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ADAPTIVE MANAGEMENT OF COMMERCIAL BANKS' SECURITIES PORTFOLIOS USING EXPLAINABLE ARTIFICIAL INTELLIGENCE

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Today, the securities portfolios of commercial banks are shaped by rapid changes in interest rates, exchange rates and liquidity conditions. Although the portfolio of the banking system of Uzbekistan has expanded considerably over the past five years, its composition remains homogeneous and its income potential is not fully utilized (Table 1).

Table 1

Key indicators of the securities portfolio of the banking system of Uzbekistan

Indicator	2020	2025	Implication for portfolio management
Share of securities in total assets, %	2.58	11.14	portfolio volume increased 4.3-fold
Share of government and Central Bank instruments, %	>90	>96	concentration in a single asset type
Share of securities income in total interest income, %	2.0	5.7	growing role of the portfolio in income
Portfolio yield / return on assets, %	–	9.0 / 15.1	portfolio income potential is underused
Portfolio-to-equity ratio, %	16.2	76.1	market risk increasingly affects capital

Source: author's calculations based on data of the Central Bank of the Republic of Uzbekistan.

When a portfolio grows rapidly relative to capital, static management approaches that are reviewed only once or twice a year cannot maintain the balance between risk and return. According to forecast calculations, under the baseline scenario the ratio of the portfolio to equity capital will exceed 100 percent in 2029–2030. This implies that sharp movements in interest rates or the exchange rate will have a direct impact on bank capital.

In international practice, this problem is increasingly addressed with artificial intelligence tools. The Financial Stability Board (FSB) has identified portfolio management as one of the most promising areas for the application of artificial intelligence and machine learning. According to the 2024 survey by the Bank of

England and the Financial Conduct Authority (FCA), 75 percent of financial firms already use artificial intelligence, and a further 10 percent plan to adopt it within the next three years. However, 46 percent of them acknowledge only a partial understanding of the technologies they use. The need to explain model decisions therefore comes to the fore: 81 percent of firms using artificial intelligence apply explainability methods, and 64 percent use the SHAP method [6]. A prominent example from practice is BlackRock's Aladdin platform, which analyzes portfolio risk for more than 190 institutions, including central banks.

In Uzbekistan, this area has been elevated to the level of state policy: Presidential Resolution No. PQ-358 of 14 October 2024 approved the Strategy for the Development of Artificial Intelligence Technologies until 2030, and the Central Bank, the National Bank and JSCB "Aloqabank" were designated as the responsible institutions in the banking sector [1].

The study integrates H. Markowitz's mean–variance theory [2], R. Merton's dynamic portfolio choice approach [3], the SHAP explanation method developed by S. Lundberg and S.-I. Lee [4], and the three-tier constrained optimization model (3T-COM). The empirical basis comprises the results of panel and ARDL models estimated on panel data for 30 banks (417 observations) and on monthly data for five selected banks over 2020–2025.

The econometric analysis identified the main determinants of banks' stock market activity. At the banking-system level, the liquidity coverage ratio proved to be the strongest positive factor and the exchange rate the strongest negative one. However, the impact of these factors varies sharply across banks (Figure 1).

