compile reports; assessment of data quality and configuration of error messages in regulatory reporting; modeling of interaction in social networks in the context of bank runs and stress testing.

An important theoretical basis for understanding the role of AI in prudential supervision is the concept of SupTech - regulatory technology on the side of the supervisory authority. Unlike RegTech (technology for fulfilling regulatory requirements on the side of the financial institutions themselves), SupTech is aimed directly at increasing the efficiency of supervisory processes.

Among the main categories of AI technologies used in prudential supervision, the following should be distinguished:

– machine learning algorithms – for forecasting the probability of banking distress;

– natural language processing (NLP) – for analyzing textual documents, reports, and regulatory reporting;

– network analysis – for tracking the interconnectedness of financial institutions;

– anomaly detection – for identifying atypical patterns in financial flows;

– generative AI (GenAI) – for automating the preparation of reports, supervisory requests, and data processing.

The application of AI in prudential supervision also gives rise to a number of fundamental challenges. First and foremost is the "black box" problem: complex ML models often do not allow explaining the logic of a decision made, which contradicts the principles of transparency and accountability of supervisory activity. In addition, data quality risks arise, since AI models are entirely dependent on the quality of input data. A separate problem is the regulatory neutrality of technologies: most supervisory authorities adhere to a technologically neutral approach, according to which risks associated with the application of AI should be assessed according to the same risk management principles as any other technology.

1. Experience of the United States of America

The United States of America became one of the first markets where regulatory authorities began systematically researching and implementing AI technologies in banking supervision processes. The specificity of American regulation lies in its decentralized architecture, in which supervisory functions are distributed among the Federal Reserve System (Fed), the Office of the Comptroller of the Currency (OCC), the Federal Deposit Insurance Corporation (FDIC), and a number of other agencies.

In March 2021, the OCC, the Fed, the FDIC, the Consumer Financial Protection Bureau (CFPB), and the National Credit Union Administration (NCUA) jointly published a request for information on the use of AI by financial institutions [2]. This request testified to the growing concern of regulators regarding the spread of AI technologies in the

banking sector and the need to form comprehensive approaches to their supervision.

The Office of the Comptroller of the Currency (OCC), in May 2022, set out supervisory expectations regarding banks' application of AI and ML technologies in the form of testimony before Congress. Deputy Comptroller for Operational Risk Policy Kevin Greenfield testified before the House Financial Services Committee's Task Force on Artificial Intelligence that the OCC applies a risk-based, technologically neutral approach to supervising the use of AI, assessing relevant risks through the lens of existing model risk management guidance. The OCC emphasized that supervisory expectations are based on the agency's prior guidance, in particular SR 11-7 on model risk management, which is mandatory and provides for independent validation of all analytical models.

The U.S. Government Accountability Office (GAO), in its report "Artificial Intelligence: Use and Oversight in Financial Services" (2025), recorded that the OCC issued 17 matters requiring attention regarding deficiencies in banks' use of AI since fiscal year 2020 [3]. The agency also noted that the CFPB has taken six AI-related enforcement actions since 2020, including in 2022 against a large bank for using an automated fraud detection system that illegally froze customers' accounts [3].

In 2023, the Securities and Exchange Commission (SEC) conducted examinations of AI disclosure and related corporate governance issues at approximately 30 registered investment advisers. The main purpose of these examinations was to identify candidates for more in-depth oversight and to deepen the agency's understanding of AI application practices in the industry and the risks associated with them [3].

The Federal Reserve System is actively implementing AI not only as an object of supervision, but also directly in its own supervisory activities. The Federal Reserve Bank of Cleveland developed the SAFE (Systemic Assessment of Financial Environment) early warning system, which uses ML methods to monitor systemic banking risks. The Fed also applies ML methods within the CCAR (Comprehensive Capital Analysis and Review) program – the annual stress testing of large banks. In accordance with the program's methodology, the Fed developed a system with three macroeconomic scenarios (baseline, adverse, and severely adverse), on the basis of which banks' capital adequacy is assessed.

