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## Assessing Artificial Intelligence Readiness in Central Banks of the Western Balkans

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**Abstract:** This study evaluates the institutional readiness of central banks in the Western Balkans to adopt and integrate Artificial Intelligence (AI) into their operations. While AI is rapidly transforming central banking functions globally, enhancing forecasting, regulatory oversight, and operational efficiency, its adoption by central banks of the Western Balkans remains underexplored. Using a structured framework adapted from Jöhnk et al. (2021), this research assesses five key readiness dimensions: strategic alignment, resources, knowledge, organizational culture, and data infrastructure; and supplements this with additional questions to gain deeper insights into the perceived practices, expectations, benefits and risks of AI by central bankers. Insights were drawn from senior professionals across six central banks in the region. The findings reveal generally low yet uneven levels of readiness for AI adoption, with particular deficiencies in data infrastructure and the strategic integration of AI. The benefits of using AI in these central banks are widely recognized, including improvements in economic forecasting and task automation. However, key barriers persist, including institutional inertia, fragmented data systems, and a lack of internal expertise. The study emphasizes the importance of aligning AI strategies with core mandates, investing in capacity-building, and fostering regional cooperation as ways to ensure that the central banks in the region can effectively fulfil their mandated functions.

**Keywords:** Artificial Intelligence, Central Banking, Digital Transformation, Financial Stability, Institutional Readiness.

**JEL classification:** E58, O33, G28

## 1. Introduction

The rapid advancement in Artificial Intelligence (AI) challenges the basic distinction between human agency and machine autonomy. With the development and advancements of AI models, the critical issue becomes defining the limits of their development and ability to ensure that the AI outputs are reliable, interpretable and aligned with human objectives and values. AI is streaming its way into the daily lives of every individual through applications in finance, medicine, education, industry and other domains. Indeed, in the last couple of years, we have witnessed unprecedented growth of interest in AI. This is primarily driven by its potential to transform how organizations operate, make more informed decisions, and interact with data across a wide range of industries. While some view AI as a potential solution to all problems of humanity (including medical advancements, economic growth and poverty reduction, improving governance and promoting peace and redefining work in its nature (Amodei, 2024), others consider possible threats from AI (security, ethical concerns, geopolitical issues, etc (Aschenbrenner, 2024)).

On a more immediate note, AI is promising better productivity of workers and financial performance of companies (Van Roy et al., 2020). While this new technological revolution is transforming the world, the financial landscape is not immune. Central banks cannot remain untouched by its influence either. But this pressure is also interrelated with the promise of a higher level of security and stability in the financial system. And while central banks are “directly affected by AI’s impact, both in their role as stewards of monetary and financial stability and as users of AI tools” they must anticipate AI’s effect and possibly harness its power in their operations (Shin, 2024, p.91). The transformative potential of AI for financial stability is especially compelling and possibly important in emerging markets like the Western Balkans. These countries have traditionally faced economic shocks and are striving for greater resilience. AI offers new ways to detect risks, improve forecasting, and enhance overall financial inclusion.

However, the current state of AI adoption in the region’s financial sector, especially by central banks, remains underexplored (Odorović et al., 2020; ReSPA, 2023). In the context of the Western Balkans’ growing IT ecosystem and skilled workforce, there is a critical need to understand how AI could be harnessed to improve financial oversight and security. This research aims to fill this gap by examining the adoption patterns and readiness of Western Balkan central banks.

The paper is structured into five main sections. After the introduction, a review of relevant literature on the use, drivers for use, challenges and limitations of

AI use in central banks is presented. The theoretical framework for analysis of readiness for AI adoption is depicted as well. The third chapter provides the main methodological choices used in this study, while the fourth chapter outlines main results of the study. The final section provides a discussion on the findings and the conclusion, offering actionable policy recommendations for the decision-makers in central banks.

## 2. Literature Review

### AI in central banking

It seems that AI is immediately recognized as a General-Purpose Technology (GPT) that could create significant economic and organizational changes. General-Purpose Technology is defined as a new method of production and invention that is important to the extent that it has a protracted aggregate impact, with electricity and Information Technology being the most prominent examples (Jovanovic & Rousseau, 2005). In AI, GPT is not restricted to a single application or use, but could be deployed for various tasks and processes (Shin, 2024; Fernández-Llorca et al., 2024; Triguero et al., 2023). The ability of AI to impose structure on unstructured data, generate predictive insights, and discover patterns in vast datasets that are nearly impossible to humans, opened a powerful new domain of both theoretical development and practical applications.

In a manner that is common for central banks, conservatively and cautiously, Artificial Intelligence (AI) is making inroads into their operations. Although central banks, especially in developed economies, are exploring AI in order to enhance their efficiency and decision-making, surveys suggest that the fully scaled implementations are still in their early stages (Araujo et al., 2025). As risk-averse and deliberate adopters, central banks are generally focusing on pilot projects and governance frameworks before deploying AI in their critical operations. As Araujo et al. report, only about 12% of central banks are not engaged in any AI or ML (machine learning) projects, based on the survey conducted by the end of 2024. Thus, it seems that the level of adoption is high, but the degree of adoption varies significantly. Araujo et al. also indicate that about 25% of the central banks have full-scale implementation of AI/ML models, while 33% and 30% of the banks have limited pilot projects or have some cases of use in early production stage, respectively. As assumed, advanced economies are leading the way in formalizing the AI efforts. The authors also report that about half of central banks from advanced economies have established AI coordination function (e.g.

