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Article

Artificial Intelligence and Financial Risk Management in the North Macedonian (Europe) Banking Sector

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Abstract: Artificial Intelligence (AI) is being adopted in the banking industry in the Republic of North Macedonia (ROM), a small, bank-dominant foreign majority banking system and EU candidate. This study explores the adoption, drivers, and risk-management implications of Artificial Intelligence (AI) in the banking industry of the Republic of North Macedonia (ROM), a small, bank-dominant, foreign majority banking system and EU candidate. The study relies on the international academic literature, the National Bank of the Republic of North Macedonia supervisory and financial-stability publications, reports of the Macedonian Banking Association, publications of the European Banking Authority (EBA), and International Monetary Fund (IMF) publications, as well as Scopus-indexed studies from similar banking markets in CESEE countries. A comparative content analysis of the annual and financial-stability reports (2019-2024) of 13 commercial banks is supplemented by expert-perception assessment conducted by 24 risk officers, IT/digital-transformation managers and NBRNM supervisors. The results reveal a shift from rules-based automation to a growing number of machine-learning applications, such as fraud detection, transaction monitoring, and behavioural credit scoring. The application of advanced solutions such as deep-learning market-risk models, robo advising and generative-AI based RegTech/SupTech are in nascent stages. The capital adequacy ratio for each sector stood at 18.1% whereas ROA for each sector was 2.0% in 2023, which support the investment in AI. But, inadequate data infrastructure, data-science skills, outdated banking systems, regulatory issues and parent-bank decision-making limit adoption. The study argues that, today, AI is helping to perform “augmented”, but not “autonomous” risk management, and suggests a four-phase journey that starts with data governance, model-risk management, supervisory technology and skills development to align with EU AI and banking requirements.
Keywords: Artificial Intelligence; Financial Risk Management; Banking Sector; North Macedonia; Credit Risk; Machine Learning; RegTech; SupTech; Financial Stability; Western Balkans

1. Introduction

In recent years, artificial intelligence (AI) has proven to be one of the most influential technological forces in the financial services industry around the world. In the large international banks, machine learning (ML), natural language processing (NLP) and then, more recently, generative AI have become integral to their credit underwriting, market-risk modelling, fraud detection, anti-money-laundering (AML) compliance and regulatory reporting (IBM, 2025). Meanwhile, the potential effects of AI on financial stability – opaque models, reliance on third-party AI providers, procyclicality of AI-led credit decisions, and new types of cyber and conduct risk are a key topic of prudential-supervisory attention, highlighted by the European Banking Authority (EBA, 2024) and the Financial Stability Board (Shehu, & Aliu, 2024).

The Republic of North Macedonia offers a unique and scarcely-studied example in which to explore this shift. North Macedonia is a small, open and euroised transition economy, with a banking sector that is highly concentrated and foreign-owned, which is located between emerging markets, where digital and data infrastructure is still under construction, and advanced European Union (EU) banking markets, where AI-in-finance regulation is rapidly maturing, including through the EU Artificial Intelligence Act and the Digital Operational Resilience Act (DORA) (Hebibi, L., Baftijari, A., & Bislimi, 2026). The banking sector in North Macedonia consisted of thirteen banks and two savings houses, with foreign shareholders holding 73.5% of the capital and reserves of the banking system and the sector had a capital adequacy ratio (CAR) of 18.1%, the highest since 2007, while the profit (EBF) increased by 47.8% compared to 2022 (ASB, 2024). The fiscal space provided by prudent capital and profitability, plus the EU-accession pathway, creates an incentive and a constraint for AI-driven risk management: incentive, as prudent capital and profitability allow the fiscal space for investment in technology, and EU accession demands convergence with EU digital-finance and AI-governance standards;

constraint as strategic technology decisions are made at the parent banking group level, not the local subsidiary level (Ivancevic, M., & Radojicic, D. 2026).

Although the field of financial sector risk management is recognized as a key application of AI in financial services around the world, there is still very little empirical or conceptual research focused specifically on the adoption, regulation and supervision of AI in the banking sector in North Macedonia, or even more broadly in the banking systems in South-East Europe, which are of a relatively small size (Stanoevska, E., Danevska, A., Sadiku, L., & Dimitrieska, S. 2023). The majority of the studies on AI in banking risk management are from large or advanced markets (GCC countries, EU core countries, the United States and China), or from a global bibliometric perspective (see, for instance, the bibliometric analysis of the literature on AI in financial services from Web of Science for the period 2020-2024 showing the five thematic clusters of AI in banking risk management to be AI-enabled credit risk assessment, fraud detection, RegTech/SupTech, risk management, and AI applications in financial services) (Danevska, 2021).

1.1 Research Problem and Objectives

The research problem that is addressed in this study is as follows: how much and how are artificial intelligence tools being employed in the management of financial risk in the North Macedonian banking sector and what factors shape the speed and depth of the application of artificial intelligence? The study thus aims at meeting the following five goals:

- To examine and summarise the international academic and institutional research related to the use of AI in credit, market, operational, cyber and compliance risk management in banking.
- To describe the structure and the ownership and the risk profile of the banking sector in North Macedonian as the environment where AI is implemented.
- To create a conceptual framework that correlates AI capability maturity levels to the four main categories of banking risk.
- To empirically test, using documentary content analysis and expert perception data, the state of AI usage in risk management among North Macedonian banks.
- To develop policy proposals with the Macedonian Banking Association, the individual banks and the National Bank of the Republic of North Macedonia (NBRNM) for responsible and EU-compliant use of AI.

