“Financial monitoring effectiveness in Kazakhstan’s bank investment operations: A mixed-methods evaluation”

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FINANCIAL MONITORING EFFECTIVENESS IN KAZAKHSTAN'S BANK INVESTMENT OPERATIONS: A MIXED-METHODS EVALUATION

Abstract

Investment activities of banks are a key driver in financial sector development, yet their effectiveness largely depends on the quality of financial monitoring, which can detect, diagnose, and correct anti-money laundering and countering the financing of terrorism (AML/CFT) weaknesses. This article aims to assess the effectiveness of financial monitoring in the investment operations of Kazakhstani banks and to identify transaction-level risk indicators that can support data-driven AML/CFT supervision. The study employs a mixed methods design that combines analysis of national AML/CFT legislation and supervisory guidance with semi-structured expert interviews and case studies of three major institutions (Halyk Bank, Kaspi Bank, and ForteBank). In the quantitative component, a synthetic dataset of 1,000 investment-related transactions, calibrated to 2019–2024 statistics from the National Bank of Kazakhstan and the Committee for Financial Monitoring, is analyzed using logistic, multilevel, and Bayesian logistic regression with cross-validation and bootstrapped confidence intervals. The models achieve high predictive performance (AUC up to 0.93, test accuracy up to 93.2%, sensitivity 82.0%, specificity 94.1%) and show that higher transaction amounts, cross-border origin, SWIFT channel use, and investment-linked operations increase the odds of being flagged as suspicious by factors of roughly 1.5-3.5. Qualitative evidence reveals uneven digitalization, fragmented data integration, and capacity gaps, especially in mid-sized banks, which limit the practical implementation of these risk-sensitive tools. The results justify targeted regulatory support for advanced analytics and provide a replicable framework for strengthening investment-related financial monitoring in Kazakhstan and comparable emerging markets.

Keywords Kazakhstan, banking sector, Bayesian logistic regression, suspicious transactions, financial regulation, multilevel modeling, digitalization

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INTRODUCTION

Kazakhstan's banking sector is undergoing rapid expansion, particularly in capital market activities and investment operations, which increasingly shape the country's financial stability and growth. In this regard, effective financial surveillance systems within banks play a crucial role in averting money laundering, terrorist funding, and other similar threats to the stability of the financial system. New reforms have enhanced the regulatory and legislative framework in accordance with international standards proposed by the Financial Action Task Force (FATF) and other organizations (Manning et al., 2021; Gaisina & Finger, 2025). Digitalization, high-quality risk analytics, and institutional capacity-building are highlighted in policy documents as pillars of the strong financial industry (Concept of the Development of the Financial Industry of the Republic of Kazakhstan until 2030), adopted as one of the important factors of a stable financial sector (Yener et al., 2024; Spankulova et al., 2025; Shilibekova & Plokhikh, 2025).

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The requirement of information exchange, enhanced surveillance, and reporting of suspicious activity is formally introduced to the work of financial institutions according to legislative acts, such as the Law "On Combating Money Laundering and Financing Terrorism.

Despite these positive changes, the difference between legal regulation and its actual efficiency in the field of financial monitoring in the investment activities of Kazakhstani banks is still significant. Small and medium financial institutions do not necessarily have access to the financial and technological resources to install the most recent AML/CFT systems, limiting them in adopting real-time and data-driven systems of monitoring. It is also becoming very challenging to differentiate between normal and suspicious investment flows due to the increased complexity of investment products, investment instruments, and media, and their cross-border nature. The lack of integrated and unified information systems that are more than a decade old also restricts the ability of banks to maintain a pool of integrated information on different business lines and conduct a thorough risk evaluation process. Concurrently, compliance quality and analytical sophistication diffuse significantly among institutions; some banks have superior analytics and skilled compliance units, while others lag behind.

In this context, the scientific issue that must be investigated in the paper is the lack of comprehension and systematic measurement of the usefulness of financial monitoring in the investment operations of banks located in Kazakhstan, especially in terms of determining the presence of transaction-level risk indicators and institutional constraints predetermining the results of AML/CFT. The research lies at the corner of the regulatory design, institutional practice, and quantitative risk modeling, and tries to explain the interaction of these dimensions in the context of transactions concerning investments in Kazakhstan's banking system.

1. LITERATURE REVIEW AND HYPOTHESES

The literature on financial monitoring and anti-money laundering (AML/CFT) has evolved significantly as global financial systems grow more interconnected and vulnerable to illicit activity. The role of regulatory standards and institutional capacity of compliance, and the use of digital tools in enhancing financial crime detection and prevention by banks, is actively investigated by scholars. A lot of this effort has focused on the transition between monitoring relying on the use of rules to monitoring grounded on risks, data, and technological improvements, which can be more responsive to the developing trends in complex financial markets. Ranging alongside these conceptual advancements, scholars aim to illustrate the issues of efficiency of financial institutions in their response to the dynamism of service and regulatory demand, cross-border capital movements, and heterogeneity of financial tools. Collectively, all these developments create the basis for observing the functioning of monitoring practices and the areas in which the system is vulnerable.

It is in this extended backdrop that the focus is now shifting to the performance of monitoring systems, as well as the weaknesses in the operation of specific systems, in emerging markets, where regulatory ability, technological maturity, and the organization of the financial sector differ significantly. Investigations into the post-Soviet and the Eurasian economies display a mixture of strong regulatory reforms and recurrent institutional barriers that dictate the practical operation of AML/CFT implementation. Other distinctive monitoring issues encountered by researchers are that investment-related transactions, which typically encompass a greater value, cross-border channel, and complex financial product, are infrequently examined in empirical studies. Although machine learning, statistical modeling, and automated surveillance tools have extended over the globe, individuals in most emerging financial systems have not fully exploited these approaches in investment-driven monitoring. The latter gaps demonstrate the significance of the globalization of knowledge and evidence collected on the regional level in the evaluation of the state of financial oversight within the Kazakh banking sector.

1.1. Theoretical framework

To identify abnormalities that may lead to money laundering or other activities that may finance terrorism, the main area of concentration used in financial monitoring is the real-time monitoring and assessment of financial transactions. The international and domestic regulation is intended to ensure the protection of financial markets and deter the illegal influx or outflow of finances; in this matter, the contemporary financial monitoring systems become the core of anti-money laundering (AML) and counter-financing of terrorism (CFT) systems.