Chief Data and/or Innovation Office) compared to only one-third of emerging economies. In addition, the majority of advanced economies have begun developing internal AI guidelines and policies, while half of the emerging economies are not even considering to develop them at this point (Araujo et al., 2025). Zitter (2022) highlights that one of the definite frontrunners in AI adoption among the central banks is the Bank of England. It has developed its own innovation lab, responsible for the creation of a cognitive search engine which uses AI technology for chatbots and predictive real-time insights (. Some of the key uses of AI in the Bank of England are anti-money laundering tools, personalized underwriting and pricing using big data, and real-time fraud detection, ensuring the monetary and financial stability in the UK. The European Central Bank (ECB) is also a good example of AI integration in their operations, primarily for the purpose of enhancing monetary policy operations and oversight. As Cipollone (2024) reports, researchers at the ECB are developing machine learning models to enhance macroeconomic forecasts, with results comparable to traditional models, even in their early stages. Similar to the Bank of England, the ECB is experimenting with unconventional data to detect early signals in global and macroeconomic trends. In addition, their automatic translator is able to translate a vast amount of text across 24 EU languages (Cipollone, 2024). In a nutshell, the use of AI is evident in large central banks of the developed world, utilizing these models to improve efficiency, increase analytical power, and develop a completely new set of tools and services. However, even these big organizations may struggle to move from isolated pilot projects to recognizing AI as a part of core operations. As identified by Jöhnk et al., (2021), only about 8% of large organizations are successful in adopting AI into their workflows at scale. Recent regional perspectives also highlight how central banks in emerging economies, such as Montenegro, are recognizing both the opportunities and threats AI presents for financial stability, operational efficiency, and cybersecurity (Vučinić & Luburić, 2024). In the next section we investigate the theoretical tools and models that could enable us to assess the readiness of organizations.

Some of the main uses of AI in central banks' operations are related to:

**Monetary Policy and Economic Forecasting.** Artificial intelligence is increasingly being used by central banks to improve monetary policy and economic forecasting. It was identified that traditional econometric models often struggle to capture nonlinear relationships, while generally being unable to process large volume of data. As such, machine learning models serve as a promising avenue of research to enhance macroeconomic forecasts, including projections for growth, inflation and unemployment. These models, such as neural networks or tree-based ensembles, have inept capability to outperform linear models, es-

pecially during periods of financial stress and high uncertainty. As such, it was found in the study of Coulombe et al. (2022) that the ability of these models to capture nonlinear effects provides significant advancement in predictive accuracy. Researchers from the Bank of England, Buckmann and Joseph (2023) demonstrated how ML models could provide more accurate one-year-ahead unemployment forecast than the traditional linear model. Essentially, their findings suggest that the central banks can improve the quality of their projections and forecast by adopting ML techniques, provided these remain explainable and usable for policymakers.

Moreover, AI is being investigated as a tool for designing more effective policy rules. One of the ways for this is the use of reinforcement learning (RL), where an AI agent learns optimal interest-rate policies within a simulated economy. A Deutsche Bundesbank working paper by Hinterlang and Tanzer (2021) illustrates this approach. By applying a Deep Deterministic Policy Gradient algorithm, the AI system learned a reaction function that not only respected real-world constraints such as zero lower bound and nonlinear economic dynamics but also outperformed standard Taylor rules and even past Federal Reserve policies in simulations. This is still highly experimental approach, however, it does exemplify the potential of AI to assist and craft the policy strategies, as long as robustness and alignment with the central bank goals are maintained.

Additional use of AI is related to real-time estimation of current economic conditions, the so-called nowcasting. Most of the central banks of developed countries, such as the FED, BoE, ECB and others are increasingly leveraging big data and machine learning models for the purpose of nowcasting. Some ML methods that are proven to be effective in handling the complexity and volume of data, such as Random Forest, together with high-frequency indicators such as online prices and similar inputs, can enable central banks to improve the accuracy of short-term inflation or GDP estimates.

**Financial Stability and Risk Assessment.** Artificial intelligence tools and models have proven to be effective in a number of tasks related to financial stability and risk assessment. Fouliard et al. (2021) investigated the potential of an ensemble of ML models in predicting systemic banking crises. They found that their approach, utilizing online learning with meta-model and aggregating signals from different individual models, can forecast financial crises up to 12 quarters (3 years) with a high degree of out-of-sample accuracy. The results of their modelling provide insights into which model drives the prediction at each point and generally outperforms any individual model. In the study by Chen et al., (2023) the banking crises were predicted with a tree-based algorithm, providing the ear-

ly warning signals that were more accurate than traditional models. They trained the model on textual data in order to identify the financial crises periods in real time. By incorporating the textual data, the authors reduced false positives and false negatives in out-of-sample data, while also flagging the Covid-19 market turmoil as a financial crisis, something that would surely be missed by purely data-driven model. One of the prominent areas of ML model development seems to be credit risk, where central banks experimented with developing their own projections of bank losses and defaults. Variety of models in the academia, aimed at accurately capturing credit risk (e.g. Giudici et al., 2020; Fan and Yang, 2018; Shen et al., 2021), inspired central banks to develop their own credit risk metrics.