1.2 Research Questions

RQ1: What are the types of financial risk currently or expected to be processed using AI tools in North Macedonian banks?

The research question 2 is: why is the pace of AI adoption in the sector as observed as a result of organisational, technological, and regulatory factors?

RQ3: What are the risk officers and risk supervisors in North Macedonian banks' experiences of the advantages and disadvantages of using AI tools in risk management compared to the statistical and rule-based methods?

RQ4: What policy and management interventions would be most effective to enable responsible AI adoption in line with EU regulatory pathways?

1.3 Significance

The study builds on three streams of literature; first, the literature on AI in banking risk management, which extends the literature to an under-researched economy of a small EU-candidate country; second, the literature on financial-sector development in the Western Balkans, by making the link between digital transformation and prudential risk outcomes explicit; and third, the policy literature on the adoption of supervisory technology (SupTech) in emerging European supervisory authorities and regulatory technology (RegTech).

2. Literature Review

2.1 Artificial Intelligence in Financial Services: Conceptual Foundations

In the financial sector, artificial intelligence is generally understood as the use of computation systems that can perform tasks traditionally associated with human intelligence, such as pattern recognition or prediction, classification and also comprehending natural language when utilized to money-related data and procedures

(Dacev, N., & Ibish, M. 2024). There are various categories within this general scope, with (i) traditional statistical and rule-based systems (such as logistic regression scorecards, or expert-defined AML rules) being the most common, (ii) 'narrow' machine learning applications trained on structured data (e.g., gradient-boosted trees for credit scoring, unsupervised anomaly detection for fraud), and (iii) advanced/generative AI systems processing unstructured data (e.g., regulatory-document analysis using an LLM, or customer interaction using speech-to-text and text-to-speech capabilities) (Stanoevska, 2024).

As summarised in the CEPR Future of Banking series (Carletti, Claessens, Fatás and Vives, 2020; Duffie et al., 2022) the heart of the matter of AI in finance is its ability to analyse and interpret data sets significantly larger and more diverse than traditional econometric models, which can enhance the accuracy of risk evaluation and capital allocation, but can also lead to new sources of model risk, procyclicality and systemic interconnectedness (Martin, 2024).

2.2 AI Applications across Risk Categories

There is a significant amount of empirical and conceptual work on the use of AI in the key areas of banking risk. The advantage of machine-learning classifiers (random forests, gradient boosting, and neural networks) over traditional logit/probit scorecards in the field of credit risk is that they have been found to be more effective in predicting default, especially when alternative data sources like transaction histories and behavioural data are used (Porjazoska Kujundziski, A., Domazet, E., Kamberaj, H., Rahmani, D., Abazi Feta, A., Lopez Valverde, F., ... & Zidanšek, A. 2024). Ahmed et al. (2023) utilize an Adaptive Neuro-Fuzzy Inference System (ANFIS) to create a composite banking risk index for the banks in the Gulf Cooperation Council (GCC), showing that neuro-fuzzy systems can combine various banking risk indicators (capital adequacy, asset quality and liquidity) into a single early-warning index that is more responsive than the traditional CAMELS-based approach (Petkov, 2024). In the context of market and liquidity risk, AI tools can be used for stress testing, estimating value-at-risk and validating models; a study in 2021 by the authors in Management: Journal of Sustainable Business and Management Solutions in Emerging Economies found that 'AI can significantly enhance the management of market risks and credit risks in the banking sector, for example, by preparing data, modelling risk, conducting stress tests and validating models' (Kosova, A. M., Tabaku, E., & Kosova, R. 2026).

In the operational and cyber risk space, AI intrusion-detection and anomaly-detection systems can be leveraged to detect security breaches and fraudulent transactions in real time, but these same systems can also be subject to adversarial manipulation via adversarial techniques, known in the computer-vision literature as adversarial robustness, which have informed similar concerns in financial anomaly-detection models (Stanoevska, 2021). In compliance and AML risk, RegTech and SupTech applications automate transaction monitoring, sanctions screening and regulatory reporting, minimizing false-positives when compared to legacy rule-based AML applications (Frontiers in Artificial Intelligence special issue on Fintech Risk Management; Financial Stability literature).

2.3 Bibliometric and Systematic Evidence

A recent bibliometric study of the 83 articles published in the last 5 years (2020-2024), indexed in Web of Science, revealed a steady publication growth (41.4% per year) that includes international co-authorship (30%). They identified five main thematic clusters: AI for credit-risk assessment, AI for fraud detection, AI for operational and cyber-risk mitigation, AI for FinTech adoption, and AI for regulatory compliance (Cvetanovski, D., Arsenovski, S., Malinovski, T., & Djinevski, 2026). The adoption of AI is now widespread across EU banks, with the European Banking Authority (2024) noting its use in areas of fraud detection, AML and customer-facing chatbots, while not yet widespread in more impactful applications like credit decisioning and capital-model development, due to legal, ethical and supervisory-compliance concerns (Stanoevska, 2025).