AML/ CFT refers to a network of regulations, technology, and standards that collaborate to prevent, identify, and address financial crime (Gaviyau & Sibindi, 2023b). The making of surety that these laws are adhered to anywhere is supervised by the Financial Action Task Force (FATF). Changes in these rules are constant due to the mutual analysis and amendments to the rules. AML/CFT models are highly significant elements of financial surveillance that can assist banks and other financial institutions to detect and reduce the risks of illegal financial transactions (Jayasekara, 2022; Shah, 2024). Among the most important parts is Customer Due Diligence (CDD). It refers to the time spent searching and researching all clients before conducting business with them sometimes (Gaviyau & Sibindi, 2023a).

One more important one is Suspicious Transaction Reporting (STR). According to the law, banks and other financial institutions must locate and disclose suspicious transactions that are not in line with a customer profile, or rather an indication of money laundering (Saxena, 2024). These reports are sent to the right national authorities, including the Financial Intelligence Unit (FIU), and they are extremely important to conduct actual investigations (McNaughton, 2024). Monitoring is further enhanced by risk assessment and profiling, where clients and transactions are grouped based on various variables involving the number of transactions, places where transactions are made, and the behavior of clients that is out of the ordinary. In 2022, academic and commercial literature demonstrated a fast pace of machine learning (ML) and artificial intelligence (AI) applications in the practices of AML/CFT (Khan et al., 2024). Can almost always: Statistical models, such as logistic regression, support machine learning, decision trees, and random forests, are used to sort and rank suspicious activity by automated monitoring systems today (Verma et al., 2022).

Recent studies show that both supervised and unsupervised machine learning methods have made significant improvements in lowering false positives and making detection more accurate. Bayesian inference has become a very useful way to find anomalies in financial data, in particular. There have been a number of new studies that have pointed out some new patterns in how advanced analytics are being used in anti-money laundering (AML) systems (Gandhi et al., 2024). There is a novel and intriguing trend toward using deep learning techniques, particularly CNNs and RNNs. Unlike rule-based systems, these models have successfully uncovered complex, non-linear, time-dependent transaction patterns (Sun & Ge, 2021).

One such method that's gaining traction is testing AML algorithms using synthetic data. Since legitimate transaction data cannot be obtained for ethical or legal reasons, researchers and organizations have begun to amass ever-larger fake datasets that mimic actual financial transactions (Dickinson, 2024). Organizations can experiment, compare models, and collaborate on development in these databases without worrying about individuals' privacy being compromised. A growing amount of AML research has focused on probabilistic and ensemble-based approaches (Alarab et al., 2020; Ebenezer et al., 2024). To assist computers in considering both known and unknown information while evaluating transactions, probabilistic graphical models such as Bayesian networks are useful (Krapu et al., 2023).

As a theory, AML/CFT is based on more than just technology. A steady hand is required when creating new statistics, following the law, and being prepared as an organization. International Monetary Fund thematic evaluations and the newly established EU anti-money-laundering authority both show how crucial it is to consistently and adaptively implement anti-money-laundering regulations. Zhou (2025) notes that AML/CFT is

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also seeing an uptick in risk-based methods. These methods use a combination of statistical data and expert knowledge to figure out how to allocate resources based on risk. Since 2022, synthetic data has been widely used in research for scalable model validation, probabilistic models, and ML-driven risk assessment (Long et al., 2025). The underlying financial ecosystems are getting more complex as a result.

1.2. Regulatory framework in Kazakhstan

The strategy of the anti-money laundering (AML) and countering the financing of terrorism (CFT) of Kazakhstan is based on a developing and more complex system of legislation and regulations consistent with international standards. A combination of major legal acts and a continuous process of adherence to the regulations of the Financial Action Task Force (FATF) shape this framework. The anti-money laundering and anti-terrorist financing system in the Federal Republic of Kazakhstan is primarily anchored on the Law of the Republic of Kazakhstan «On combating money laundering and the financing of terrorism. The latest update, which followed the passing of the law in 2009, was in 2024. This act establishes the fundamental guidelines of detection, reporting, and stopping money-laundering plans that breed terrorists. It characterizes money laundering and terrorist funds as criminal offences, subjects companies to reporting, and allows the government to seize and freeze any assets of criminal conduct. It is stipulated to perform customer due diligence (CDD) and beneficial ownership identification to retain documents post-amount of risk, as well as to do it after performing customer due diligence. The key regulatory agency currently engaged in the enforcement of the AML/CFT regulations adherence by financial institutions is the Committee for Financial Monitoring (CFM) (Zhamiyeva et al., 2022). Additional tasks of the CFM are extra due diligence on high-risk customers and accurate disclosure of the cross-border transactions. The amendments to the rules over the last few years have made it clear what is required to be disclosed as an adverse transaction, simplified cooperating with law enforcement agencies, and simplified the process of freezing and recovering the illicit funds under the criminal law.

Kazakhstan is part of the Eurasian Group on Combating Money Laundering and Financing of Terrorism (EAG), which is like the FATF (Lacroix, 2023). The 40 FATF recommendations are the greatest strategy to stop money laundering and terrorist funding around the world, and the country's legislation and laws are based on them (Nanyun & Nasiri, 2021). Some of these ideas include strong laws that make money laundering and terrorist financing illegal, strong actions to stop these crimes from happening in the first place, mechanisms for countries to work together, and targeted financial sanctions. Kazakhstan has made significant progress in implementing these proposals and putting them into practice. The country's most recent EAG Mutual Evaluation and the FATF's 2023 assessment both say that most technical provisions are being followed, but they also say that more work needs to be done on practical implementation, especially when it comes to reporting requirements for certain non-bank financial institutions and designated non-financial businesses and professions (DNFBPs). Kazakhstan's AML/CFT laws and rules have been changed recently, and these changes have made several important improvements: The range of businesses and activities that are subject to AML monitoring has grown to include virtual assets and new financial technology. Cooperation among regulatory bodies, the Financial Intelligence Unit (FIU), and law enforcement is essential, particularly for the completion of national risk assessments and the coordination of policies (Reznik et al., 2023). In order to assess bonds and make better financial decisions, management accounting is becoming more significant (Mynbayeba et al., 2018).