**Regulatory and Supervisory Functions.** Without doubt, there is huge potential for use of AI in regulatory and supervisory functions of the central banks. Anomaly detection and compliance seems to be among the most prominent uses. Machine Learning models have been extensively tested to uncover irregular patterns in bank data, which can ultimately signal errors, fraud or misconduct. Breeden (2024) from the Bank of England emphasizes this role of AI, accentuating the need for establishing monitoring systems that are capable of detecting anomalies, especially when AI systems are involved in risk assessment, trading or compliance tasks. Natural language processing (NLP) is also being introduced to interpret and apply regulatory rules.

**Communication and Sentiment Analysis.** Pfeifer and Marohl (2023) show that fine-tuned transformers can classify and interpret central bank communication more accurately than generic language models. Gambacorta et al. (2024) suggested that their NLP model significantly outperformed off-the-shelf models in predicting masked words in central bank idioms and in classifying the hawkish/dovish stance of policy statements. Ahrens et al. (2024) study investigates how the speeches of FED officials influence the market movements. They are applying supervised NLP while extracting implied forecasts for macroeconomic indicators. Their findings suggest that the content of speeches shift the projected economic outlook, which ultimately could help explain the changes in stock and bond market volatility, especially in the tails of distribution. As the study suggests, speeches delivered by the FED Chair have a particularly strong market impact, while a speaker's hawkish or dovish orientation strongly affects how the market interprets the message. Ultimately, this research highlights how AI could be used to help central banks in assessing the effectiveness of their communication and refine their messaging strategies. Larsen et al. (2021) from Norges Bank use machine learning models to investigate how the media articles and news narratives influence household inflation expectations.

## External drivers for AI adoption

Until now we have presented some of the main internal drivers for central banks to adopt AI in their operations. This research highlights that AI and ML models could improve forecasting accuracy, strengthen early warning systems, improve risk assessment and reveal new insights in text communication, all quite important aspects for central bankers, facing rapidly changing economic environment. This, however, was not designed to be an extensive list of ways central banks could utilize AI. In the near future, we could expect to see the deployment of AI models for climate risk, payment system monitoring, digital currency regulation and a number of other purposes. However, besides internal drivers, there are a number of external drivers compelling the adoption of AI in central banks.

One of the crucial external drivers for AI adoption in central banks is the growing use of these models in private financial institutions. This means that supervisors and regulators must develop internal AI capabilities to understand, supervise and audit these complex models. As noted by Shin (2024, p.92), private banks and financial institutions “increasingly employ AI tools, which will change how they interact with and are supervised by central banks”. One of the main examples is related to credit scoring and lending. It was noted that some of the early Machine Learning models unintentionally incorporated discrimination and bias, based on biased historical or nonrepresentative datasets, which, if left unsupervised, could lead to higher income gaps (Hay et al., 2023). This ultimately means that the adoption of AI in central banks is not a choice to adopting innovation for innovation’s sake, but to be able to properly audit and regulate financial industry and AI models. This is also related to the issues of fairness, ethics, transparency and accountability which, if not properly addressed, could undermine the legality of the financial system. Thus, the central banks are expected to embed democratic values into AI governance.

In addition, in practice, the AI and ML models, especially deep neural networks, are often regarded as “black boxes” due to their opacity and limited interpretability. It is a mandate of central banks to guard against these opaque models that have been increasingly employed by private banks and pose significant potential for bias and risk. In practice, this has led to experimentation among big central banks with their own AI tools. Thus, we have an ML robot created by the Brazilian central bank to automatically download and categorize consumer complaints, with the goal of potentially identifying patterns of misbehaviour of banks (Kearns, 2023).

## Limitations and challenges

Despite the growing interest in AI and its potential, it has to be noted that central banks face substantial challenges and constraints in adopting these technologies effectively. One of the most significant barriers is a shortage of skilled human capital. The survey conducted by Araujo et al. (2025) suggests that this is, in fact, a crucial and mostly reported challenge for implementation of AI reported by central bankers. In addition, many central banks rely on outdated IT and data infrastructures. Legacy systems that are often observed with the central banks are poor inputs for the big data analytics, enabling central banks to develop only small-scale AI projects. As the authors indicate, scaling up requires substantial upgrades, both in capacity and infrastructure, and reconfiguring operations within organizations. This is because the AI usually requires clean data that is integrated and accessible across departments.

Additionally, cloud-based and external platforms are usually not appropriate, due to restrictions related to security concerns. The inherent nature of machine learning and AI models presents an additional challenge. These models are often perceived as 'black boxes', difficult to interpret and explain, raising concerns in environments where transparency and accountability are critical. Possible issues with bias, fairness and ethical integrity could pose significant reputational threat for the central banks. One of the additional risks is a possibility of increasing financial fragility of the system. Namely, in an environment where many central banks and institutions are using similar models, we could observe herding behaviour. This could be especially dangerous when AI generates false outputs, while over-reliance on dominant AI models could lead to disastrous consequences (Kearns, 2023).