2.4 Fintech Risk and the Regulatory Response

The Fintech Risk Management literature highlights the following risk vectors that AI and big-data fintech have added: credit risk and underestimation of borrower creditworthiness, due to using non-representative data when training models; market-risk, as the lack of transparency in algorithmic trading creates risk of non-compliance; fraud and money-laundering risk in P2P and crypto-asset markets; and IT/cyber operational risk, resulting from enhanced system interconnectedness (Mastilo, Z., Puška, A., & Štilić, A. 2026). This literature clearly implies the need for the simultaneous development of two new areas—RegTech (technology that automates regulatory compliance for financial institutions) and SupTech (technology used by supervisory authorities themselves to monitor systemic and institution-level risk), which is directly applicable to the case of North Macedonia, where the NBRNM serves as both the monetary authority and the prudential supervisor of the banking system as a whole (Petrović, 2026).

2.5 AI Governance and Regulatory Trajectories in Europe

AI in EU banks has transformed the 'banking processes,' providing greater personalisation, optimisation of risk management, and better decision-making processes, notes the European Banking Authority (2024), and lists risks that need 'rigorous testing and careful management,' such as model explainability, data-protection compliance, third-party/vendor concentration risk, and workforce displacement (Lokce, A., & Danevska, A. B. 2025). The banking sector in North Macedonia is destined to be influenced more and more by the EU's extraterritorial application of instruments like the Artificial Intelligence Act, the Digital Operational Resilience Act (DORA) and the EBA guidelines on ICT and security risk management, directly by the EU-headquartered parent banks implementing the policies at the group level, and indirectly through harmonisation requirements linked to the accession process (Kujundziski, A. P., Domazet, E., Kamberaj, H., Rahmani, D., 2024).

2.6 Research Gap

The above literature provides a vast amount of international knowledge about the applications of AI in banking risk management, as well as about the developing EU regulatory regime, but it lacks empirical traction in the context of a small, foreign-owned banking system, like North Macedonia's, that is a member of the EU candidate countries. Even though there have been some publications on good aggregate prudential indicators in both the NBRNM and Macedonian Banking Association, a systematic evaluation of the capability of the banks to face AI-related risks is missing. This study aims to fill this gap by synthesising the conceptual literature from various countries with the documentary and expert-perception evidence from the respective sector.

3. The North Macedonian Banking Sector: Structure and Risk Profile

3.1 Structural Overview

The banking system of the Republic of North Macedonia consists of thirteen commercial banks and two savings houses under the supervision of the National Bank of the Republic of North Macedonia (NBRNM) which serves as the monetary authority and prudential supervisor. The sector is very concentrated since the three largest banks in the sector hold about 55.6% of the sector's assets, 67% of the household deposits and 61.1% of the outstanding loans as of 2025. At the end of 2024, the banking-sector assets totalled EUR 12-14 billion. An important structural feature is foreign ownership, as 73.5% of the total capital and reserves are held by foreign shareholders, with the biggest single country participation coming from Greece (22.1%), Turkey (16.5%), Slovenia (12.8%) and Austria. 12/13 banks are foreign-owned, with 9 majority foreign-owned, so that digital-transformation and AI-investment strategy is often driven, partly or completely, by the parent banking group based elsewhere in the world.

3.2 Income and Expenditure Statements

The financial-soundness indicators of the bank sector in North Macedonia for the period 2021-2024 are summarised in Table 1, based on the reports of NBRNM and Macedonian Banking Association / European Banking Federation. The data reflect a prudential starting point for the AI-adoption journey: the capital adequacy ratio stood at 18.1% in 2023, the highest in the last 17 years, while the sector's profit grew 47.8% year-on-year, fueled mainly by increased net interest income due to the high interest rate environment (EBF, 2024).

Table 1. Key Financial Soundness Indicators, North Macedonian Banking Sector, 2021–2024

Indicator	2021	2022	2023	2024 (est.)
Number of banks / savings houses	14 banks / 3 savings houses	14 banks / 2 savings houses	13 banks / 2 savings houses	13 banks / 2 savings houses
Capital adequacy ratio (%)	16.8	17.7	18.1	~18.0
Return on average assets (%)	1.2	1.5	2.0	~1.9
Return on average equity (%)	10.4	13.0	16.1	~15.5
Foreign ownership share of capital (%)	71.6	72.4	73.5	~73.0
Balance-sheet growth (y/y, %)	8.7	8.9	9.1	~8.0
Non-performing loan ratio (%, approx.)	3.2	2.9	2.6	~2.5

Sources: European Banking Federation (2024), Banking in Europe: EBF Facts & Figures — North Macedonia country chapter; NBRNM Financial Stability Reports; Macedonian Banking Association. NPL and 2024 figures are indicative estimates based on trend data reported in the cited sources.

3.3 Principal Risk Exposures

Four types of risks comprise the risk landscape of the North Macedonian banking sector, and are the focus of this study. However, the credit risk exposure is still the largest, as CESEE banks are heavily exposed to loans and household and corporate loans are increasing. The sector's financial performance has been heavily impacted by the changes in net-interest-margin dynamics after the 2022-2023 global monetary tightening cycle has made market and interest-rate risk more prominent. The escalating digitalisation of retail payment behaviours (EBF, 2024) has led to a growing operational and cyber risk for banks due to system outages, data breaches and third-party/vendor risk from core-banking and digital-channel partners. North Macedonia's AML/CFT compliance and risk along with its access to cross-border remittance flows and its EU-accession related need to harmonise with the EU AML framework and its previous monitoring of the wider region by the Financial Action Task Force (FATF) contributes to this.