These regulations and standards help Kazakhstan's banks monitor their money in a disciplined way. Included in this are robust internal controls, frequent notifications of questionable behavior, staff training, and automated monitoring of transactions. In order to help stabilize developing nations' budgets, Karabayev et al. (2021) discuss how external public audits might find issues and provide solutions. This emphasizes the importance of audits as a tool for ensuring that spending plans do not increase the national debt while still meeting long-run development objectives. Certain types of large and suspicious transactions must be reported by banks immediately. They risk administrative fines,

reputational harm, and, worst-case scenario, license revocation if they don't. Due to its responsiveness to evolving international standards and its recent legislative reforms, Kazakhstan is an integral part of the global AML/CFT community (Khamzaev, 2024). But it's still not easy to guarantee that every industry is following the new regulations and adapting fast enough to the ever-changing nature of financial goods and services.

1.3. Empirical research from other countries

Research from Russia and other countries that are part of the Eurasian Economic Union (EAEU) gives us useful information about how AML standards are employed in the banking industry, especially when it comes to leveraging modern technology to monitor financial activity. To monitor transactions and detect fraud, major Russian banks such as Sberbank and VTB have developed sophisticated machine learning algorithms (Etembekov, 2021). To identify out-of-the-ordinary patterns, these models rely on supervised algorithms that have been trained on labelled historical transaction data. These methods include logistic regression, decision trees, and random forests. However, most of the published research in this area focuses on the technical aspects of model performance, rather than the institutional context or qualitative factors that influence the implementation of these models and adherence to their rules. The challenges and potential solutions of Russian mortgage finance are discussed by Niyazbekova et al. (2023). They claim it has the potential to alleviate housing issues and raise living standards. Ilyina (2022) concludes that innovation-driven investment projects require stronger state regulation and supportive infrastructure to ensure sustainable economic development. It also finds that EU countries, such as the Czech Republic, Poland, Slovakia, and Hungary, outperform transitional economies in innovative capacity and development outcomes.

The actions to enhance AML/CFT controls in Belarus and Armenia have utilized predictive analytics, data mining parameters to assist in reporting needs and position suspicious activity reviews first on the list. Indicatively, Belarusian state-owned banks use logistic regression and clustering algorithm-based classification models to detect the presence of transaction anomalies significantly (Boeri, 2024). Recently, the Central Bank of Armenia has been supporting plans to introduce technologies that use AI to conduct due diligence in the country to accelerate the compliance procedure and simplify the process of providing a response to regulators (Schrepel & Groza, 2023). Assumptions are not often checked or observed in relation to actual life, in particular, with the help of quantitative techniques and qualitative insights, which are often utilized simultaneously, when it comes to controlling investment activity, which implies more complex financial instruments, and this requires more time to finalize a transaction. As Koziuk et al. (2024) discovered, the motivation behind the preferences given to CBDC anonymity is more institutional trust and biases in behavior rather than cultural ones, with low trust driving users to choose convenience over privacy. It concludes that CBDC design should be country-specific, which will not interfere with the choice of consumers and the role of the central bank in terms of policymaking. Niyazbekova et al. (2022) discuss the development of new financial services in the digital era and compare the practice of online and Internet banking in Kazakhstan, France, Sweden, Brazil, and the United Kingdom. The research indicates that innovations that affect digital banking vary among nations. Among the countries studied, France has the lowest fees for Internet banking services. Vovchak et al. (2018) also discovered that financial sustainability in the Ukrainian banking system is impeded by a lack of capitalization, a significant institutional risk, and an increase in insolvent banking establishments between 201217. It concludes that, even though some of the indicators are at the necessary standards, the sector experiences unmet issues of capital shortage and concentration, which will need focused efforts on improving capitalization and long-term sustainability. According to Rybalchenko et al. (2022), anti-crisis management systems need to be tightened in Ukraine's banking sector, particularly during the Russia-Ukraine war, revealing the lack of stability, risk management, and institutional resilience. It concludes that to raise the capacity to respond during crises and provide long-term financial stability, the integration of digital infrastructure, powerful data-processing tools, and specific optimization measures is necessary.

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1.4. Gaps and research motivation

Regardless of the great improvement of the regulatory framework to address anti-money laundering (AML) and counter financing of terrorism (CFT) in Kazakhstan, an empirical study that combines both the institutional case-based analysis and statistical modeling to evaluate the underlying effects of real-life financial monitoring methods, particularly in the context of investment operations, is still very lacking. The majority of existing studies are oriented toward the next activities of following guidelines or taking a closer look at the big picture of finances. Moreover, few in-depth studies have been conducted using modern statistical techniques that are developed towards the organization and dynamics of the Kazakhstani financial sector. Limited literature on the topic has examined ways in which logistic regression models, multilevel (hierarchical) logistic models, and Bayesian models may be utilized in classifying or predicting suspicious transactions within the local setting. These models are built upon a lot of research in international financial monitoring, yet little research has been conducted on applying these models to Kazakhstan-specific data sets or contexts, including monitoring investment-related flows.

The three effective quantitative tools employed in this study to fill these gaps are Standard logistic regression which sets a baseline of predictive ability where important financial and transactions variables are involved and Multilevel logistic regression (mixed-effects model) which demonstrates differences in participating banks in investment monitoring and Bayesian logistic regression which gives a more accurate and clear estimation of the probability of suspicious transactions based on previous regulatory and domain knowledge. The use of the Committee for Financial Monitoring (CFM) public violation records and case studies of big banks in Kazakhstan supplements this modeling. These case studies help to understand both the regulatory environment and the activities of particular organizations because both qualitative and quantitative approaches are combined. Combining advanced statistical research with practical applications, this work brings something new to the ever-growing body of AML/CFT research in Central Asia. It is possible to develop future work with real or anonymized financial data on this basis.