## Readiness for adoption

AI is different to previous technological advancements, primarily due to its complexity. In contrast to some solutions in the past that could be mainly characterized as easy-to-use and easy-to-deploy, AI requires specific knowledge and technical characteristics (Jöhnk et al., 2021). As Jöhnk et al. point out, in this context, AI readiness is defined as the ability of institution to effectively adopt AI and use it for their own benefits. This readiness includes a much wider set of requirements, not only 'installing' AI, but requires resources, data infrastructure, skills, and strategic commitment of an organization. If some of the crucial elements are missing, even big companies could fail in its adoption. Some of the scholars that proposed robust framework for systematic analysis of AI readiness are Jöhnk et

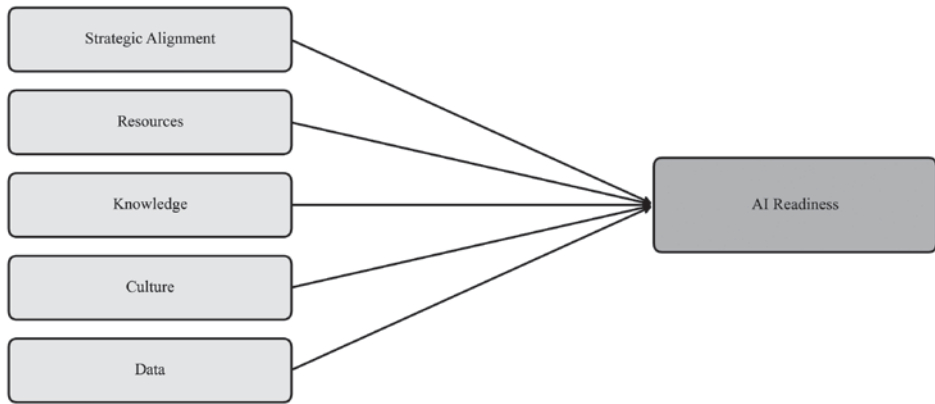
al. (2021) who argue that this readiness could be summarized into five categories: strategic alignment, resources, knowledge, culture and data. They constructed the framework on the basis of results from the research covering 25 AI expert interviews from various backgrounds and institutional contexts (e.g. level of AI adoption, size of organisation, stage of AI adoption, etc.).

- **Strategic alignment** refers to how well AI fits within an organization's goals. It includes factors such as business potential, top management support, process compatibility and data driven decision making. In central banks, this includes AI's potential to enhance core mandates like financial stability and the integration of data-driven decision-making.
- **Resources** are related to all potential technical and financial resources that are required for successful implementation of AI. Jöhnk et al. (2021) recognized budgeting, dedicated AI personnel and appropriate IT infrastructure as core resources required for successful implementation and adoption of AI. All of these could be directly translated to central banks requirements in the process of AI adoption.
- **Knowledge** refers to the specific skills and expertise within the organization that could be utilized to understand and develop AI solutions. In the context of central banks, this could include training in AI ethics and bias in financial decision-making and upskilling staff to ensure basic understanding how AI could support and improve the functions of central banks like supervision, monetary policy and risk assessment.
- **Culture** refers to overall mindset of the organizations towards innovations. With this respect, the items used to measure organizational readiness to adopt AI are innovativeness, based on the amount and pace of adaptability that organizational members possess, then collaborative work, as a crucial component for building cross-functional teams, and change management that helps employees to reduce possible misconceptions regarding AI such as job loss (Jöhnk et al., 2021). One specificity for the central banks may be fostering collaboration between economists, data scientists, and IT staff.
- **Data** seems to be of crucial importance in assessing AI readiness, comprising of the relevant amount and types of data, which is required by the AI models to be trained and generate accurate predictions (Jöhnk et al., 2021). Within this, three aspects are to be considered: data quality, data accessibility, and data flow. While central banks typically have rich datasets, problems may arise due to data fragmentation across departments, restricted accessibility due to security or legacy systems, and ensuring that the data is properly structured and governed for effective use in AI models.

### 3. Methodology

This chapter outlines the methodology employed to examine the readiness of central banks in the Balkans to adopt artificial intelligence, in line with the study's objectives. The study was done on the basis of expert surveys conducted in the period from February to April 2025. A total of six expert surveys were conducted with senior professionals from the following institutions: National Bank of the Republic of North Macedonia, Croatian National Bank, Central Bank of Montenegro, Bank of Albania, National Bank of Serbia, and Central Bank of Bosnia and Herzegovina. Interviewees were selected using purposive sampling, with the aim to capture the individuals knowledgeable both about current development of AI and its application in their banks, primarily from the leadership positions. As such, positions of respondents included Chief Economists, Advisors to the Governor, Directors of IT, heads of research or supervisory departments, and others.

The survey was constructed in three main segments. The first segment aimed to capture the AI readiness of the central banks in the region. This segment adopted the conceptual framework proposed by Jöhnk et al. (2021) that identifies five key dimensions of organizational readiness: strategic alignment, resources, knowledge, culture and data infrastructure (Figure 1). For the purpose of identifying and measuring these five dimensions, we used questions and items proposed by Jöhnk et al. (2021) but adapted for the purpose of acknowledging specific features of central banks. In particular, for the strategic alignment there were 4 items, for the resources, knowledge and culture 3 items, and 2 items for the data infrastructure. Each of these items is ranked on the 5-point scale, where each point had a qualitative representation of current state in the central bank (e.g. To what extent has the central bank systematically assessed AI's role in monetary policy, financial supervision, and risk management? (1) No assessment conducted; (2) AI is being informally explored, but no structured assessment (3); AI potential has been assessed in specific areas, but not widely adopted; (4) AI is actively being evaluated for multiple use cases; (5) AI applications have been formally incorporated into strategy and decision-making). Interview responses were quantitatively summarized. Each of the five dimensions (strategic alignment, resources, knowledge, culture, and data) was scored on a scale from 1 (very low readiness) to 5 (very high readiness), based on the respondent assessments. These scores were aggregated and visualized to facilitate the comparison across countries and dimensions, as presented in the results section.