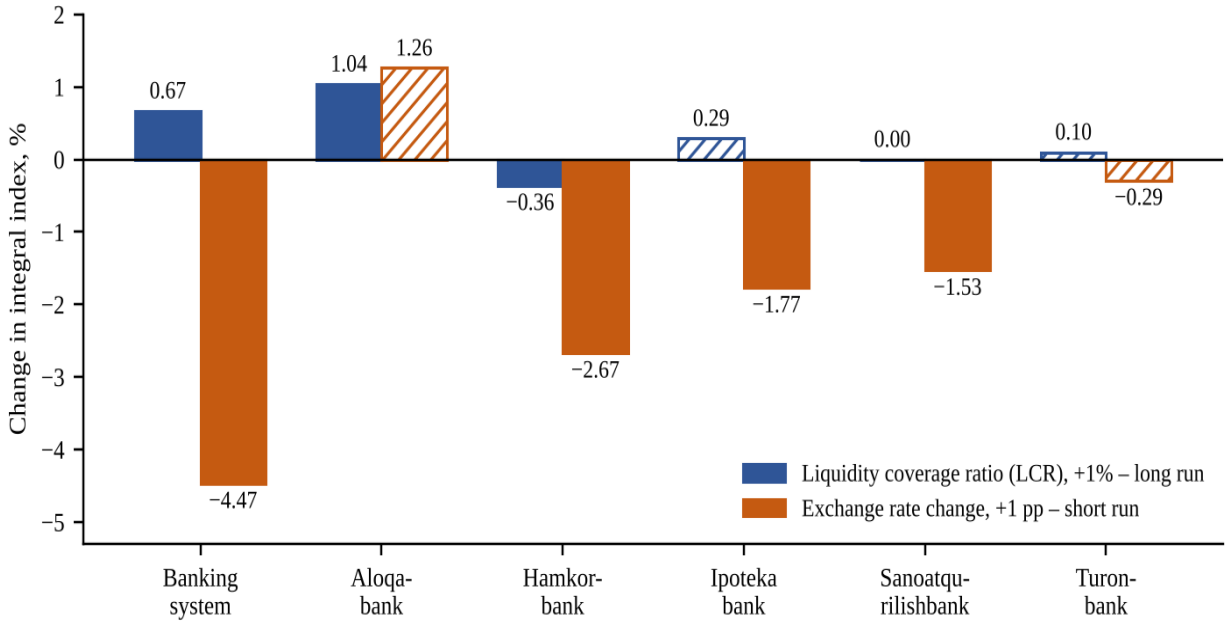


Figure 1. Change in the integral index of banks' stock market activity in response to a 1% (1 pp) change in the key factors, %

Note: hatched bars denote statistically insignificant estimates. Source: author's calculations.

As the figure shows, the effect of the liquidity coverage ratio is 1.04% at Aloqabank but −0.36% at Hamkorbank, while the effect of the exchange rate is −4.47%

for the banking system as a whole and insignificant for some banks. Consequently, the portfolio is affected by many factors whose strength varies across banks and over time. Management based on a single rigid model with constant weights cannot adapt to such conditions. The study by S. Gu, B. Kelly and D. Xiu demonstrates that machine learning forecasts generate substantial economic gains for investors compared with traditional regression-based strategies [5]. Nevertheless, complex models must not turn into a “black box”: the rationale behind each decision has to remain understandable.

On this basis, the XAI-DPO methodology is proposed. It forms a closed loop of five interrelated blocks (Figure 2).