The existing literature shows that effective AML/CFT in banking relies on the interaction of robust regulatory frameworks, institutional capacities, and increasingly sophisticated data-driven monitoring tools. However, empirical evidence that jointly examines institutional practices and advanced statistical models for monitoring investment-related transactions in emerging markets, and specifically in Kazakhstan, remains scarce. This gap is particularly pronounced with respect to the application of logistic, multilevel, and Bayesian methods to transaction-level data in the context of banks' investment operations.

The purpose of this study is to evaluate the effectiveness of financial monitoring in the investment operations of Kazakhstani banks and to identify transaction-level risk indicators using a mixed-methods design that combines institutional case analysis with logistic, multilevel, and Bayesian modeling.

Study hypotheses are as follows:

H1: Higher transaction amounts and cross-border investment transactions are associated with a significantly higher probability of being classified as suspicious in Kazakhstani banks.

H2: SWIFT-based and investment-linked transactions exhibit significantly higher AML/CFT risk than domestic, non-investment payment transactions, controlling for other factors.

H3: Multilevel and Bayesian logistic regression models provide higher out-of-sample classification performance (AUC and accuracy) than a standard logistic regression baseline for identifying suspicious investment-related transactions.

H4: Banks with more advanced digitalization and integrated monitoring systems generate more frequent and granular suspicious

transaction alerts in investment operations than banks with lower levels of technological and analytical capacity.

2. METHODOLOGY

The study used a mixed-method research design, which incorporates both qualitative and quantitative methods to take a comprehensive approach in investigating the practice of financial monitoring among the investment activities of banks in Kazakhstan. The qualitative element aims to study the regulatory realization, institutional challenges, and AML/CFT practices in the selected banks using approaches that include same-bank analysis, semi-structured interviews, and the case study. This is supplemented by the quantitative part of the study, which constructs and estimates logistic, multilevel, and Bayesian logistic regression models on synthesized and aggregated transactional data. These models consider some very crucial factors, including the size of the transaction, the type of instrument used, and the country of origin, in an effort to establish the existence of potentially fraudulent transactions. Addressing gaps in the literature and providing valuable information to regulators and financial institutions, the methodology provides an in-depth understanding of the contextual factors that have an effect on financial monitoring and the predictive quality of statistical models.

The qualitative component included a systematic review of Kazakhstan's key regulatory texts, including the AML/CFT Law, as well as official publications from the EADB, NBK, and AIFC to capture current requirements and sector expectations. Semi-structured interviews were conducted with compliance and risk experts from Halyk, Kaspi, and representatives of the CFM to obtain insights on monitoring practices, technological use, and regulatory adaptations. Additionally, in-depth case studies of two to three major banks with substantial investment portfolios selected due to AML system deployment or documented regulatory audits were developed to document automated surveillance processes, reporting integration, institutional responses to audits, and common operational challenges in monitoring investment-related transactions.

The quantitative component employed probabilistic models, classical logistic regression, multilevel (mixed-effects) logistic regression, and Bayesian logistic regression to evaluate the detection of suspicious investment-related transactions in Kazakhstani banks. These models were selected for interpretability, suitability for hierarchical bank-level structures, and ability to incorporate regulatory priors. All estimations were implemented in R using the *rstanarm*, *caret*, *boot*, and *lme4* packages. The dataset combined official aggregated statistics from the National Bank of Kazakhstan and CFM reports, including transaction amount, instrument type, channel, geographic origin, and investment status.

Logistic regression models the log-odds of the probability of a binary outcome (suspicious vs. not suspicious transaction):

$$\log\left(\frac{P(Y=1/X}{1-P\left(Y=1/X\right)}\right)=\beta^0+\beta_{1,x1} \quad (1)$$
$$+\beta_{2,x2}+\ldots+\beta_k,$$

or, equivalently

$$P(Y=1/X=\frac{1}{1+e^{-\left(\beta 0+\sum_j^k=1\,\beta_{jxj}\right)}}. \quad (2)$$

In a logistic regression model, Y represents the binary outcome (e.g., whether a transaction is sus-

Table 1. Key variables used in the modeling process

Variable	Description
txn_amount_log	Log-transformed transaction amount (in KZT)
instrument_type	Type of financial instrument (Card, Payment Order, SWIFT, Other)
geo_origin	Geographical origin of transaction (Domestic, Cross-border)
txn_channel	Channel (Mobile, ATM, POS, SWIFT)
investment_active	Binary indicator (1 = investment-related transaction)
bank_id	Bank-specific ID (used for random effects in a multilevel model)
is_suspicious	Target variable: binary flag indicating if the transaction is suspicious (1) or not (0)

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picious), while x_1, x_2, ..., x_k are predictor variables such as $^{txn\_amount\_log}$ or $^{geo\_origin}$. The intercept term β_0 reflects the baseline log-odds of the outcome when all predictors are zero. Each coefficient β_j corresponds to a predictor x_j and quantifies how a one-unit increase in that predictor changes the log-odds of the outcome, holding all other variables constant. Together, the model estimates the log-odds of the outcome as the sum of the intercept and the weighted predictors. When observations are nested, e.g., transactions within banks multilevel model includes random intercepts for groups (banks).

$$\log\left(\frac{P(Y=1/X}{1-P\left(Y=1/X\right)}\right)=\beta_0+\sum_{j=1}^{k}\beta_j x_j+u_j. \quad (3)$$

In this multilevel (hierarchical) logistic regression model, Y_{ij} represents the binary outcome indicating whether transaction i in bank j is flagged as suspicious. The term $u_j \sim N(0, \sigma_u^2)$ is a random intercept capturing institution-level heterogeneity, allowing each bank to have its baseline risk level due to differences in compliance systems and monitoring capabilities. The predictors x_{kij} represent transaction-level features (such as amount, location, or user behavior) for transaction i in bank j. This modeling approach accounts for both individual transaction characteristics and variability in risk assessment practices across institutions. Bayesian logistic regression estimates the posterior distribution of coefficients by combining the likelihood with prior beliefs: Likelihood Function.

$$P(B)=\prod_{i=1}^{N}\left[\frac{1}{1+e^{-\left(\beta_0+\sum_{j=1}^{k}\beta_j x_j\right)}}\right] \times\left[\frac{1}{1+e^{-\left(\beta_0+\sum_{j=1}^{k}\beta_j x_j\right)}}\right]^{(1-y_i)}. \quad (4)$$

Prior Distributions, β_j Normal (μ_j, τ_j^2), where μ_j: prior mean (e.g., high for SWIFT risk channel) and τ_j^2: prior variance (uncertainty).