**Figure 1: Conceptual framework for AI readiness**

Note: Adapted from Jöhnk et al. (2021)

The second segment of the survey focused on understanding how senior professionals within the central banks perceive the strategic opportunities and risks associated with AI adoption. It aimed to capture the respondents' views on the potential of AI to transform central bank operations, particularly in areas such as economic forecasting, regulatory compliance, and decision-making processes. It also aimed at identifying perceived vulnerabilities, including data privacy concerns, ethical implications, and institutional inertia. This segment was designed to assess the balance between optimism and caution, potentially revealing the extent to which central banks in the region view AI as an enabler of innovation and in which areas versus seeing it as a source of operational or reputational risk.

The third segment of the survey consisted of open-ended questions intended to provide greater nuance and contextual understanding. This qualitative component encouraged reflection on priorities in the bank regarding the AI, internal capabilities, and institutional attitudes toward innovation. It allowed respondents to elaborate more on existing initiatives, articulate some specific organizational barriers, and propose actionable strategies for responsible AI adoption. This segment was especially valuable in capturing forward-looking perspectives and understanding the diverse pathways through which central banks envision integrating AI into their long-term strategic agendas.

This study used both quantitative and qualitative approach. Data for the AI readiness was mainly treated as quantitative, using statistical methods for analysis, and implemented in programming language Python. Such analysis enabled cross-

country comparison and visualisation of the readiness dimension. On the other hand, the open-ended questions were analysed using MAXQDA software, extracting thematic analysis and identification of recurring themes in the responses.

While the research design provides valuable insight into the state of AI readiness in central banks across the Western Balkans, several limitations must be acknowledged. First limitation is the choice of methodology, that is the use of expert surveys as a primary data collection method. Although this was found to be the most appropriate method for the purpose of this study, it can sometimes lead to relatively shallow insights, especially when relying on structured responses. In order to mitigate this shortcoming of the survey as a data collection method, this study included an open-ended section where respondents could elaborate more on their perspectives and provide richer, and context-specific narratives.

Second limitation is related to self-reporting bias. Participants may portray their institutions in a more favourable way and interpret readiness in subjective terms. This could be particularly relevant in an environment where the strategic initiatives are politically sensitive and/or tied to leadership perceptions. In order to mitigate this, all questions that are closed ended and used for evaluation of readiness are carefully designed to reduce ambiguity and social desirability bias through structured, behaviourally anchored response options. Rather than asking evaluative questions (to be subjectively ranked on the scale 1 to 5), items were formulated to prompt respondents to assess concrete institutional practices and processes, thus encouraging more objective and comparable responses. While some degree of self-reporting bias may have persisted in the responses, it is believed that the scores provided, although cannot be treated as precise indicators of institutional capabilities, they remain useful for identifying trends and gaps.

Third, a potential limitation lies in the decision to include only one respondent per each central bank in a sample. The choice of one respondent may result in lower diversity of views and may not be able to capture fully the internal dynamics or operational differences that could exist across departments. However, this approach was adopted to ensure that the survey responses are coming from the high-level professionals that are knowledgeable on both topics of AI and the internal institutional operations. Thus, the aim was to prioritize depth and expertise over quantity, reducing the potential risk of receiving inconsistent or superficial insights from less-informed staff.

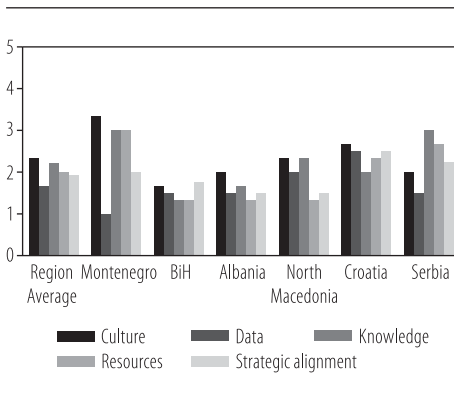
Overall, despite some of these limitations, it is believed that the research design is robust for the exploratory purposes of central banks' readiness for AI adoption and provides foundation for further empirical work and comparative studies.

## 4. Results

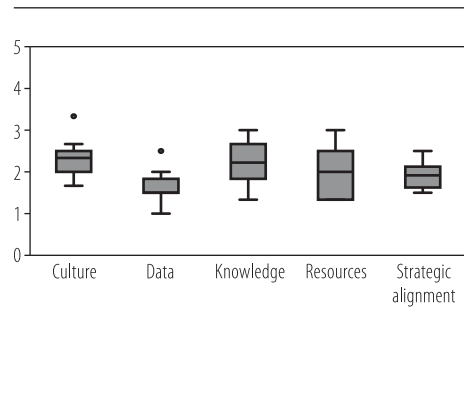
As discussed in the methodology section, the results were obtained based on the expert interviews from six central banks in the region, National Bank of the Republic of North Macedonia, Croatian National Bank, Central Bank of Montenegro, Bank of Albania, National Bank of Serbia and Central bank of Bosnia and Herzegovina. Responders generally covered managerial positions in these banks, including Chief Economist, Advisor to the Governor, Directors of specific sectors, IT specialist and similar. Only one responder had experience less than 3 years in the central bank, while three of them had experience between 8 and 15 years, and two of them more than 15 years.