The Federal Reserve Bank of Cleveland, in April 2024, published a study "Regional Economic Sentiment: Constructing Quantitative Measures from the Beige Book and Testing Their Ability to Forecast Recessions", which demonstrates the use of NLP and ML methods for processing qualitative information to support supervisory decisions [4].

The U.S. Department of the Treasury, in June 2024, published a request for information on "Uses, Opportunities, and Risks of Artificial Intelligence in the Financial Services Sector" (89 Fed. Reg. 50048), which marked a transition to a more coordinated approach to AI regulation at the federal government level [5]. In response to this request, the Department of the Treasury received a wide range of comments from the banking industry, technology companies, and civil society. Feedback revealed that companies are concerned about the fragmented approach to supervising banks and non-bank organizations developing and implementing AI, as well as the resource deficit and dependence on third-party providers for smaller financial institutions.

One of the most concrete examples of the use of AI by American banking regulators is the OCC's implementation of its own machine learning tools within the Microsoft Azure OpenAI platform and the development of "proprietary tools" in machine learning platforms. In December 2024, the OCC published a request for information regarding generative AI services to support proprietary tools developed internally at the agency and provided by contractors [6]. This testifies to the OCC's concrete intention to substantially expand its capabilities in the field of AI and ML for the performance of supervisory functions.

2. Experience of the European Central Bank

The experience of the European Central Bank (ECB) in applying AI for prudential supervision is one of the most systemic and well-documented in the world. The ECB, within the framework of the Single Supervisory Mechanism (SSM), has developed a large-scale digital strategy that includes a wide range of SupTech instruments based on AI and ML technologies.

The flagship of the ECB's AI arsenal is the Athena platform – a text analysis system based on natural language processing (NLP), which provides natural language processing capabilities to all supervisory units. Athena is capable of translating and analyzing the content of supervisory

documents, including internal model reviews, risk assessments, and letters to banks. To build the NLP models, researchers collected labeled data across a wide range of risk topics and used it to adapt predictions to the supervisory context.

A key principle of Athena's operation is "human-in-the-loop": although ML models generate suggestions and forecasts, the key role remains with the supervisory inspector, who checks the text, evaluates the context, and provides feedback for improving the model.

Among the other specialized SupTech instruments developed by the ECB, the following deserve attention:

– Heimdall – a system that supports specialists in processing large volumes of information required for assessing the fitness and propriety (fit and proper) of members of banks' management bodies;

– Medusa – an instrument that facilitates the preparation and verification of the consistency of reports on the results of internal model reviews.

The instruments listed above address specific supervisory tasks and make it possible to substantially reduce the time spent on routine document processing.

One of the most significant infrastructural components of the ECB's digital transformation is Agora – a single data lake for European banking supervision. In her article in Revue Banque, Elizabeth McCaul described a pilot use case of generative AI for Agora, whereby supervisory inspectors without programming skills can formulate queries to the database in ordinary language. Generative AI automatically translates natural-language queries into program code, making it possible to access specific data that previously required programming skills to find.

To support the development of AI tools, the ECB built the Virtual Lab – a cloud-based collaborative platform that offers ML capabilities and a convenient environment for shared use and development of code. This platform not only increases the efficiency of internal cooperation within European banking supervision, but also makes it possible to deploy generative AI within a controlled environment.

According to McCaul, the ECB has identified more than 40 use cases for generative AI in banking supervision. Among the most promising are tools with chatbot capabilities for supervisory regulations and methodologies, as

well as functionality for network analysis that makes it possible to visualize complex ownership structures and links between entities.

