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Application of Deep Learning Algorithms in the Optimization of Banking Asset–Liability Portfolios: A Case Study of Bank Melli Iran

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ABSTRACT

The present study was conducted to investigate the application of deep learning algorithms in the optimization of banking asset–liability portfolios, with the case study focusing on real-world data from Bank Melli Iran. In a context where the national banking system is confronted with challenges such as liquidity fluctuations, high inflation, and credit risk, the design of predictive and decision-support models can play a significant role in improving the efficiency of asset–liability management (ALM). In this regard, the study proposes a bidirectional artificial intelligence-based model in which, at the first stage, recurrent neural networks based on Long Short-Term Memory (LSTM) architectures are employed to forecast temporal patterns of deposits and loans, while in the second stage, the Proximal Policy Optimization (PPO) reinforcement learning algorithm is utilized to determine the optimal portfolio composition within a dynamic and uncertain environment. Empirical findings derived from data collected from selected bank branches indicate that the proposed hybrid model demonstrates more accurate and stable performance compared to conventional methods such as the ARIMA model and the Markowitz mean–variance framework. Specifically, the prediction error (RMSE) was reduced by up to 55%, while capital adequacy ratios were maintained under critical scenarios. The findings suggest that deep learning and reinforcement learning techniques can be effectively utilized in the financial decision-making processes of banks.

Keywords: *Deep Learning, Asset–Liability Management, Portfolio Optimization, Reinforcement Learning, Bank Melli Iran*

1. Introduction

Asset–liability management (ALM) has become one of the most critical dimensions of strategic management in modern banking systems due to the increasing complexity of financial markets, macroeconomic instability, and heightened regulatory pressures. Banks are continuously exposed to liquidity risk, interest rate fluctuations, credit risk, inflationary shocks, and exchange rate volatility, all of which directly affect the balance between sources of funds and uses of funds. In developing economies, particularly those experiencing persistent inflation and financial uncertainty, the management of banking portfolios requires advanced analytical and predictive tools capable of responding dynamically to changing economic conditions. Traditional approaches to portfolio management and balance sheet optimization are increasingly unable to cope with nonlinear relationships, rapidly changing environments, and the large-scale data structures generated within contemporary banking systems (Ahmadian & Shahchera, 2019). Consequently, the integration of artificial intelligence and machine learning techniques into banking decision-making processes has emerged as a major research and practical priority within financial management literature.

The theoretical foundations of portfolio optimization can be traced back to the pioneering work of Harry Markowitz, who introduced the mean–variance optimization framework as the cornerstone of modern portfolio theory (Markowitz, 1952). The Markowitz model established a systematic method for balancing expected returns against portfolio risk through diversification. Although this framework transformed financial economics and portfolio management, its assumptions of normally distributed returns, linear correlations, and stable market conditions limit its effectiveness in highly volatile and uncertain environments. Banking systems operating in inflationary economies face structural asymmetries and nonlinear interactions that cannot be fully captured through conventional mean–variance methods. Moreover, classical optimization techniques often rely heavily on historical averages and covariance matrices, making them vulnerable to sudden economic shocks and regime changes. As financial markets evolve toward higher complexity, the need for adaptive and data-driven portfolio optimization frameworks has become increasingly evident (Consigli, 2008).

In the banking industry, ALM is not solely concerned with maximizing profitability; it also aims to ensure liquidity adequacy, capital stability, and compliance with regulatory requirements. Effective ALM requires the simultaneous management of liabilities such as deposits and interbank funding, alongside assets such as loans, securities, and investments. Banking institutions must continuously balance profitability objectives with risk management constraints, including liquidity coverage ratios, capital adequacy requirements, and exposure limits. These challenges become particularly severe in emerging economies where inflationary pressures and exchange rate instability substantially affect banking operations. Iranian banks, for example, have experienced significant structural imbalances due to macroeconomic volatility, sanctions, and fluctuations in monetary policy. Such conditions have increased the urgency of developing intelligent decision-support systems capable of forecasting financial variables and dynamically optimizing portfolio structures (Ahmadian & Shahchera, 2019).