Figure 2 presents the comparative snapshot of AI adoption readiness dimensions (culture, data, knowledge, resources and strategic alignment) across central banks in countries of the region. First observation that has to be noted is that all countries are far from high level of maturity in this segment. There are, however, some differences. It seems that Montenegro, Serbia and Croatia are outperforming the regional average, with culture for Montenegro, knowledge for Serbia, and strategic alignment for Croatia driving these higher results. Figure 3 shows that data and strategic alignment seem to be the major concerns for the region as a whole. It seems that fragmented, outdated and inaccessible data is a common problem across the region. Given that data is prerequisite for any AI implementation, this represents a structural barrier that needs priority attention. This could be even more problematic if we have in mind the low results on strategic alignment.

**Figure 2: Average Score by Country/Region**



**Figure 3: Distribution of Average Scores by Item**



**Table 1: Descriptive Statistics of Readiness Scores by Country**

Country	Mean	Std Dev	Variance
Montenegro	2.533	1.060	1.124
BiH	1.533	0.640	0.410
Albania	1.600	0.737	0.543
North Macedonia	1.867	0.990	0.981
Croatia	2.400	0.632	0.400
Serbia	2.333	0.900	0.810

As shown in Table 1, readiness scores vary across the analysed countries. Montenegro achieved the highest mean score (2.53), followed by Croatia (2.40) and Serbia (2.33), indicating relatively higher perceived readiness in this group of countries. On the other hand, BiH (1.53) and Albania (1.60) recorded the lowest mean scores, suggesting limited progress or capacity across assessed dimensions. Also, Montenegro exhibited the highest standard deviation (1.06), implying greater variability in readiness across categories, whereas Croatia and BiH showed more consistent scoring patterns (standard deviation is 0.63–0.64).

**Table 2: Spearman Correlation of Readiness Scores Between Countries**

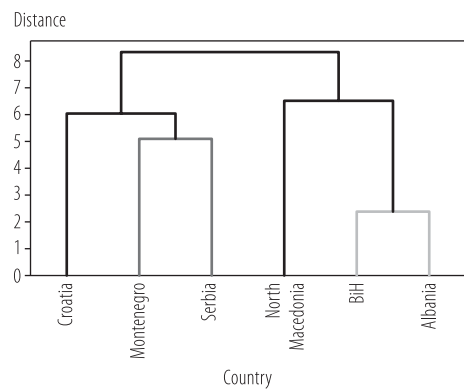
	MNE	BiH	AL	NMK	CRO	SRB
MNE	1.000	-0.067	0.188	0.225	-0.130	0.503
BiH		1.000	0.774	0.279	0.724	0.038
AL			1.000	0.375	0.527	0.174
NMK				1.000	0.218	0.221
CRO					1.000	-0.342
SRB						1.000

Table 2 presents Spearman correlations. The strongest positive correlation appears between BiH and Albania ( $\rho = 0.774$ ), indicating highly similar response patterns. Also, BiH and Croatia ( $\rho = 0.724$ ) show a strong alignment. In contrast, Croatia and Serbia ( $\rho = -0.342$ ) exhibit a moderate negative correlation, suggesting divergent readiness profiles. These patterns reflect both shared regional development trajectories and country-specific differences in policy or implementation focus.

The K-Means clustering, presented in Figure 4, grouped countries into relatively coherent clusters based on their readiness profiles. The average silhouette score<sup>1</sup> of 0.244 indicates moderate cluster validity, suggesting that while some countries are well grouped, others may lie near the boundaries of multiple clusters. This is supported by the underlying statistics and correlation patterns: countries with high similarity (e.g., BiH and Albania) cluster closely, while those with broader variation (e.g., Montenegro and Serbia) form distinct groupings. Together, the clustering and correlation analyses underscore both regional commonalities and individual national profiles within the Western Balkans.

Looking towards the future, more precisely for the next five years, respondents from the central banks reported that the AI will gradually reshape the central bank operations. Some anticipate profound impact, such as redefinition of workforce roles, faster decision making and regulatory adaptation, while others are more inclined to believe in incremental changes, primarily due to institutional conservatism and complex regulatory environment in which central banks operate. However, there is a broad consensus that AI will aid central banks in automation of routine processes, data analysis and

**Figure 4: K-Means Clustering Results**



<sup>1</sup> The Silhouette score is a metric used to evaluate the quality of clustering results. It reflects how similar a data point is to its own cluster compared to other clusters.

For a given data point  $i$ , the Silhouette score is defined as:

$$s(i) = \frac{b(i) - a(i)}{\max\{a(i), b(i)\}}$$

Where:

- $a(i)$  is the average distance between point  $i$  and all other points in the same cluster (intra-cluster distance).
- $b(i)$  is the minimum average distance from point  $i$  to all points in another cluster (nearest-cluster distance).

The score ranges from  $-1$  to  $+1$ . The interpretations of scores are as follows:

- $s(i) \approx 1$ : well clustered.
- $s(i) \approx 0$ : point is on or near the boundary between clusters.
- $s(i) < 0$ : point may be assigned to the wrong cluster.

The average silhouette score across all data points indicates the overall quality of the clustering. Higher values indicate clusters that are more coherent.

detection of systemic risks and financial crimes. Some prerequisites for this are staff training, strong governance, and cultural transformation that will enable overcoming institutional inertia and ensure effective implementation of AI solutions.