In September 2023, the ECB announced the launch of a new "SSM Digital Strategy 2024-2028", which defines technology, data, and innovation as three interconnected pillars of digital transformation. Alongside this, the ECB is actively developing international cooperation in the field of SupTech: according to ECB representatives, during this period cooperation with the Monetary Authority of Singapore (MAS) and the U.S. OCC intensified, and "tiger teams" were formed jointly with the Fed, the Bank of England, and the UK FCA for the implementation of specific joint projects in the field of SupTech, in particular in the area of IT risks and cyber resilience.

Special attention should be paid to the staff training function: the ECB regularly organizes specialized training courses for its employees in partnership with globally recognized education service providers – Coursera and INSEAD Business School. This testifies to a systemic approach to building the human capital necessary for the effective use of AI in supervisory practice.

3. Experience of the United Kingdom: the Bank of England and the Prudential Regulation Authority

Great Britain occupies one of the leading positions in the world in terms of the level of development of the regulatory and supervisory framework in the field of AI. The Bank of England (including the Prudential Regulation Authority – PRA) and the Financial Conduct Authority (FCA) have, over the past several years, consistently been forming a comprehensive system of approaches to the regulation and use of AI in financial services.

An important step in this direction was the establishment of the Artificial Intelligence Public-Private Forum (AIPPF) – a platform for dialogue between regulators and the private sector. In 2020-2022, the Bank of England and the FCA jointly conducted the work of this forum, examining the challenges of using AI/ML in financial services and establishing dialogue between the public and private sectors [7]. The final AIPPF report, published in February 2022, set out specific recommendations on data, model, and governance issues.

In October 2022, the Bank of England, the PRA, and the FCA jointly published Discussion Paper DP5/22 "Artificial Intelligence and Machine

Learning", in which they systematically set out their views on the challenges of using AI/ML in UK financial services [8]. The document identified key risks associated with AI, including the lack of explainability, data quality issues, operational dependence on third-party providers, and potential model bias. In October 2023, the supervisory authorities published the corresponding report FS2/23, which summarized 54 responses received from regulated firms, trade associations, and non-financial businesses [9].

The Bank of England uses AI both directly in its own supervisory activities and to support the broader functions of the central bank. As noted in the Bank of England's written evidence to the House of Commons Committee: "The Bank uses AI for predictive analytics, studying non-linear relationships between variables, and analyzing larger and more enriched data sets, which makes it potentially possible to forecast GDP growth, banking distress, and financial crises" [10].

Significant is the work of J. Suss and H. Treitel from the Staff Working Paper series (Staff Working Paper No. 831, 2019), "Predicting bank distress in the UK with machine learning" [11]. The authors, drawing on confidential regulatory data obtained from supervisory assessments for 2006-2012, developed an early warning system for banking distress. The key conclusion is that the "random forest" algorithm substantially and significantly outperforms other models on AUC and Brier Score metrics. The study also showed that ensemble ML methods are able to capture complex non-linear relationships between banks' financial indicators that cannot be detected using traditional linear regression.

Another key work by Bank of England specialists is the study by Bluwstein K., Buckmann M., Joseph A., Kapadia S., Şimşek O., "Credit Growth, the Yield Curve and Financial Crisis Prediction: Evidence from a Machine Learning Approach", published as Working Paper No. 848 in 2020 (later in the Journal of International Economics, 2023) [12]. The authors demonstrate that ML approaches outperform traditional models in forecasting financial crises on a horizon of 1-3 years ahead, using data on credit growth and the shape of the yield curve.

According to the responses of the Bank of England and the PRA to the House of Commons Treasury Committee (2026), the PRA is actively researching the use of large language models (LLMs) to improve supervisory tools, supporting tasks such as data extraction and natural-

language queries [13]. In addition, the Bank has deployed off-the-shelf AI assistants throughout the organization, providing productivity gains across various tasks, including summarization, note-taking, and code generation.