Posterior,

$$P\left(\beta/Y\right)\propto P\left(Y/\beta\right)\cdot P\left(\beta\right). \quad (5)$$

Bayesian estimation yields the posterior mean, credible intervals, and full uncertainty distributions for the effects of each variable. This is particularly useful in AML modeling where prior regulatory knowledge (e.g., SWIFT transactions are high-risk) can meaningfully inform model calibration.

Each model was assessed using accuracy, sensitivity (true positive rate), specificity (true negative rate), and area under the ROC curve (AUC). Bayesian models additionally provided posterior distributions, adding interpretability and flexibility in modeling financial transaction risk. Table 3 captures core transactional, instrumental, and geographic risk characteristics used to evaluate model performance across accuracy, sensitivity, and specificity.

Table 2. Software packages

Software Packages	Purpose
rstanarm	Bayesian logistic regression using Hamiltonian MCMC
lme4	Multilevel logistic regression with random effects
caret	Cross-validation and model evaluation
boot	Bootstrapping regression coefficients for robustness
ggplot2	ROC curve, coefficient (forest) plot visualization

Table 3. Model variables and evaluation metrics

Variable	Description	Evaluation Metric
Scope (Transaction Amount, log)	Log-transformed monetary value of the transaction, indicating magnitude and financial impact	Accuracy, Sensitivity, Specificity
Type of Instrument	Payment or transfer method (e.g., Card, Payment Order, SWIFT) representing varied risk profiles	Accuracy, Sensitivity, Specificity
Geographical Origin	Indicator of domestic vs cross-border transactions, flagging increased AML/CFT risk for cross-border flows	Accuracy, Sensitivity, Specificity

The research was structured into three steps, which started with thorough data collection. The documents included 26 regulatory and institutional documents, among them the AML/CFT Law of Kazakhstan (2009, revised 2024), methodological guidelines of the CFM, and 14 reports of the National Bank of Kazakhstan issued between 2019 and 2024. The selection of documents was done according to their direct relevance to financial monitoring, investment activities, and AML/CFT compliance, and omitted those that were not pertinent to them. Eight compliance officers and risk managers working at Halyk, Kaspi, and ForteBank, and management officials working at the CFM, having at least three years of AML/CFT experience, participated in the semi-structured interviews. Ethical protocols governing the interviews, like informed consent, confidentiality, and anonymization, aimed at regulating the procedures, technology, and operational issues, and supervisor expectations were ensured. Based on monitoring systems, training practices, and institutional reactions to audits and sanctions, case analysis was conducted on Halyk Bank, Kaspi Bank, and ForteBank, using 11 publicly available regulatory filings and audit reports (20182024) and interview insights. In the final stage, the study developed and tested three probabilistic models, standard logistic regression, multilevel (hierarchical) logistic regression, and Bayesian logistic regression, to classify suspicious versus legitimate investment-related transactions. The baseline model predicts the log-odds of a transaction being suspicious:

$$\log it\left(p_i\right)=\ln\left(\frac{p_i}{1-p_i}\right)=\beta_o+\beta_1 txn_{amount\,i}+\beta_2 instrument_i+\beta_3 geo_{origin\,i}+\beta_4 channel_i+\beta_5 investment_i, \quad (6)$$

where p_i is the probability that transaction i is suspicious.

To account for institutional heterogeneity (transactions nested within banks), random intercepts were introduced:

$$\log it\left(p_{ij}\right)=\beta_0+u_j+\beta_1 txn_{amount\,ij}+\beta_2 instrument_{ij}+\beta_3 geo_{origin\,ij}+\beta_4 channel_{ij}+\beta_5 investment_{ij}, \quad (7)$$

where p_{ij} is the probability of transaction i in bank j being suspicious, and $u_j \sim N(0, \sigma^2)$ captures unobserved bank-level differences in compliance systems.

Bayesian estimation combines the likelihood of the logistic model with informative priors based on regulatory knowledge (e.g., SWIFT and cross-border transactions assumed to carry higher risk):

$$\log it\left(pi\right)=\beta_0+\beta_1 txn_{amount\,i}+\beta_2 instrument_i+\beta_3 geo_{origin\,i}+\beta_4 channel_i+\beta_5 investment_i, \quad (8)$$

with priors:

$$u_j \sim N\left(0,\sigma^2\right),\ \text{e.g.,}\quad \mu_{SWIFT}=1.0,\ \ \sigma^2=0.5. \quad (9)$$

Posterior distributions were estimated via Hamiltonian Monte Carlo (HMC) using the *rstanarm* package in R, yielding means, credible intervals, and uncertainty estimates. Models were implemented in R using *rstanarm*, *lme4*, *caret*, and *boot* on a synthetic dataset of 1,000 transactions calibrated to NBK and CFM statistics (2019–2024). A 70/30 train-test split, five-fold cross-validation, and 1,000 bootstraps ensured robustness. Model fit (Hosmer-Lemeshow), pseudo-R^2, accuracy, sensitivity, specificity, and AUC were evaluated, with VIF < 2.5 and Bayesian stability checks (trace plots, $\hat{R}$ < 1.05). All models identified transaction amount, cross-border origin, SWIFT use, and investment status as key predictors.

Banks were selected using two criteria: (1) active, sizable investment operations that involve complex, high-value capital market flows posing greater AML/CFT monitoring challenges; and (2) public availability of information on regulatory violations or notable compliance system implementation. Institutions with documented fines or audits provided insight into system weaknesses, while technologically advanced banks illustrated emerging best practices. This dual approach ensured balanced evidence on problems, innovations, and policy-relevant institutional experience.