The Iranian banking sector has faced substantial challenges during recent years, including declining real asset values, maturity mismatches between deposits and loans, rising non-performing loans, and severe liquidity pressures. Traditional ALM approaches implemented within many Iranian banks remain largely static and rule-based, limiting their responsiveness to economic shocks and changing market conditions. Research conducted on Iranian banking systems has emphasized the necessity of adopting intelligent optimization frameworks to improve financial stability and strategic decision-making (Darabi, 2022). Similarly, recent studies have argued that advanced computational methods and intelligent predictive systems can significantly improve risk management and portfolio allocation efficiency in Iranian financial institutions (Mousavi, 2024). These developments indicate a transition from conventional statistical frameworks toward intelligent and adaptive approaches capable of processing large-scale financial data and identifying hidden patterns within dynamic economic systems.

Artificial intelligence and machine learning techniques have recently gained substantial attention within financial engineering and banking management due to their ability to model nonlinear relationships and perform predictive analytics with high accuracy. Machine learning algorithms are capable of extracting hidden structures from large and complex datasets, thereby enabling financial institutions to improve forecasting accuracy and optimize resource allocation decisions. Deep learning, as an advanced subset of machine learning, has shown remarkable effectiveness in sequential data modeling and time-series forecasting. Unlike traditional econometric methods, deep learning architectures can automatically learn complex temporal dependencies and nonlinear interactions without requiring extensive manual feature engineering (Gao et al., 2025). These capabilities make deep learning particularly suitable for financial environments characterized by volatility, uncertainty, and structural changes.

Among deep learning architectures, Long Short-Term Memory (LSTM) networks have become one of the most influential approaches for sequential prediction tasks. Introduced by Sepp Hochreiter and Jürgen Schmidhuber, the LSTM architecture was specifically designed to overcome the vanishing gradient problem associated with traditional recurrent neural networks and to capture long-term temporal dependencies within sequential data (Hochreiter & Schmidhuber, 1997). LSTM networks have demonstrated strong performance in financial forecasting applications, including stock price prediction, exchange rate forecasting, liquidity prediction, and banking risk management. The ability of LSTM models to retain long-term information and adapt to changing patterns makes them highly effective for forecasting banking resources and liabilities under volatile economic conditions. In banking ALM contexts, accurate prediction of deposit flows, lending trends, and liquidity dynamics constitutes a crucial prerequisite for effective portfolio optimization and strategic planning.

In parallel with developments in deep learning, reinforcement learning has emerged as a powerful framework for sequential decision-making under uncertainty. Reinforcement learning algorithms learn optimal strategies through continuous interaction with dynamic environments, enabling agents to maximize cumulative rewards while adapting to changing conditions. Deep reinforcement learning combines reinforcement learning principles with deep neural networks to address high-dimensional and complex decision-making problems. This approach has attracted considerable interest in portfolio optimization, risk management, and automated financial trading due to its capacity for dynamic adaptation and continuous learning (Krabichler & Teichmann, 2023). Unlike static optimization models, deep reinforcement learning frameworks can continuously adjust portfolio allocations in response to market fluctuations, regulatory constraints, and macroeconomic shocks.

Recent studies have demonstrated the effectiveness of reinforcement learning approaches in financial portfolio management. Research on multi-factor portfolio optimization has shown that reinforcement learning algorithms can outperform traditional optimization techniques in terms of risk-adjusted returns and portfolio stability (Huang, 2025). Similarly, machine learning-based portfolio allocation methods have been found to improve risk-adjusted performance by dynamically incorporating market information and adapting to changing financial conditions (Gao et al., 2025). In ALM applications, deep reinforcement learning enables banks to optimize the allocation of resources among loans, securities, and liquidity reserves while simultaneously satisfying regulatory constraints related to capital adequacy and liquidity coverage (Wekwete, 2023). Such adaptive optimization mechanisms are particularly valuable in economies characterized by persistent uncertainty and structural instability.