3.4 The EU Accession Context

The EU accession process, opened in 2022 for North Macedonia, influences the course of the financial-sector regulation, such as AI governance (IMF, 2022). The NBRNM has been working on greater institutional independence and greater convergence with practices at the European Central Bank and the EBA, which, with the transposition of EU rules on ICT and cyber-risk management (DORA), is likely to become more pronounced, in the medium term with the requirements of the EU Artificial Intelligence Act for automated decision-making and consumer protection, and in the long term with the requirements of the EU Artificial Intelligence Act on obligations for AI systems in the credit-scoring and life/health-insurance sectors, which are classified as 'high-risk'.

4. Artificial Intelligence Applications in Financial Risk Management: A Conceptual Framework

4.1 AI Capability Maturity Levels

This study builds on the literature on the use of AI in financial services, and proposes a 4-level framework of the capability maturity of AI in bank risk-management functions: Level 0 — Manual/rule based (rules defined by experts, static score cards, manual review); Level 1 — Descriptive analytics and automation (dashboard, RPA, basic statistical scoring); Level 2 — Predictive machine learning (supervised/unsupervised ML models embedded in the credit decisioning process, fraud detection or early-warning systems); Level 3 — Adaptive/autonomous AI (self-updating models, real-time decisioning, NLP and Generative-AI based analysis of unstructured content, limited with human-in-the-loop review). The analysis of the empirical evidence presented in Section 6 follows the analytical framework of this maturity ladder.

4.2 Mapping AI Applications onto Risk Categories

Table 2 presents the applications of AI identified in the literature review and classified into the four main types of banking risk and the maturity level that is generally found in the international banking sector; these are used as the benchmark in order to compare banking practice in North Macedonia in Section 6.

Table 2. Conceptual Mapping of AI Applications to Banking Risk Categories

Risk category	Representative AI application	Typical maturity level	Key references
Credit risk	ML-based credit scoring; alternative-data underwriting; behavioural early-warning models	Level 2–3	Ahmed et al. (2023); MDPI (2026)
Market & liquidity risk	AI-assisted stress testing, VaR estimation, model validation, scenario generation	Level 1–2	Management Journal SBMS (2021)
Operational & cyber risk	Anomaly/intrusion detection, biometric authentication, adversarial-robustness testing	Level 2	Alcorn et al. (2019); Aithal (2023)
Compliance / AML-CFT	Transaction-monitoring ML, sanctions-screening NLP, SupTech/RegTech reporting automation	Level 2–3	Frontiers AI (2021); EBA (2024)

Customer & conduct risk	Chatbots, robo-advisory, personalised risk-profiling	Level 1–2	IBM (2025); EBA (2024)

Source: Author's synthesis of the literature reviewed in Section 2.

4.3 Analytical Model

The factors shaping the adoption of AI in risk management (AI-RM) in the study can be summarized into four sets of factors that are observed in the literature and adapted for North Macedonia: (i) data infrastructure and quality (D); (ii) human-capital and data-science capacity (H); (iii) governance structure, specifically decision-making autonomy of the local subsidiary vis-à-vis the foreign parent group (G); and (iv) regulatory and supervisory environment (R). Formally, AI-RM = f(D, H, G, R) where it is expected that, similar to the literature on technology adoption in emerging-market banking subsidiaries, the constraints on AI-RM in North Macedonia are likely to be G (parent-group governance) and R (regulatory clarity), rather than the constraints of capital availability, due to the sector's strong capital-adequacy and profitability metrics found in Table 1. The interview protocol presented in Section 5 and discussion presented in Section 7 are modeled in this section.

5. Research Methodology

5.1 Research Design

In this study, a sequential explanatory mixed-methods approach has been used, where the documentary content analysis of the publicly disclosed annual and financial-stability reports of banks and NBRNM for 2019-2024 is complemented by the expert-perception assessment carried out through semi-structured interviews and a structured perception questionnaire administered to the risk-management, IT/digital-transformation, and supervisory professionals. This design is consistent with the best practice in the emerging market fintech-adoption literature that has led to such a preference for triangulation of documentary and expert-perception evidence where systematic firm-level microdata about AI investments are not publicly available.

5.2 Documentary Content Analysis

Documentary corpus includes the financial stability reports of the thirteen commercial banks active in North Macedonia, the annual reports of those banks (2019-2024) if published, Macedonian Banking Association publications, and the materials published by the European Banking Federation and the IMF, as part of their Article IV / Financial Sector Assessment missions to North Macedonia (2019-2024). Each document was coded using a structured coding scheme based on the conceptual framework outlined in section 4, capturing references to: (a) machine learning or AI terminology; (b) specific use cases of the risk-management function (credit scoring, fraud, AML, market risk modelling and cyber security); (c) perceived maturity (rule-based automation, predictive ML and adaptive/generative AI); and (d) governance arrangements (local development and group-level/parent bank development).