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3. RESULTS

Document analysis was based on 12 primary bodies of law and control documents of 2009–2024, such as the Law of the Republic of Kazakhstan on Fighting Money laundering and Financing Terrorism (2009, amended 2024), official acts of the Committee on Financial Monitoring (CFM), and has been carried out on the guidelines of the National Bank of Kazakhstan Supervisory reports (20192023). Another point was achieved through Kazakhstan's participation in the Eurasian Group (EAG) mutual evaluations and Financial Action Task Force (FATF) assessment reports. Such records constantly focus on essential customer due diligence (CDD) and reporting of suspicious activities, as well as ensuring that internal systems comply with international AML/CFT guidelines. The outcome directly answers Research Question 1 (RQ1): How do Kazakhstani banks influence AML/CFT regulations in the field of investment operations, to be more precise? By demonstrating that the legislative framework is deeply adjusted to FATF 40 Recommendations and has the role of upholding the CFM to enforce the effective application of recommendations, the analysis provides the regulatory framework by which institutional practices and monitoring systems developed on investment activities may be evaluated.

This legislation provides a comprehensive compliance plan, which comprises customer due diligence (CDD), ongoing supervision of transactions, reporting of suspicious transactions, and cooperation with international supervisory bodies. With the Ministry of Finance, the rules and explanations that are issued by the Committee of Financial Monitoring (CFM) are legally binding. The CFM is in collaboration with the National Bank of Kazakhstan. The international standards, and in particular the FATF 40 Recommendations, have had a great impact on Kazakhstan's AML/CFT agenda. These have compelled the nation to comply with the international standards of combating money laundering. There are some improvements in the Eurasian Group (EAG), but risk-based transaction monitoring systems cannot yet be enforced in all financial institutions, especially in areas with higher risks, such as investments and the international movement of capital. To understand the institutional application of these regulations, three case studies were conducted, focusing on major banks representing a range of AML/CFT implementation maturity:

For instance, Kaspi Bank's use of data from its extensive mobile payment infrastructure enables faster anomaly detection, while Halyk Bank has invested in algorithmic risk scoring models that adapt to high-frequency investment flows. ForteBank illustrates the challenges mid-tier banks may face in catching up to compliance expectations, having implemented system upgrades only after facing public regulatory sanctions.

Insights from semi-structured interviews with six professionals, including three compliance managers, one regulator, and two operational analysts, revealed key practitioner-level themes:

Respondents emphasized the critical role of digital transformation and called for better regula-

Table 4. Case study analysis

Bank	Focus Area	Key Observations
Halyk Bank	Implementation of an advanced AML system	Applied an AI-based scoring model; integrated system with CFM's real-time platforms
Kaspi Bank	Innovation in customer monitoring	Utilized digital payment ecosystem and data franchises for transaction surveillance
ForteBank	Regulatory violations and remediation	Subject to fines (2017–2021); revamped reporting frameworks and internal controls

Table 5. Thematic insights on challenges and developments in financial crime monitoring

Thematic Area	Summary of Insights
Challenges in Monitoring	Real-time detection is difficult due to system fragmentation, staff training limitations
Technological Gaps	Smaller banks cannot adopt AI/ML-based systems; they rely on rules-based filtering
Digitalization	Mobile and app-based banking (e.g., Kaspi) enables better customer behavior tracking
Regulatory Ambiguity	Complexity in interpreting thresholds and reportable cases across sectors

tory feedback loops to support continuous improvement. While larger institutions benefit from economies of scale in system development, smaller banks often struggle to operationalize even baseline transaction monitoring metrics. Across documents, case studies, and interviews, findings indicate a *maturing but uneven* AML/CFT landscape. Halyk and Kaspi display advanced, digitally integrated monitoring for investment transactions, while ForteBank represents persistent compliance challenges. Fragmented systems, technological disparities, and inconsistent supervisory feedback were recurring themes. These qualitative patterns inform and contextualize the quantitative models by illustrating institutional differences relevant to *H1-H4*.

A synthetic dataset (n = 1,000), calibrated to NBK and CFM statistics, reproduced observed sectoral distributions for instrument type (card 88%), cross-border activity (8%), SWIFT usage (1%), and investment-active transactions (30%). This dataset enabled systematic testing of suspicious-transaction prediction models.

Incorporate *bank-level heterogeneity* using multilevel modeling (generalized linear mixed-effect model), especially when data spans across multiple banks (Halyk, Kaspi, Forte, etc.). Banks vary in compliance systems, investment activities, and reporting rigor. A fixed-effect model does not account for this structural variation. A probabilistic logistic regression model was developed based on a synthetic dataset calibrated using official statistics from the National Bank of Kazakhstan and the Ministry of Finance. To account for bank-level variation in financial monitoring systems, a hierarchical logistic regression model with random intercepts was also estimated. Robustness was ensured using 5-fold cross-validation and bootstrapped confidence intervals. Variables included transaction type, volume, instrument, cross-border indication, transaction channel, and bank investment activity. The resulting model was evaluated for accuracy, specificity, sensitivity, AUC, and model fit using Hosmer-Lemeshow and McFadden R^2 statistics.

Calculations based on a synthetic dataset (n = 1,000) calibrated to official aggregate statistics from

Table 6. Variables and distribution targets

Variable	Distribution Target
txn_amount	Log-normal distribution (median ≈ 500,000 KZT, long-tail)
instrument_type	Cards (88%), payment orders (10%), other (2%)
geo_origin	Domestic (~ 92%), CrossBorder (~ 8%)
txn_channel	Mobile/internet (79%), ATM/POS (20%), SWIFT (1%)
investment_active	Binary: 1 = from active-investment banks (~ 30%)
is_suspicious	Imputed: ~ 5-10% suspicious cases

Table 7. Logistic and multilevel logistic regression estimates for suspicious transaction prediction

Source: Author's calculations.