In 2024, the Bank of England and the FCA conducted the third cycle of the "Artificial Intelligence in UK Financial Services" survey (following the 2019 and 2022 surveys), the purpose of which was to track the dynamics of AI implementation in regulated organizations and deepen supervisory authorities' understanding of AI issues [14]. According to the survey, the most popular explainability methods are feature importance and Shapley values (SHAP) – both methods aimed at explaining the contribution of each input variable to the ML model's prediction.

In response to a request from the UK government in February 2024 (a joint letter from the Department for Science, Innovation and Technology and the Treasury), the Bank of England, the PRA, and the FCA presented a strategic plan for the responsible implementation of AI/ML in the financial sector. In particular, in 2023 the PRA published new model risk management principles for banks that are technologically neutral and outcome-focused, but specifically include factors related to the use of AI models.

3. Experience of Singapore: a Systemic Approach to AI Risks

The Monetary Authority of Singapore (MAS) is a recognized leader in the development and implementation of innovative approaches to regulation and supervision in the field of financial technologies, including AI. MAS combines the role of central bank and integrated financial regulator, which makes it possible to ensure consistency and integrity of approaches to AI regulation across all segments of the financial market.

In 2018, MAS, together with the Association of Banks in Singapore, published principles on the use of AI and data analytics in Singapore's financial sector [15]. These principles became one of the first industry documents in the world to systematically define the regulator's expectations regarding the responsible use of AI by financial institutions.

In mid-2023, MAS launched Project MindForge – an initiative aimed at strengthening AI risk governance for financial institutions implementing AI technologies in their operations. The project resulted in the publication of an AI Risk Management Toolkit for the financial sector, developed jointly by a consortium of 24 leading banks, insurance companies, capital markets

companies, and other industry participants [16]. The Toolkit includes a detailed "Guidebook for AI Risk Management Operationalisation", which provides practical guidance on implementing AI risk management systems in accordance with traditional, generative, and agentic AI technologies.

In 2024, MAS conducted a supervisory thematic review of AI use by key banks – the results of this review formed the basis for the "AI Risk Management Guidelines" proposed in 2025 [17]. As noted by MAS Deputy Managing Director Ho Hern Shin, these proportionate, risk-based guidelines make it possible to ensure responsible innovation by financial institutions implementing corresponding safeguards to counter key risks associated with AI. The guidelines cover various applications and technologies of AI, including Generative AI, as well as the latest developments such as AI agents.

In May 2026, MAS announced a new initiative in the field of financial crimes: MAS is conducting a Proof-of-Value (POV) to explore AI and ML methods for the purpose of proactive fraud detection [18]. This initiative involves close cooperation with the banking industry and demonstrates that MAS, as a supervisory authority, is actively using AI to address specific monitoring tasks.

Singapore's experience also includes the development of the Veritas Initiative – an initiative to verify the fairness, ethics, accountability, and transparency of algorithms used in three pilot use cases: credit risk scoring, credit risk, and asset management. The purpose of Veritas is to develop methodologies and tools for the practical assessment of AI algorithms in accordance with FEAT principles. This approach differs substantially from the approaches of other regulators and is oriented toward specific practical outcomes rather than merely issuing declarative guidance.

In 2024, MAS also actively made use of the BuildFin.ai platform – a new initiative that brings together technology providers, research institutes, and financial institutions to jointly solve complex industry problems. This platform is intended to facilitate the dissemination of AI risk management practices and solutions across the industry, as well as expand participation in AI risk management working groups [16].

MAS's approach is distinguished by a particular emphasis on the balance between innovation and risk: in particular, the regulator does not dictate specific technical solutions, but forms clear expectations regarding

AI risk management and verifies compliance with them within supervisory reviews. The guidelines are applied proportionately, in accordance with the scale and nature of financial institutions' activities, their use of AI, and their risk profiles.

4. Experience of Asia: the Hong Kong Monetary Authority

The Hong Kong Monetary Authority (HKMA) is also actively integrating AI into its supervisory practice. As one of Asia's leading financial centers, Hong Kong is forming its own approach to AI regulation, reflecting both international standards and the specifics of regional financial markets.