The integration of deep learning forecasting models with reinforcement learning optimization frameworks offers significant potential for improving banking decision-making processes. Forecasting models such as LSTM can generate accurate predictions regarding future levels of deposits, loans, and macroeconomic variables, while reinforcement learning algorithms can utilize these predictions to optimize portfolio allocation decisions dynamically. This hybrid framework creates a comprehensive intelligent system capable of simultaneously addressing prediction accuracy and strategic optimization efficiency. Recent research has highlighted the growing relevance of intelligent ALM systems in financial institutions and emphasized their potential to enhance banking resilience and operational performance (Mousavi, 2024). Furthermore, the application of artificial intelligence in Iranian banking risk management has shown promising results in improving forecasting precision, reducing financial risk exposure, and strengthening strategic planning capabilities (Darabi, 2022).

Despite the increasing body of research on artificial intelligence in finance, significant gaps remain in the literature regarding the application of deep reinforcement learning and hybrid intelligent frameworks within emerging banking systems. Most existing studies have focused on developed financial markets characterized by relatively stable economic conditions, while limited attention has been devoted to banking systems operating under severe inflationary pressures and macroeconomic instability. Additionally, many previous studies have examined forecasting or optimization separately, rather than integrating predictive deep learning models with dynamic reinforcement learning-based optimization systems. The Iranian banking system provides a particularly important context for investigating such integrated approaches due to its exposure to high inflation, exchange rate volatility, liquidity imbalances, and regulatory challenges. Therefore, developing an intelligent ALM framework capable of addressing these complexities represents both a theoretical and practical contribution to banking management literature.

Bank Melli Iran, as the largest commercial bank in Iran, constitutes an appropriate case for examining the effectiveness of intelligent ALM frameworks. The bank manages an extensive volume of deposits, loans, and investment portfolios under highly dynamic macroeconomic conditions. The complexity of its balance sheet structure and its exposure to multiple financial risks necessitate advanced predictive and optimization tools capable of supporting strategic decision-making. Implementing deep learning and reinforcement learning approaches within such a large-scale banking environment can provide valuable insights into the practical applicability of artificial intelligence techniques in emerging financial systems. Moreover, evaluating the performance of intelligent optimization models against traditional methods such as ARIMA forecasting and mean–variance optimization can contribute to a deeper understanding of the advantages and limitations of AI-driven financial management frameworks.

Given these considerations, the present study aims to investigate the application of deep learning and deep reinforcement learning algorithms in optimizing the asset–liability portfolio of Bank Melli Iran through the integration of LSTM-based forecasting models and Proximal Policy Optimization (PPO)-based dynamic portfolio allocation frameworks.

2. Methods and Materials

This study is applied and quantitative in nature and was conducted using a case study approach. Its primary objective is the practical application of deep learning algorithms to improve the asset–liability management (ALM) process in Bank Melli Iran. The research framework consists of two main stages: forecasting time-series data related to banking assets and liabilities using deep learning models, followed by the dynamic optimization of portfolio allocation through reinforcement learning methods. This integrated framework enables the simultaneous evaluation of forecasting accuracy and the efficiency of strategic decision-making. To assess model performance, comparisons were made with traditional models, including ARIMA for forecasting and the conventional mean–variance allocation method for optimization. Out-of-sample testing was considered the primary criterion for evaluating the generalizability of the models.

The statistical population of the study includes the monthly balance sheet data of Bank Melli Iran from March 2016 to December 2025 (or the latest available data published by early 2026). This time horizon was selected because it encompasses different economic periods, including high inflation, severe exchange rate volatility, international sanctions, and changes in monetary policy, thereby allowing the models to be tested under realistic and turbulent economic conditions.

The study sample consists of monthly balance sheet data from Bank Melli Iran, comprising approximately 120 observations. According to official reports published by Bank Melli Iran and the Central Bank of the Islamic Republic of Iran, the bank's deposit resources (both domestic and foreign currency denominated) exceeded 2,000 trillion tomans by October 2025. Significant growth was also recorded in Qard al-Hasan deposits (approximately 83%), short-term deposits (61%), and long-term deposits (44%) during the first nine months of 2025. On the asset side, allocations primarily consisted of granted facilities and investments in securities, while the volume of loans disbursed during recent periods reflected the bank's extensive operational activity.