Variable	Logistic Regression (Logit)	Std. Error	z-value	p-value	Multilevel Logistic (Bank Random Intercept)	Std. Error	z-value	p-value
Intercept	–4.985	0.612	–8.15	< 0.001	–5.214	0.644	–8.09	< 0.001
Transaction Amount (log)	0.412	0.078	5.28	< 0.001	0.398	0.079	5.04	< 0.001
Instrument: PaymentOrder	0.684	0.213	3.21	0.001	0.662	0.216	3.06	0.002
Instrument: Other	0.543	0.250	2.17	0.030	0.511	0.253	2.02	0.044
Geo Origin: CrossBorder	0.993	0.198	5.01	< 0.001	0.957	0.199	4.81	< 0.001
Channel: ATM	0.285	0.181	1.57	0.116	0.270	0.182	1.48	0.138
Channel: POS	0.384	0.177	2.17	0.030	0.372	0.179	2.08	0.037
Channel: SWIFT	1.223	0.387	3.16	0.002	1.237	0.398	3.11	0.002
Investment Active (= 1)	0.571	0.160	3.57	< 0.001	0.538	0.161	3.34	0.001
Bank-Level Variance (σ^2)	–	–	–	–	0.233 (SD = 0.483)	–	–	–

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the National Bank of Kazakhstan (2019–2024) and the Committee for Financial Monitoring (CFM, 2019–2024). Values represent model estimates produced in R (packages: rstanarm, lme4, caret, boot). Data were constructed to reflect observed transaction distributions (Table 6), while ensuring anonymity and compliance with confidentiality requirements.

Table 8. Model fit statistics

Metric	Logit Model	Mixed Model
AIC	839.2	831.1
McFadden R^2	0.313	0.329
Accuracy (on test set)	91.8%	93.2%
Sensitivity (Recall)	78.0%	82.0%
Specificity	92.9%	94.1%
AUC (ROC area)	0.910	0.927
Hosmer-Lemeshow p-value	0.726	0.682

Table 7 represents the results of the regression, which show that both the conventional and multilevel logistic models are quite good at finding suspicious transactions in Kazakhstan's banking industry. Key factors that have a big impact are the amount of the transaction (log-transformed), the type of instrument used, and where the transaction came from. Higher-value and cross-border transactions are far more likely to be noticed. SWIFT transactions are the most likely to be linked to suspicion, which supports worldwide AML risk typologies. Payment requests and transactions relating to investments are also signs of high risk.

Table 10. Model performance & diagnostics

Metric	Standard Logit Model	Multilevel Mixed Model
AIC	839.2	831.1
McFadden R^2	0.313	0.329
Hosmer-Lemeshow Test (p-value)	0.726	0.682
Cross-Validated AUC (CV-5fold)	0.910	0.927
Accuracy (Test Set)	91.8%	93.2%
Sensitivity (TPR)	78.0%	82.0%
Specificity (TNR)	92.9%	94.1%

Multivariate binary logistic regression was used to classify suspicious transactions based on calibrated synthetic data representing the Kazakhstani banking sector. To adjust for institutional heterogeneity, a multilevel logistic model with bank-level random intercepts was estimated. Both models included independent variables for transaction amount, payment instrument, origin, channel, and bank investment activity.

Bayesian logistic regression allows explicit prior specification on model parameters, making it suitable for financial monitoring and AML applications where regulatory knowledge or subjective expertise guides variable expectations. Using R packages such as rstanarm and brms, the following features are supported: Explicit priors for regression coefficients and intercept, Hierarchical/multilevel modeling, Output of full posterior distributions (mean, standard deviation, credible intervals). Integration of expert/regulatory opinion (e.g., higher risk for SWIFT transactions).

Table 9. Logistic and multilevel logistic regression results: suspicious transaction classification in Kazakhstani banks

Variable	Logit Estimate (SE)	p-value	Mixed Effects Estimate (SE)	p-value	Bootstrapped 95% CI (BCa)
Intercept	–4.99 (0.62)	< 0.001***	–5.21 (0.64)	< 0.001***	[–6.21, 3.80]
Transaction Amount (log)	0.41 (0.08)	< 0.001***	0.40 (0.08)	< 0.001***	[0.26, 0.58]
Instrument: Payment Order	0.68 (0.21)	0.001 **	0.66 (0.22)	0.002 **	[0.25, 1.17]
Instrument: Other	0.54 (0.25)	0.03 *	0.51 (0.25)	0.044 *	[0.05, 1.05]
Geo Origin: Cross–Border	0.99 (0.20)	< 0.001***	0.96 (0.20)	< 0.001***	[0.61, 1.42]
Channel: ATM	0.28 (0.18)	0.12	0.27 (0.18)	0.14	[–0.08, 0.60]
Channel: POS	0.38 (0.18)	0.030 *	0.37 (0.18)	0.037 *	[0.07, 0.81]
Channel: SWIFT	1.22 (0.39)	0.002 **	1.24 (0.40)	0.002 **	[0.52, 2.08]
Investment Active (=1)	0.57 (0.16)	< 0.001***	0.54 (0.16)	0.001 **	[0.22, 0.89]
Random Intercept (Bank)	–	–	SD = 0.483 (Var = 0.233)	–	–

Note: * p < 0.05, ** p < 0.01, *** p < 0.001; 95% confidence intervals estimated via bootstrapping (BCa method, 1000 resamples).

Table 11. Bayesian model

Variable	Posterior Mean	Posterior SD	2.5% Credible Interval	97.5% Credible Interval
Intercept	−5.10	0.65	−6.38	−3.98
Txn Amount (log)	0.42	0.08	0.26	0.58
Instrument: PaymentOrder	0.69	0.23	0.24	1.19
Instrument: Other	0.54	0.26	0.02	1.04
Geo Origin: CrossBorder	1.01	0.21	0.61	1.45
Channel: ATM	0.29	0.18	−0.06	0.64
Channel: POS	0.39	0.16	0.08	0.70
Channel: SWIFT	1.28	0.42	0.59	2.11
Investment Active	0.56	0.17	0.23	0.88

Bayesian credible intervals confirm strong positive effects for cross-border, SWIFT, payment orders, and investment-related transactions, supporting *H2* and *H3*.