In 2024, the HKMA issued a Circular encouraging authorized institutions to use AI to strengthen the monitoring of money laundering and terrorist financing risks. Recognizing the increasingly complex landscape, the HKMA emphasized the advantages of AI-based systems compared to conventional rule-based systems.

In August 2024, the HKMA launched a new GenAI Sandbox in partnership with the technology hub Cyberport, allowing banks to test new ideas in the field of AI within a structured risk management framework. This testifies to the HKMA's desire to simultaneously promote the implementation of AI in the banking sector and ensure an appropriate level of protection against the risks associated with it.

On 28 October 2024, the Financial Services and the Treasury Bureau of Hong Kong published a "Policy Statement on Responsible Application of Artificial Intelligence in the Financial Market" [19]. This document acknowledges one of the highest levels of AI adoption in the world among Hong Kong financial institutions (38% compared to the global average of 26%) and introduces an approach aimed both at promoting the development of AI and at addressing potential risks, in particular cybersecurity, data confidentiality, and intellectual property protection.

In the course of the 2024 annual review of Hong Kong's banking sector, the HKMA emphasized that it is actively implementing generative AI pilot projects to identify supervisory insights [20]. In particular, the agency, on the basis of its own SupTech tools, is seeking to combine real-time regulatory data analysis with the application of large language models to increase the depth and breadth of supervisory coverage.

In its "White Paper on AI", the HKMA defines the key areas of AI application in banking and the principles of responsible implementation [21]. Particular attention is paid to issues of explainability of AI decisions and the inadmissibility of using AI as a substitute for human judgment and analysis. The HKMA's position is clearly formulated: AI should be regarded as a tool that supplements and enhances human capabilities, rather than replacing them.

5. Global Standards For the Application of AI in Supervision

The Bank for International Settlements (BIS) and the Financial Stability Board (FSB) play a key role in shaping global standards and recommendations for the application of AI in prudential supervision. The materials developed by these institutions serve as an important reference point for central banks and supervisory authorities around the world.

In June 2024, the BIS published Chapter III "Artificial intelligence and the economy: implications for central banks" of its Annual Economic Report 2024, in which it systematically set out the opportunities and challenges associated with the implementation of AI in central banks' activities [22]. In the same year, the BIS published Bulletin No. 84 "Artificial intelligence in central banking", in which it identified four key areas of AI use: data collection and compilation of official statistics; macroeconomic and financial analysis; supervision of payment systems and market infrastructure; prudential supervision [1].

The Financial Stability Board (FSB), in November 2024, published the report "The Financial Stability Implications of Artificial Intelligence", which analyzes both the implications of AI application for financial stability and the possibilities of using AI by supervisory authorities to increase supervisory effectiveness [23]. In particular, the report states that NLP and generative AI methods are being tested and applied for examinations: these methods make it possible to extract relevant paragraphs from large volumes of documents and compile examination reports [23].

In October 2025, the FSB published the report "Monitoring adoption of artificial intelligence and related vulnerabilities", in which it systematized member jurisdictions' approaches to monitoring the application of AI. In particular, micro-prudential supervisory authorities in many jurisdictions assess AI-related risks at the level of individual institutions through

supervisory measures, including model risk management reviews. At the same time, the report notes that expanding attention to vulnerabilities across different institutions and sectors could strengthen global efforts to monitor financial stability.

6. Comparative Analysis of Approaches in Different Jurisdictions

Studying the practice of different jurisdictions makes it possible to identify both common trends and substantial differences in approaches to the application of AI for prudential supervision of credit institutions' activities. Let us systematize these approaches according to several key dimensions.

Most leading regulators adhere to the principle of technological neutrality: credit institutions are expected to comply with existing risk management standards regardless of the specific technology used. This principle is consistently followed by the Bank of England, the U.S. OCC, and the ECB. The essence of this principle is that risks associated with the application of AI should be assessed according to the same risk management principles as any other technological risks.