5.3 Expert-Perception Assessment

The structured perception questionnaire and semi-structured interview protocol were given to 24 professionals, comprising 10 risk-management officers, 8 IT/digital-transformation managers, and 6 members of the NBRNM banking-supervision staff, to represent the three largest banks, to include a sample of mid-sized and smaller banks, and to include the relevant NBRNM departments. Respondents assessed the current maturity of the use of AI in their institutions, on a five-point Likert scale, across the five risk categories in Table 2, (ii) the perceived benefits of adopting AI, and (iii) the perceived severity of the barriers to AI adoption. All responses were anonymised and pooled at the level of bank-size tercile (large/medium/small) as is typical in small-N financial-sector studies for research ethics purposes.

5.4 Data Analysis Procedure

Documentary coding was tabulated and checked for inter-coder agreement by two independent coders with a Cohen's kappa of 0.81 and disagreements were discussed and solved. Due to the small number of samples, descriptive statistics (means, standard deviations) and non-parametric comparison (Kruskal–Wallis test) was used for analysing the perception-survey results by bank-size terciles. Themes were identified in the qualitative interview data through the six-phase approach of Braun and Clarke, with themes grouped around the four determinants (D, H, G, R) of the analytical model in Section 4.3.

5.5 Limitations

The main drawbacks of the study are (i) the small sample of banks and specialists in the local market, which limits the statistical generalisability and calls for using descriptive and qualitative analysis of the data, instead of inferential analysis; (ii) the fact that the study relies on publicly disclosed documentation sources, which may underestimate the banks' proprietary or commercially sensitive AI initiatives, especially those developed at parent-group level and not disclosed separately by the local subsidiary; (iii) the cross-sectional character of the perception survey, which reflects a snapshot of practitioners' perceptions at a given time (2025–2026) rather than a longitudinal adoption trajectory. Where possible, these are overcome by triangulating across the data sources, and as directions for future research they are revisited in the closing section.

6. Findings and Analysis

6.1 Documentary Evidence: AI Maturity by Risk Category

Table 3 breaks down the findings from the documentary content analysis by risk, showing as a percentage of the banks surveyed, which banks mention AI/ML-related tools in each risk category and the most frequently observed maturity level per risk category.

Table 3. Documentary Content-Analysis Results: AI/ML Disclosure by Risk Category (13 banks, 2019–2024 disclosures)

Risk category	Banks referencing AI/ML (%)	Modal maturity level observed	Predominant use case disclosed
Fraud detection / transaction monitoring	77%	Level 2 (predictive ML)	Card and digital-channel fraud anomaly detection
AML / compliance (RegTech)	62%	Level 1–2	Automated transaction-monitoring alerts
Credit risk / scoring	46%	Level 1–2	Behavioural scoring supplementing statistical scorecards
Customer service (chatbots/NLP)	54%	Level 1	Rule-based / basic NLP virtual assistants
Market & liquidity risk modelling	23%	Level 1	Group-level stress-testing tools, limited local disclosure
Cybersecurity / operational risk	69%	Level 2	AI-assisted intrusion and anomaly detection

Source: Author's documentary content analysis of publicly available bank and NBRNM disclosures, 2019–2024.

AI use in banks in North Macedonia is most prevalent in fraud detection and cybersecurity (where AI-based predictive machine-learning tools (Level 2) are relatively common); it is least prevalent in market and liquidity-risk modelling, with fewer than a quarter of banks reporting that they use AI or that they have developed AI applications in this area. Credit-risk scoring sits in between: the behaviours or alternative data with which it is based are included in the majority of European banks' credit-risk scoring models, with about half of banks referring to these elements in addition to (and not instead of) traditional, statistically based scorecards, as described by the EBA (2024) on European banks' 'more measured approach' to using AI in core credit-decisioning activities.

6.2 Expert-Perception Survey Results

Table 4 shows descriptive statistics of the expert-perception survey (n = 24) and presents the mean values (on a 1- to 5-point Likert scale, with 1 = very low and 5 = very high) of the variables current AI maturity, perceived benefit, and perceived severity of barriers to AI.

Table 4. Expert-Perception Survey Results by Bank-Size Tercile (Mean Likert Scores, 1–5 Scale)

Dimension	Large banks (n=9)	Medium banks (n=9)	Small banks (n=6)	Overall mean
Current AI maturity — credit risk	3.2	2.6	1.8	2.6
Current AI maturity — fraud/AML	3.9	3.1	2.4	3.2
Current AI maturity — market risk	2.1	1.7	1.3	1.8
Perceived benefit of AI for risk management	4.3	4.0	3.8	4.1

Barrier: data quality / infrastructure	3.0	3.9	4.4	3.7
Barrier: data-science talent shortage	3.4	4.2	4.6	4.0
Barrier: regulatory / supervisory clarity	3.1	3.3	3.5	3.3
Barrier: parent-group decision dependency	3.8	3.0	2.1	3.1

Source: Author's expert-perception survey, 2025–2026 (n = 24). Higher scores denote higher maturity, higher perceived benefit, or greater barrier severity, respectively.

As expected, based on the analytical model outlined in Section 4.3, the survey results indicate that large, foreign-owned banks are more likely not only to be the most mature with AI, but also to feel the least constrained by decision dependency with the parent group (mean 3.8). On the other hand, small and medium banks have significantly higher scores for data-quality/infrastructure (up to 4.4) and data-science talent shortage (up to 4.6) indicating that they have a gap in their capabilities that could further deepen the competition and risk-management gap between systemically important banks and smaller banks. There are statistically significant differences among bank-size terciles for AI maturity in credit risk and for the talent-shortage barrier ($p < 0.05$), with no statistically significant differences for perceived overall benefit of AI, suggesting a general, size-independent agreement that AI brings some value in the realm of risk management.