It is important to note that it was a convergence of qualitative and quantitative evidence that showed emphatic and stable convergence of all sources of data, attesting to the correctness of all four hypotheses (*H1* to *H4*) and answering the research questions comprehensively. Concerning *H1* to *H2*, the analysis of regulatory documents, supervisory reports, and institutional case study indicates that high-value flows, cross-border transactions, transfers through SWIFT, and the activity related to investments are considered in FATF/EAG assessment and CFM guidelines as primary AML/ CTF risk indicators; it is consistent with the findings of the models that indicate that these variables are the most significant predictors of suspiciousness. This is also demonstrated in weak links in the monitoring of cross-border and complex instruments, as in the case of ForteBank, where regulatory violations were directed by the weaknesses of the monitoring of these transactions, and which validates the hypotheses according to which such transactions are vulnerable to a much greater AML/CFT risk. In relation to *H3*, the quantitative findings of the study show high predictive performance at both logistic, multilevel, and Bayesian, and the random intercept of a multilevel specification embodies substantial predictive performance in terms of bank-level variance. As far as *H4* is concerned, the results of the interview and cases demonstrate that the greater digital infrastructure that banks have, in particular, Halyk and Kaspi, the higher the monitoring and detection of anomalies in their occurrence, directly corresponding to the greater impact of these factors at the level of institutions, which is reflected in the hierarchical models. Ultimately, the close correspondence of both the statistical results and institutional realities held by the fact that using synthetic and calibrated data due to the confidences limitations will have to be improved later on the live transaction records, the close proximity in the results of the Bayesian and multilevel model suggests that the two approaches offer a viable, scalable, and institution-sensitive basis on enhancing the AML/CFT surveillance in the investment activities in Kazakhstan

4. DISCUSSION

The empirical result of the logistic and other related probabilistic models in this study is widely correlated with the global evidence of AML analytics in banking. Amoako et al. (2025) and Rafiq and Sohail (2023) are also research works that reveal that logistic regression is one of the most applicable techniques to identify fraudulent or suspicious financial transactions due to its interpretability, flexibility, and ability to fit various financial data. The results of our study in the context of Kazakhstani banks with high sensitivity and accuracy coincide with the findings in Russia, EU jurisdictions, and Central Asia, as Salina et al. (2021), Kazantsev et al. (2021), and Nichkasova et al. (2021) demonstrated that logistic and multilevel models can deliver similarly high classification results in the banking and payment systems. In this regard, we can confirm that such methods are still relevant benchmarks when monitoring transactions, especially when institutional comparability and model transparency are critical.

The finding that cross-border activity, SWIFT transactions, and payment orders are some of the most significant risk factors is also entirely in line with the global typologies of AML/CFT and em-

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pirical studies with regard to the region. FATF and EAG testing considers such instruments and channels to be particularly susceptible to money laundering and terrorist financing, and Eastern European and Eurasian research echoes this finding, with transaction structure and type of instrument, as well as international reach, being positive predictors of suspiciousness. It is these variables, however, which have proved persistent in our models, thus strengthening instead of averting the risk-based paradigm.

The fact that Bayesian and machine learning-inspired solutions are used in our AML models aligns with the larger international tendency to adopt sophisticated analytics in AML systems (Alexandre & Balsa, 2023; Kute et al., 2021; Rakhmetulayeva et al., 2025). As demonstrated by Lettieri et al. (2023), Bayesian logistic regression is, in particular, an effective way to detect financial crime due to its ability to incorporate prior regulatory assumptions and more effectively manage data imbalances – a quality we were able to evaluate in our case with synthetic but precisely calibrated data. At the organizational level, Rybalchenko et al. (2022) recognize that banking systems experiencing stress like Ukraine's will have to undergo digitalization and strategic changes to ensure their resilience; our results propose that the banks of Kazakhstan should be digitalized further and that they should have more advanced monitoring systems that would allow leveraging the opportunities of probabilistic models.

Our outcomes are also in agreement with the wider context of financial and developmental conditions that are detailed in Osatiuk et al. (2024) and Prokopenko et al. (2019). Osatiuk et al. (2024) demonstrate that financial instruments play a crucial part in attracting investment and risk management in Ukraine. However, their effectiveness is linked to transparency and strong links between government and industry, which, as our case studies show, remains lacking in investment monitoring in Kazakhstan. According to Prokopenko et al. (2019), banks play a strategic role in national innovation systems as the authors assert that innovation-based banking and collaborative mechanisms would help the countries, including India, the UK, and Norway, to enhance their monitoring performance, which our findings that technologically advanced banks in Kazakhstan can contribute to higher monitoring performance confirm innovation plays a central role in both state building and financial integrity (Khalilova et al., 2022). Last but not least, Khalilova et al. (2022) and Rybalchenko et al. (2022) discuss digital banking based on distributed ledger technology, Basel II principles, and P2P lending and how tokenization and market modelling can increase profitability; our findings indicate that similar digital and analytical breakthroughs in Kazakhstan may reinforce both AML/CFT mechanisms and optimize efficiency of investment-related intermediation.

CONCLUSION

This study aimed to assess the effectiveness of financial monitoring of investment activities of Kazakhstani banks by combining both qualitative institutional evidence with probabilistic statistical modeling. The findings indicate that, despite the relatively elaborate nature of the AML/CFT regulatory framework in Kazakhstan, rates of implementation vary at different banks. Most leading banks, including Halyk Bank and Kaspi Bank, have implemented sophisticated and digitally integrated monitoring systems, while other banks, such as ForteBank, did the same, only after being forced by regulators to point out that there remains persistent institutional heterogeneity in terms of maturity in compliance practices.

The results of the quantitative models established during the study logistic, multilevel and Bayesian regressions, showed great predictive force and continued to recognize cross-border flows, transactions valued over 50,000, or more, transactions over 50,000, and more transactions supported by investment as the most probable features of suspicious behavior. These results verify that data-driven modeling has the potential to be a valuable supplement to current methods of supervision, assisting institutions in enhancing the accuracy and consistency of transaction monitoring.

The key finding is that effective AML/CFT oversight of investment activity involves effective regulatory bases and institution-specific analytical abilities. The results are regulatory convergence and predictive modeling, which would give a better view of the risk concentrations and would inform the banks to enhance their detection systems. To regulators, the findings remind the importance of helping technological upgrading, minimizing interpretive ambiguity, and promoting differentiated supervisory strategies in accordance with institutional capabilities.

Further research should be aimed at validating these models using anonymized real transaction-level data, as this will allow the models to be tested under realistic operating conditions.

Additional investigation of machine-learning methods such as neural networks, hybrid systems, and anomaly-detection systems can improve the accuracy of predictions as the complexity of transaction flows increases. Comparative studies in the countries of the EAEU would also play a role in benchmarking Kazakhstan's development and finding the best practices that could be transferred to the region to monitor investment-related AML/CFT.

AUTHOR CONTRIBUTIONS

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