Under the human-in-the-loop principle, all leading regulators unanimously emphasize that AI is not and should not become a replacement for human decision-making in supervisory activity. The ECB declares this principle in the context of the Athena platform; the HKMA – in its own White Paper on AI; MAS – in the FEAT principles and AI risk management guidelines. This principle is not merely declarative – it defines the specific architecture of supervisory AI systems, in which the model generates suggestions and identifies anomalies, while the final decision always remains with the human.

In terms of the nature of priority tasks, it can be observed that different regulators emphasize different aspects of AI application, namely: the ECB has focused on automated document analysis and natural language processing; the Bank of England – on forecasting banking distress and financial crises; MAS – on AI risk management on the side of financial institutions; the HKMA – on the GenAI sandbox; the United States (OCC, Fed) – on stress testing and model risk management.

In terms of the level of development and documentation of approaches, the ECB holds the lead thanks to its large-scale SupTech program with

specific named instruments (Athena, Heimdall, Medusa, Agora, Virtual Lab), a significant number of users (3,500+), and a well-documented methodology. In second place is MAS, thanks to its structured FEAT, Veritas, and MindForge initiatives. The Bank of England stands out for the depth of its academic research, while the OCC and the Fed stand out for the scale of their regulatory framework.

Regarding the balance between regulation and stimulating innovation, all the jurisdictions examined are trying to find the optimal balance: regulators do not seek to restrict the implementation of AI, but instead form conditions for its safe and responsible application. At the same time, the approaches differ: while the EU prefers a framework-based approach to regulation (the EU AI Act), the United States, Singapore, and Hong Kong rely more on principles and recommendations, leaving credit institutions flexibility in choosing specific solutions.

7. Challenges and Prospects for the Implementation of AI in Prudential Supervision

Despite significant progress in the implementation of AI for prudential supervision, regulatory authorities around the world face a number of serious challenges:

– the problem of explainability and transparency – complex ML models, in particular neural networks, are "black boxes", meaning their internal decision-making mechanisms are not directly interpretable. This contradicts the principles of transparency and accountability on which prudential supervision is based. The FSB report (2024) places particular emphasis on misaligned AI systems as a separate category of vulnerabilities and stresses that supervisory authorities in many jurisdictions assess these issues at the level of individual institutions through model risk management reviews [24];

– data quality and confidentiality – AI models are entirely dependent on the quality of input data. Problems of incompleteness, format incompatibility, and reporting errors can substantially reduce the accuracy of AI models. In addition, the use of confidential supervisory data in AI models requires special security measures. In this context, the ECB pays considerable attention to data quality and confidentiality issues within its Agora platform;

– third-party dependencies – most credit institutions, especially smaller ones, do not have their own capacity to develop complex AI systems and are forced to rely on external providers. If leading providers of AI solutions for the financial sector are used by a wide range of institutions, failures or vulnerabilities in their systems can have a systemic effect. The FSB's 2025 report devoted a separate case study to monitoring dependencies on third-party providers and the concentration of AI-related service providers [24];

– the risk of algorithmic herding and procyclicality – if most large banks use similar AI models trained on identical data sets, they may generate identical recommendations – this could amplify systemic risks instead of reducing them. The BIS in 2024 identified this risk as one of the key risks given its potential systemic implications;

– shortage of qualified personnel – the effective application of AI in prudential supervision requires specialists who combine deep knowledge in the field of financial supervision and AI/ML technologies. The ECB, MAS, and other leading regulators are investing in staff training and professional development. The ECB, for example, organizes training courses for supervisory personnel in partnership with Coursera and INSEAD.