6.3 Thematic Findings from Qualitative Interviews

The semi-structured interviews were analyzed using thematic analysis which revealed 4 common themes that corresponded with the 4 determinants of the analytical model, namely D-H-G-R:

1. Data fragmentation and Legacy Core banking System (D): Several risk officers stated that the core banking systems were not developed with data fragmentation in mind and thus they had to invest in costly middleware for the sake of realising the ML models.
2. Medium and small banks experienced challenges in attracting and keeping data scientists, with some ceding the job to regions with fintech assets or to jobs offered by Western European firms that are located overseas.
3. Parent-group governance (G): The interviewees at foreign-owned banks always referred to a dual approach, in which credit-decisioning models are still under group model-risk-management sign-off processes that may lead to a delay of adapting the approach for the Macedonian market and currency/regulatory environment, whereas fraud-detection-and-AML tools are often implemented through group-wide platforms, and this is accelerating adoption.
4. The regulatory anticipation (R) score was attributed based on NBRNM supervisory staffs' statements of their activity in the monitoring of the EU developments and their plan to issue a sectoral guidance on model-risk management and ICT/cyber resilience, but no specific regulatory instrument adopted exclusively for AI use in financial risk management was identified as of the time of the study, meaning that banks are subject to existing general regulations on ICT-risk management, outsourcing, and anti-money laundering.

6.4 Comparative Regional Positioning

Table 5 shows that North Macedonia is in the 'follower' range in terms of its maturity in the banking sector, since it is making progress on some areas with AI in the banking sector, such as fraud and AML, while underperforming on the other areas, like credit and market-risk models.

Table 5. Indicative Comparative Positioning of AI-in-Banking Maturity

Market group	Fraud/AML AI maturity	Credit-risk AI maturity	Market-risk AI maturity	Regulatory framework maturity
EU-core (e.g., Western Europe)	High	High	Medium–High	High (AI Act, DORA, EBA guidance in force)

CESEE EU member states	Medium–High	Medium	Medium	Medium–High (transposing EU rules)
North Macedonia (candidate)	Medium	Low–Medium	Low	Low–Medium (general ICT/AML rules; no AI-specific framework)
Wider Western Balkans (non-EU)	Low–Medium	Low	Low	Low

Source: Author's synthesis based on EBA (2024), MDPI (2026) bibliometric evidence, and the study's own documentary and expert-perception findings.

7. Discussion

The conclusions drawn in Section 6 resonate and build on the international literature on the use of AI in banking risk management in a few significant ways. Second, North Macedonian banks have a clear stratification in their adoption: faster in 'fraud' and 'cyber security' — arguably the areas where the consequences of a wrong decision are more visible and immediate — and slower in 'credit' and 'market-risk modelling' where cost considerations of model-risk-management, explainability and supervisory approval are more prominent. This is a similar pattern as the five thematic clusters found in the bibliometric literature from 2020-2024 (credit-risk assessment, fraud detection, operational/cyber-risk mitigation, FinTech adoption, and regulatory compliance), where North Macedonian practice is most similar to the two clusters of fraud detection and operational/cyber-risk mitigation (Kacani, J., Trunk, A., Nechkoska, R. P., Xhafa, B., Qorraj, G., Jahic, H., & Kopani, S. 2026).

Second, the study's result that foreign parent-group governance acts both as a catalyst and as a barrier to technology adoption provides a nuanced twist to the technology-adoption literature, which has previously assumed foreign ownership of emerging-market banking is always a positive technology-adoption mechanism (Velichkovska, K., Mitić, P., & Kojić, 2025). The evidence here indicates a more complex panorama: group level platforms can promote the adoption of standardised, low-customisation applications (fraud/AML); the adoption of risk-management applications that need local calibration (credit scoring calibrated to the Macedonian denar-denominated foreign-currency-indexed loan book, or market-risk models reflecting local sovereign and interbank market characteristics) can be hampered by group-level platforms. This is in line with the larger body of corporate-finance literature on autonomy of the subsidiaries in a multinational financial group, and extends that literature with a risk-management focus (Belsoska, M. M., & Blagoeva, 2020).

Third, the significant size-related disparity in data infrastructure and talent (Table 4) poses a financial-stability question that is not yet well discussed in the literature specifically relating to AI in banking risk: if AI-driven risk management is a real competitive and prudential advantage then that advantage is likely to be disproportionately realised by the three large, dominant banks that together account for 55.6% of the sector's assets, and the ensuing concentration in the North Macedonian banking market is likely to have implications for competition-policy and financial-stability oversight that should be considered by the NBRNM and the National Competition Authority (Malchev, B., Cvetkoska, V., & Trpeska, M. 2024).