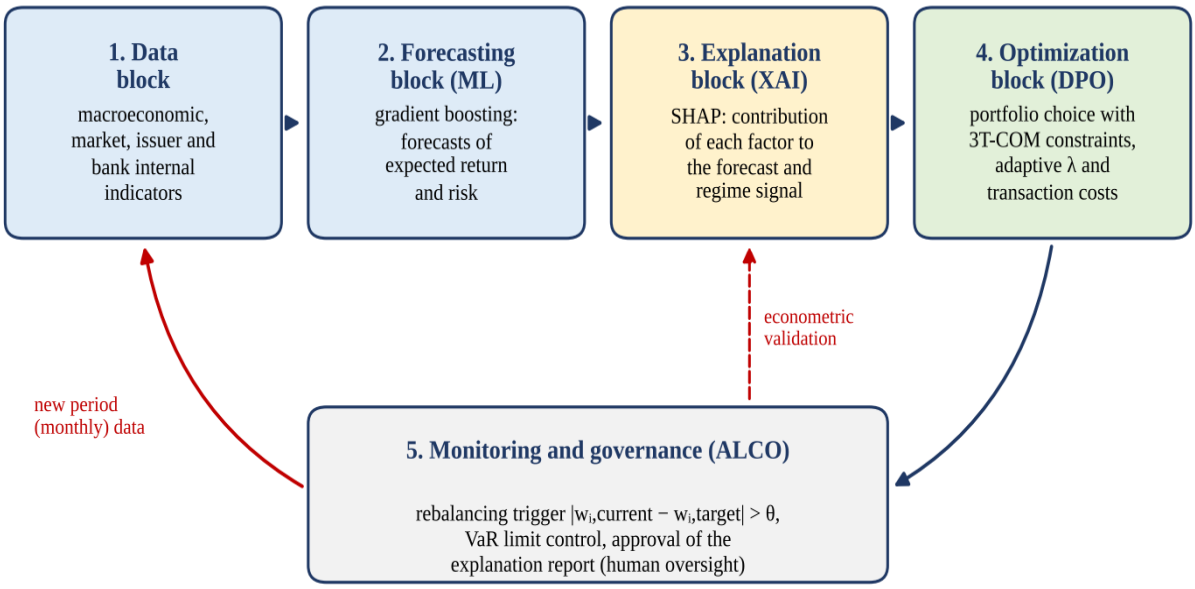


Figure 2. The XAI-DPO methodology for securities portfolio management

Source: developed by the author.

In the forecasting block, a machine learning model estimates the expected return and risk of each instrument. In the explanation block, each forecast is decomposed into factor contributions using the SHAP method:

$$\hat{\mu}_{i,t} = \varphi_0 + \Sigma_k \varphi_{k,i,t},$$

where $\hat{\mu}_{i,t}$ is the forecast return of instrument i, φ_0 is the base (average) value, and $\varphi_{k,i,t}$ is the contribution of factor k (liquidity, exchange rate, interest rate, issuer indicators). The importance of factor contributions is compared with the econometric estimates: if the factors ranked by the model as most important contradict the results of the econometric analysis, the case is reported to the risk committee.

In the optimization block, the portfolio is re-selected in each period by solving the following problem:

$$\max_w [\, w_t^T \hat{\mu}_t - \lambda_t \cdot w_t^T \Sigma_t w_t - \kappa \cdot \Sigma_i |w_{i,t} - w_{i,t-1}| \,],$$

where λ_t is the risk aversion coefficient that varies with the SHAP signal, and κ is the transaction cost coefficient that limits excessive trading. The problem is solved subject to the 3T-COM constraints: the $VaR_{99\%}$ limit, the liquidity constraint, the exclusion of issuers with an Altman Z-score below 1.81, and the bounds on the shares of the three tiers. The rules for adapting to market conditions are presented in Table 2.

Table 2

Rules for adapting to market regimes in the XAI-DPO methodology (recommended parameters)

Market regime	XAI and risk signals	Portfolio tiers (1 / 2 / 3), %	Risk coefficient λ	Review frequency
Stable	FX factor contribution < 20%; VaR limit utilization < 70%	30 / 45 / 25	baseline	monthly
Warning	FX factor contribution 20–35%; VaR limit utilization 70–90%	35 / 45 / 20	1.5 × baseline	every 2 weeks
Stress	FX factor contribution > 35%; VaR limit utilization > 90%	40 / 45 / 15	2 × baseline	weekly

Note: tier 1 – liquidity core; tier 2 – stable income core; tier 3 – growth core. Source: developed by the author.

In the proposed approach, portfolio rebalancing is triggered not only by a time schedule but also by signals: when an instrument's weight deviates from its target by more than a predefined threshold, or when the XAI block indicates a regime change. Each decision is submitted to the Asset and Liability Management Committee (ALCO) together with an explanation report. This preserves human oversight and meets regulatory transparency requirements.

Conclusion

– the securities portfolio of the banking system is expanding rapidly, yet it is concentrated in a single type of asset, its yield is below the average return on assets, and its risk relative to capital is increasing;

– the portfolio is driven by many factors whose strength differs sharply across banks and over time; therefore, static management methods with constant weights are insufficient;

– machine learning improves forecast accuracy, while explainable artificial intelligence (SHAP) reveals the rationale behind each decision and makes it possible to validate model results against econometric estimates;

– dynamic optimization adapts the portfolio to market changes through the 3T-COM constraints, a risk coefficient that varies with the market regime, and signal-based rebalancing.

Based on the above, an XAI-DPO multi-factor adaptive optimization methodology has been proposed, which integrates explainable artificial intelligence (XAI) and dynamic portfolio optimization (DPO) approaches in order to ensure the balance between risk and return and adaptability to market changes in securities portfolio management.

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