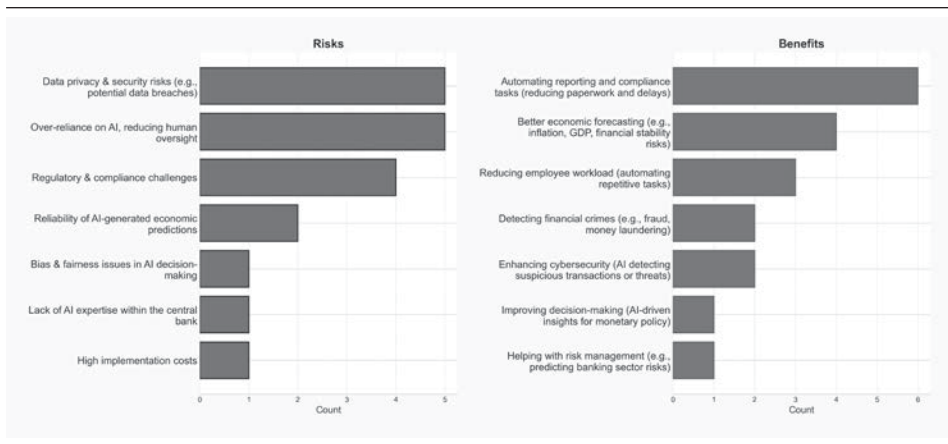
The adoption of AI in central banking presents a wide array of opportunities and challenges. There seems to be a consensus among the respondents from the central banks that the most important benefit is reporting and compliance automation (Figure 5). It was cited in all six responses, clearly suggesting recognition of AI's potential to streamline administrative processes, alleviate manual work and reduce delays and bottlenecks, especially in areas such as regulatory reporting and supervisory functions. This benefit is followed by an improvement of economic forecasting, highlighting the value of AI in enhancing predictive accuracy for some of the key indicators and measurements calculated by central banks such as inflation, GDP, and systemic risks. This might be especially relevant in the areas where timely data-driven insights are crucial for overall mandate of central banks such as macroprudential oversight and monetary policy. Third benefit, reduction of employee workload suggests that the central banks see growing interest in AI due to its ability to support internal operations. Some other benefits, such as detecting financial crimes, enhancing cybersecurity, and improving decision-making were mentioned less frequently, but indicate growing interest in AI's ability to support internal operations and strategic analysis, and the importance of AI in improving surveillance and identifying patterns in fraud or money laundering activity. Overall, the responses suggest that central banks view AI as a tool for increasing efficiency, improving risk monitoring, and strengthening analytical capabilities across multiple core functions.

Responses also highlight a clear set of shared concerns around AI adoption. Three most cited risks were data privacy and security risks, regulatory and compliance challenges, and over-reliance on AI reducing human oversight (Figure 5). These concerns are a definite result of sensitive nature of the data handled by central banks. In addition, the results suggest the need for clear regulatory framework that could support the integration of AI, but without compromising accountability and public trust. Although there is interest in advanced analytics and automation, the high emphasis on reducing human oversight suggests that there is a reluctance to give too much control to algorithms. Other challenges such as the reliability of AI-generated economic predictions, lack of internal expertise, implementation costs, and ethical concerns were mentioned less frequently, though these could be also obstacles to be dealt with. Overall, the findings suggest that the AI adoption in central banks requires a multi-dimensional approach. Namely, there is a need for strengthening data governance and cybersecurity, while

at the same time updating legal and supervisory frameworks, and promoting systems that support human-machine collaboration. Also, it has to be noted that the risks identified do not reflect opposition to AI itself but rather obstacles that highlight the areas where careful planning, investment, and policy support are most urgently needed.

To ensure responsible adoption, along with proper strategic support and investments in data infrastructure, respondents underscored the importance of developing robust regulatory and ethical frameworks. Within this, key steps include systemic data standardization, regulatory alignment, clear definition of responsibilities and limitations and delimitation of AI use. It seems that the capacity building through training, reskilling and awareness-raising could be crucial steps in fostering institutional readiness.

**Figure 5: Perceived risks and benefits**



## 5. Conclusion and Discussion

This study investigates the readiness of central banks in the Western Balkan countries to adopt Artificial Intelligence. It was carried out based on expert surveys with senior professionals within the six central banks. For this purpose, the conceptual framework for the adoption of innovation was adapted, including five dimensions (strategic alignment, resources, knowledge, organizational culture, and data). The findings suggest limited and uneven readiness among these central banks. Some central banks, like Serbia, Montenegro and Croatia, show some relative strengths in terms of knowledge or culture, but there is no consist-

ent high level of readiness within all categories. There is, however, evident weak performance of all central banks related to dimensions of data infrastructure and strategic alignment. Having in mind that modern AI systems require clean, accessible and robust data, and clear strategic vision and commitment, this undeniably presents a challenge.

Also, none of the respondents viewed AI as a threat in and of itself. While privacy concerns, over-reliance on automated systems, and a lack of in-house expertise were seen as the most important risks, key benefits identified included automating compliance, improving economic forecasting, and reducing employee workload. Thus, responsible governance and the development of human-centred AI systems appear to be crucial pathways for an effective and ethical integration of AI in central banking. One of the crucial insights from this research is that AI adoption is not a technical upgrade for the central banks. It is a systemic transformation that requires cultural shifts, leadership advocacy, talent development, and institutional reform. But it is also unavoidable. In a legitimate search for efficiency and profit, private financial institutions are rapidly adopting AI and ML models. This ultimately creates pressure on central banks to develop the capabilities needed to audit, supervise and regulate increasingly complex and opaque systems which, if left unchecked, could pose risk to financial stability.