Fourth, the study's conclusion that the NBRNM is developing a regulatory framework for AI in financial services that is not yet binding but likely to be soon, is in line with the country's status as an EU candidate: The NBRNM has been following a strategy of adopting to EU practice in its institutional agenda (IMF, 2022), which suggests that binding rules on AI in finance, most likely based on the 'high-risk' category of some credit-scoring systems in the EU AI Act, together with other requirements for ICT and third-party risk management (Fetaji, B., Fetaji, M., Hasan, A., Rexhepi, S., & Armenski, G. 2025), are likely sometime in the near future, and banks that already have developed model-risk-management and AI-governance capability therefore have lower transition costs.

The perception of value in AI for risk management, which is largely size-independent (Table 4) indicates that there is not a lack of managerial appetite for the use of AI, but a mix of capability constraints (data, talent) and governance/regulatory factors (G, R in the analytical model) which has direct implications for the policy recommendations developed in Section 9.

8. Barriers, Risks and Regulatory Considerations

8.1 Technical and Organisational Barriers

The findings in the evidence in Section 6 determine four main technical and organisational challenges to AI-based risk management in North Macedonia: legacy core banking systems (C#) that limit real-time data access; non-smooth and inconsistent data quality cross product and channel systems; limited talent pool for data-science and machine-learning-engineering, with the challenge of recruiting data-specialists from both the region and internationally; and, for smaller banks in particular, the lack of scale to justify independent investment in AI infrastructure, necessitating joint or Macedonian Banking Association (MBA) coordinated solutions (Ilievski, A., Štambuk, A., Pečarić, M., & Tomevska-Ilievska, E. 2026).

8.2 Model Risk and Explainability

Just as in the wider AI-in-finance sector, the incorporation of machine learning models in credit decisioning and risk-rating processes introduces new model-risk-management question: how to interpret the results of complex models, like those using ensembles or neural networks, which are not as easy to understand as scorecards?; What are the risks of bias in the data used to train such models that can lead to discriminatory or procyclical credit outcomes?; How to address the risks of model drift as macroeconomic conditions evolve? Adversarial-robustness literature from computer vision which shows that neural networks can be reliably fooled by inputs that are deliberately or accidentally outside of the distribution of input spaces that they were trained on, has direct analogues in models used for fraud-detection and credit-scoring, emphasizing the need for robust model-validation and challenger-model practices (Jolevski, L., & Dicevska, S. 2022).

8.3 Cybersecurity and Third-Party/Vendor Risk

New risk factors have emerged and are associated with the same AI systems that introduce operational and fraud risk, such as reliance on external cloud and AI-model vendors, potential concentration risk in the case of multiple SIBs using the same third-party AI provider, and increased attack surfaces due to the integration of AI tools via APIs into the core-banking systems (Petkov, 2024). The cybersecurity literature also chronicles the potential for AI to be used to help detect threats and the converse threats that are posed when adversarial parties use AI for attack methods, an ‘AI arms race' situation which is becoming more and more applicable to the small banking system with relatively limited cybersecurity resources.

8.4 Regulatory and Supervisory Gaps

At the present time, North Macedonia has no binding regulation specifically for financial services and AI, but rather the more general ICT-risk, outsourcing and AML/CFT regulation. As outlined in Section 6.3, the lack of binding regulation in North Macedonia specifically for financial services and AI is reflected in the general regulation of ICT-risk, outsourcing and AML/CFT. This provides 'short-term flexibility' to experiment with AI but ‘medium-term uncertainty' for banks planning multi-year AI investment programmes as it is likely that in the future they need to adapt to EU AI Act's ‘high-risk’ classification of their credit-scoring and insurance risk-assessment systems, and to requirements for ICT-resilience which are aligned with the EU version of DORA, that is easier to implement from the beginning and likely be more expensive to duplicate afterwards.

8.5 Data Protection and Consumer-Conduct Risk

The use of AI in credit scoring and in the creation of tailored products generates new consumer-protection concerns in relation to the personal-data-protection law in place in North Macedonia (which is harmonised with the EU GDPR) as well as the new conduct-risk expectations of consumers in the context of automated credit decision-making, including the right to meaningful information about and the right to challenge automated credit decisions, which is explicit in EU law and is increasingly mentioned in EBA’s supervisory guidance.

9. Policy and Managerial Recommendations

In light of the above results and analysis, this study formulates a series of recommendations to the three groups of stakeholders: the National Bank of the Republic of North Macedonia and other regulators, Macedonian Banking Association, and individual banks, respectively, for each of the identified stages.

9.1 Recommendations for the NBRNM and Regulators

1. Give appropriate supervisory guidance on the management of risk from AI/ML models based on the EBA guidelines, setting minimum expectations for the documentation, validation, explainability and continuous monitoring of the models, in accordance with the size and risk significance of the institution.

2. Build SupTech capacity in NBRNM's own supervisory function to allow for more granular, real-time monitoring of sector-wide credit, liquidity and cyber-risk indicators in line with SupTech focus in the international RegTech/SupTech literature.
3. Implement a regulatory 'sandbox' or a framework for structured dialogues to give banks the opportunity to test AI-based risk-management tools with the supervision of the regulator before their widespread use, thereby minimizing uncertainty for banks regarding the compliance requirements, and asymmetries between banks and supervisors concerning their use of AI tools.
4. To ensure future transition costs for the sector are minimised, phase in the EU AI Act risk-classification approach and the DORA requirements for ICT and third-party risk-management, in line with the country's EU-accession timetable.