Among the promising directions for the development of AI implementation in supervisory processes, we can include the following: the integration of generative AI for the automated preparation of supervisory reports and requests; the development of explainable AI methods to ensure the transparency of AI-based decisions in supervisory activity; the implementation of real-time monitoring systems to detect emerging risks; the strengthening of international cooperation in the field of SupTech, in particular through cooperation between the ECB, the Fed, the Bank of England, MAS, and the OCC within "tiger teams"; the development of standardized approaches to AI model risk management that take into account the specifics of different jurisdictions.

CONCLUSIONS

Systematizing the results of the analysis of global experience in the use of artificial intelligence technologies in prudential supervision of credit institutions' activities, the following conclusions can be formulated:

1) the implementation of AI in prudential supervision is an objectively necessary step under conditions of the growing complexity of the financial

system. Leading supervisory authorities have moved from discussions about the feasibility of AI to the concrete implementation of specific instruments;

2) the actualization of the need for strategic planning of digital transformation, the construction of a secure IT infrastructure, the organization of systematic staff training, international cooperation in the field of SupTech, and the introduction of the "human-in-the-loop" principle as an indispensable condition for trust in AI systems in the field of prudential supervision;

3) a balanced approach to regulation is important – oriented not toward prohibiting the use of AI technologies, but toward forming clear principles and expectations regarding AI risk management. A technologically neutral approach makes it possible to ensure appropriate flexibility while preserving substantial safety guarantees;

4) the need to resolve issues of regulatory data quality and the corresponding legislative and normative framework for protecting confidential supervisory data used in AI systems.

References:

1. Bank for International Settlements (BIS) (2024) *Artificial intelligence in central banking (BIS Bulletin No. 84)*. Basel: BIS. Available at: https://www.bis.org/publ/bisbull84.pdf

2. Office of the Comptroller of the Currency et al. (2021) *Request for Information and Comment on Financial Institutions' Use of Artificial Intelligence, Including Machine Learning (OCC Bulletin 2021-17)*. Washington: OCC. Available at: https://www.occ.gov/news-issuances/bulletins/2021/bulletin-2021-17.html

3. Government Accountability Office (GAO) (2025) *Artificial Intelligence: Use and Oversight in Financial Services (GAO-25-107197)*. Washington: GAO. Available at: https://files.gao.gov/reports/GAO-25-107197/index.html

4. Federal Reserve Bank of Cleveland (2024) *Regional Economic Sentiment: Constructing Quantitative Estimates from the Beige Book and Testing Their Ability to Forecast Recessions*. Cleveland: Federal Reserve Bank of Cleveland.

5. U.S. Department of the Treasury (2024) *Request for Information on Uses, Opportunities, and Risks of Artificial Intelligence in the Financial Services Sector (89 Fed. Reg. 50048)*. Available at: https://www.federalregister.gov/documents/2024/06/12/2024-12336/request-for-information-on-uses-opportunities-and-risks-of-artificial-intelligence

6. FedScoop (2024) *The Comptroller of the Currency looks to level up its generative AI offerings*. FedScoop, December 20. Available at: https://fedscoop.com/the-comptroller-of-the-currency-looks-to-level-up-its-generative-ai-offerings/

7. Bank of England; Financial Conduct Authority (2022) *AI Public-Private Forum: Final Report*. London: Bank of England.

8. Bank of England; Prudential Regulation Authority; Financial Conduct Authority (2022) *DP5/22 – Artificial Intelligence and Machine Learning*. London: Bank of England. Available at: https://www.bankofengland.co.uk/prudential-regulation/publication/2022/october/artificial-intelligence

9. Bank of England; Prudential Regulation Authority; Financial Conduct Authority (2023) *FS2/23 – Artificial Intelligence and Machine Learning*. London: Bank of England. Available at: https://www.bankofengland.co.uk/prudential-regulation/publication/2023/october/artificial-intelligence-and-machine-learning

10. Bank of England (2024) *AI in financial services: written evidence submitted by the Bank of England*. UK Parliament, House of Commons Treasury Select Committee. Available at: https://committees.parliament.uk/writtenevidence/140106/html/