Overall, there are few policy recommendations that could be used for evidence-based decision-making for the adoption of AI at central banks:

**Prioritize Strategic Alignment of AI with Core Mandates.** According to the findings of this study, the strategic alignment scored among the lowest of all readiness dimensions, signalling a gap between AI experimentation and core objectives of the central banks. As emphasized by Jöhnk et al. (2021) and reflected in central banks of developed countries, such as the Bank of England and the ECB, AI adoption must be strategically aligned with the core mandates of the central bank, including risk analysis, monetary policy, supervision and financial stability. Within central banks of developed countries, this is done not only through isolated pilot projects, but also by establishing dedicated leadership roles to steer AI strategy and integrate it into its operational framework and ensure cross-departmental coordination (Araujo et al., 2025). By ensuring strong oversight by the designated AI leadership role and/or top management, it will transform isolated efforts into mission-align innovation, that would align AI with the core mandates of a modern central bank.

**Establish Internal AI units and Governance.** One of the results of this study is that the AI innovation is not solely about tools and models. It is about structure,

institutional agility and leadership. Without formalizing internal coordination, there is a high risk that AI innovations and efforts remain unscalable, experimental and fragmented. As seen in the developed countries, central banks are increasingly institutionalizing AI innovations through formal roles and dedicated units (Araujo et al., 2025). This allows for great accountability, strategic oversight and cross-departmental alignment. However, the surveyed central banks, as revealed by this study, have no formal institutional mechanisms, resulting in low strategic alignment and slow overall progress. Thus, in addition to developing AI strategies and roadmaps, adopting a formal structure, such as appointing AI data coordinators and establishing AI innovation units, could go a long way toward aligning the efforts of these central banks with those of developed countries.

**Data Infrastructure and Data Governance Reform.** One of the results of the study suggest that data infrastructure is a clear structural barrier for the Western Balkan countries to adopt AI. Legacy and outdated systems, fragmented and siloed data may severely limit the ability to deploy efficient ML tools. Despite the fact that these are institutions in possession of large volumes of financial and macroeconomic data, when the data is in this form, it can rarely be used for AI/ML models that rely on clean, well-governed datasets. Therefore, some of the foundational prerequisites for the scalable and reliable AI deployment are developing IT infrastructure to support large-scale analytics. This includes standardization and integration of databases and datasets across internal departments, as well as the implementation of data governance protocols that ensure quality control, access management, and auditability.

**Build Technical and Ethical AI in-house Competencies.** The research reveals that a lack of internal expertise is one of the crucial risks for AI adoption. Despite the evident and perceived benefits of the AI solutions, central banks seem to have a shortage of staff with technical and conceptual understanding and expertise in AI. However, as Jöhnk et al. (2021) argue, AI readiness does not assume only technical skills, but also broader familiarity with AI bias, model explainability and responsible innovation. Fear of job displacement in the central banks of Western Balkan could further hinder AI adoption and building human-centred AI systems. For these reasons, there are different methods that should be utilized to develop and to retain in-house talent, through designing role-specific training pathways, create partnerships with universities for life-long learning, in-corporate AI ethics and bias awareness trainings to address the misconception of job displacement and others.

**Establish Regional Cooperation and Knowledge-Sharing Platform.** The research identifies that the central banks in the region face similar structural limi-

tations. Moreover, they are often constrained by the size of the institutions and limited budget, which makes it difficult to independently develop and properly adopt AI systems. For that reason, regional cooperation emerges as a logical solution. Most of the obstacles identified in this study could be supported by the shared initiatives to address skill shortages, fragmented and non-adequate computing infrastructure and low culture. On the other hand, the heterogeneity of the development of different factors of readiness in these countries, could further induce peer learning and resource pooling. One of the actionable recommendations for this purpose is establishing the regional AI forum for central banks, to share knowledge and develop AI solutions, either under the umbrella of this initiative or by supporting this initiative. Thus, it could also serve as a platform for exchanging practical tools and projects. Also, shared partnership would be in a position to better utilize EU institutions and funding and engage in partnerships with the regional universities to increase their overall AI capabilities. Overall, such regional network would enable central banks in the Western Balkan region to develop scalable innovations in coordinated way with significantly lower resources required (per central bank).

**Update Regulatory Framework to reflect the Integration of AI.** One of the common concerns reflected in this study is related to raising questions about transparency, accountability, and legal compliance. This generally reveals looming regulatory challenge, namely, how to amend the existing legal framework that is not equipped to address most of the AI-specific risks. Respondents suggested that over-reliance on opaque models, data privacy, and the lack of clear guidance are all concerns regarding AI adoption. In addition, as suggested by the literature, some of the AI tools used in private banks, if left unsupervised, could introduce a new form of bias and opacity. For that reason, the regulators must be equipped with competencies and legal and regulatory foundation to audit and oversee these innovations (e.g. Shin, 2024; Hay et al., 2023). This should be done with review of the regulatory framework within developed countries, developing the minimum standards for AI systems that could be used in financial institutions supervised by central bank(s), developing internal AI policies and guidelines, and participating in international standard-setting initiatives. Ultimately, this would be a further step forward in treating AI as an embedded function of central bank(s) and not just a temporary fad. This would also serve the overall goal of central banks for externally demanded accountability and innovations.

## **Declaration of AI Use**

*During the preparation of this manuscript, the authors used ChatGPT (OpenAI) on a limited basis for language editing and grammar improvement. All AI-assisted outputs were critically reviewed and approved by the authors, who take full responsibility for the final content of the manuscript.*

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