9.2 Recommendations for the Macedonian Banking Association

1. Coordinate a cross-sector data-science talent-development program, possibly with national universities and local providers of data-science training, to overcome the talent-shortage barrier that was felt as the biggest problem among SMBs (Table 4).
2. Discuss shared-infrastructure or shared-service approaches for AI-based fraud detection and AML transaction monitoring between smaller banks that don't have the scale to invest in these solutions on their own, and lessen the competitive gap outlined in Section 7.
3. Create a sector working group on AI governance to create common voluntary model documentation and explainability standards before binding ones, putting the sector ahead of the curve of the imminent EU-aligned requirements.

9.3 Recommendations for Individual Banks

1. Invest in modernisation of core-banking data-infrastructure as a precursor to yield scalable AI deployment, especially real-time data-extraction capabilities identified as a binding technical constraint by interviewees.
2. In the case of foreign-owned subsidiaries, agree clear local-customisation provisions in the group-level AI governance model; ensure that credit- and market-risk models are not simply replicated from the group level as 'templates', but are adapted for the local environment, taking into account Macedonian macroeconomic, currency and regulatory conditions.
3. Set up or reinforce internal functions for model risk management (MRM) that are separate from the model-development teams to ensure quality challenge to AI/ML models applied in credit and risk-rating.
4. Follow an AI-Maturity Roadmap that involves incremental progression, starting from descriptive automation, up to predictive machine learning, in the credit and market-risk space, instead of trying to jump straight to adaptive/autonomous AI without the data and governance pillars.

9.4 A Phased Implementation Roadmap

The recommendations above are synthesized and summarised in a three-phase implementation roadmap indicated in the following table, which is aligned with the expected EU-accession process of North Macedonia, and grouped under short term (0-2 years), medium term (2-4 years) and long term (4 years and beyond).

Table 6. Indicative Phased Roadmap for AI-Enabled Risk Management Development

Phase	Time horizon	Priority actions	Responsible stakeholders
Phase 1: Foundations	0–2 years	Data-infrastructure modernisation; sector talent programme; NBRNM model-risk guidance; sandbox pilots	Banks; MBA; NBRNM
Phase 2: Scaling	2–4 years	Expansion of ML-based credit and market-risk models; shared AML/fraud infrastructure for smaller banks; SupTech deployment	Banks; MBA; NBRNM
Phase 3: EU alignment	4+ years	Full alignment with EU AI Act risk classification and DORA ICT-resilience	NBRNM; Ministry of Finance; Banks

		requirements; mature model-governance frameworks	

Source: Author's synthesis based on study findings and the EU accession trajectory described in Section 3.4.

10. Conclusion

This study aimed to explore the degree of penetration, motivations and risk management consequences of using artificial intelligence in the banking sector of the Republic of North Macedonia. Based on the analysis of the international academic literature, as well as an expert-perception survey and interview programme with risk-management, IT and supervisory professionals at thirteen commercial banks, the study concludes that North Macedonian banks are using AI in a selective, and to some extent an uneven, manner across the categories of risk: where AI is being used, it is most advanced in fraud detection, transaction monitoring and cyber-security, and most limited in credit-risk modelling, where AI is being used alongside traditional statistical approaches; and least in the modelling of market and liquidity risks, where the advanced capability, if present, is being implemented at the level of foreign parent banking groups and not locally disclosed or developed. This is reflective of the study's analytical framework which shows that the AI capability maturity is connected to the organization's data infrastructure, human capital, parent-group governance and regulatory clarity. A characteristic structural characteristic of the North Macedonian banking sector (73.5% share of foreign ownership of capital and reserves) has both positive and negative impacts on the models for credit and market risk, which are customised for the local market and require group-level approval: it can accelerate the use of the more standardised applications of AI transferred from parent groups, while also preventing the customisation of credit- and market-risk models that would benefit the local markets, but require group-level approval. However, the three largest, systemically dominant banks have a lower level of data-infrastructure and human-capital constraints than small and medium banks, posing a competition and financial-stability challenge that should not be overlooked: the potential for further concentration within the sector through the application of AI.

Given the sector's strong financial capital and profitability position (with a capital adequacy ratio of 18.1%, and a 47.8% year-on-year profit growth as of 2023), financial capacity is not a limiting factor in AI investment, as evidenced by the importance of the data infrastructure, talent, governance and regulatory clarity levers. As part of North Macedonia's EU-accession path, the likelihood of convergence of the domestic financial regulation with EU instruments, like the Artificial Intelligence Act or the Digital Operational Resilience Act, is high and a phased roadmap (Table 6) is proposed to help the sector to prepare proactively for such convergence rather than adapt reactively upon the implementation of binding instruments. This study provides a structured, source triangulated analysis of AI in a little-studied field of financial risk management in a small foreign-owned banking system in preparation for becoming an EU-candidate country, and provides a conceptual and empirical framework that can easily be adapted to other similar Western Balkan systems in similar structural settings. This analysis should be continued over time as the EU-accession process continues in North Macedonia, and as binding AI-specific financial regulation comes into effect, and should be expanded by gaining access to proprietary bank-level AI-investment data (where it is permitted to do so) to complement the documentary and perception-based evidence presented here with more granular quantitative analysis of the relationship between AI adoption and realised risk outcomes (such as non-performing-loan rates, fraud-loss rates, and operational-risk capital charges).

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