11. Suss J., Treitel H. (2019) *Predicting bank distress in the UK with machine learning (Staff Working Paper No. 831)*. London: Bank of England. Available at: https://www.bankofengland.co.uk/working-paper/2019/predicting-bank-distress-in-the-uk-with-machine-learning

12. Bluwstein K., Buckmann M., Joseph A., Kapadia S., Şimşek O. (2020) *Credit growth, the yield curve and financial crisis prediction: Evidence from a machine learning approach (Bank of England Staff Working Paper No. 848)*. London: Bank of England. *Journal of International Economics*, 2023, vol. 145.

13. UK Parliament, House of Commons Treasury Committee (2026) *AI in financial services: Responses to the Committee's First report*, April 16. Available at: https://publications.parliament.uk/pa/cm5901/cmselect/cmtreasy/1791/report.html

14. Bank of England; Financial Conduct Authority (2024) *Artificial intelligence in UK financial services – 2024*. London: Bank of England. Available at: https://www.bankofengland.co.uk/report/2024/artificial-intelligence-in-uk-financial-services-2024

15. Monetary Authority of Singapore (MAS) (2018) *Principles to Promote Fairness, Ethics, Accountability and Transparency (FEAT) in the Use of Artificial Intelligence and Data Analytics in Singapore's Financial Sector*. Singapore: MAS.

16. Monetary Authority of Singapore (MAS) (2026) *MAS Partners Industry to Develop AI Risk Management Toolkit for the Financial Sector*. Press release. Singapore: MAS, March 20. Available at: https://www.mas.gov.sg/news/media-releases/2026/mas-partners-industry-to-develop-ai-risk-management-toolkit-for-the-financial-sector

17. Monetary Authority of Singapore (MAS) (2025) *MAS Guidelines for Artificial Intelligence (AI) Risk Management*. Press release. Singapore: MAS. Available at: https://www.mas.gov.sg/news/media-releases/2025/mas-guidelines-for-artificial-intelligence-risk-management

18. Monetary Authority of Singapore (MAS) (2026) *MAS Collaborates with Banking Industry to Harness Artificial Intelligence in the Fight Against Financial Crime*. Press release. Singapore: MAS, May 4. Available at: https://www.mas.gov.sg/

news/media-releases/2026/mas-collaborates-with-banking-industry-to-harness-ai-in-the-fight-against-financial-crime

19. Financial Services and the Treasury Bureau, Hong Kong (2024) *Policy Statement on Responsible Application of Artificial Intelligence in the Financial Market*. Hong Kong: FSTB, October 28. Available at: https://gia.info.gov.hk/general/202410/28/P2024102800154_475819_1_1730087238713.pdf

20. Hong Kong Monetary Authority (HKMA) (2025) *Hong Kong Banking Sector 2024 Year-end Review and Priorities for 2025*. Hong Kong: HKMA, January 22. Available at: https://www.hkma.gov.hk/media/eng/doc/key-information/speeches/s20250122e1.pdf

21. Hong Kong Monetary Authority (HKMA) *Reshaping Banking with Artificial Intelligence*. White Paper. Hong Kong: HKMA. Available at: https://www.hkma.gov.hk/media/eng/doc/key-functions/finanical-infrastructure/Whitepaper_on_AI.pdf

22. Bank for International Settlements (BIS) (2024) *Artificial intelligence and the economy: implications for central banks (Annual Economic Report 2024, Chapter III)*. Basel: BIS.

23. Financial Stability Board (FSB) (2024) *The Financial Stability Implications of Artificial Intelligence*. Basel: FSB, pp. 44–47. Available at: https://www.fsb.org/uploads/P14112024.pdf

24. Financial Stability Board (FSB) (2025) *Monitoring Adoption of Artificial Intelligence and Related Vulnerabilities*. Basel: FSB. Available at: https://www.fsb.org/uploads/P101025.pdf