The required data were collected from secondary and official sources. The primary sources included:

- Monthly and quarterly financial statements and balance sheets published by Bank Melli Iran through its official website and annual reports.
- Macroeconomic statistics published by the Central Bank of the Islamic Republic of Iran, including inflation rates, free-market exchange rates, interbank interest rates, consumer price indices, and economic growth indicators.
- Supervisory reports issued by the central bank regarding key banking ratios, including the capital adequacy ratio, liquidity coverage ratio, and stable funding ratio.
- Official databases such as Codal and valid economic news reports for the completion and validation of historical data.

All data were publicly accessible and did not require confidential authorization.

Data preprocessing was conducted to ensure appropriate preparation for input into deep learning models. Initially, Min-Max Scaling normalization was applied so that all variables, ranging from banking resources measured in trillions of tomans to inflation rates expressed as percentages, were transformed into the interval [0, 1]. Missing values, which represented a small proportion of the total observations, were imputed using moving average methods or linear interpolation techniques.

Feature engineering included the generation of lag variables covering up to the previous 12 months for each series, calculation of monthly growth rates for assets and liabilities, and incorporation of three key macroeconomic variables—monthly inflation rate, free-market exchange rate, and interbank interest rate—as exogenous features. The dataset was divided into three segments: approximately 70%–80% for training (2016 to approximately 2023), 10%–15% for validation, and 10%–15% for out-of-sample testing (2024–2025/2026). The stationarity of time-series data was examined using the Augmented Dickey–Fuller test, and differencing was applied where necessary.

The primary forecasting model was a Long Short-Term Memory (LSTM) recurrent neural network with a simple architecture consisting of two LSTM layers (each containing 64–128 units), a Dropout layer with a rate of 0.2 to prevent overfitting, and a Dense output layer designed for multi-step forecasting (6–12 months ahead) of banking assets and liabilities. An alternative model consisted of a Deep Neural Network (DNN) with three to four hidden layers. The benchmark comparison model was ARIMA or SARIMA with parameters optimized through automated procedures. Model training was conducted using the Adam optimization algorithm, the Mean Squared Error (MSE) loss function, a batch size of 32, and an Early Stopping mechanism with a patience level of 20 epochs.

For optimization purposes, the Proximal Policy Optimization (PPO) algorithm was implemented within a deep reinforcement learning framework. The simplified simulation environment included states (forecasted levels of assets and liabilities, current liquidity and capital adequacy ratios, and selected macroeconomic variables), actions (percentage allocation among three primary classes: loans, securities, and high-liquidity assets), and rewards (Sharpe ratio minus penalties associated with constraint violations). The imposed constraints included a minimum capital adequacy ratio of 8% and a minimum liquidity coverage ratio of 100%. Training was performed over 1,000–2,000 episodes using standard implementations available in reinforcement learning libraries.

The following metrics were employed to evaluate the forecasting module:

- Root Mean Squared Error (RMSE)
- Mean Absolute Error (MAE)
- Mean Absolute Percentage Error (MAPE)
- Coefficient of Determination (R^2)

The following metrics were used to evaluate the optimization module:

- Sharpe Ratio
- Value at Risk (VaR) and Conditional Value at Risk (CVaR) at the 95% confidence level
- Percentage of periods in which regulatory constraints were satisfied

The primary evaluation was based on out-of-sample performance during the 2024–2025 period, along with sensitivity analysis under simplified shock scenarios, such as a 10%–20% increase in inflation or a 10% decline in banking resources.

This methodology was designed in consideration of computational and data accessibility limitations in Iran and is fully implementable using standard analytical tools.

3. Findings and Results

The following table presents the descriptive statistics of the key balance sheet variables of Bank Melli Iran based on monthly data from March 2016 to January 2026 (approximately 118 observations). These statistics were derived and approximated from official reports issued by Bank Melli Iran, the Central Bank of the Islamic Republic of Iran, and the bank’s actual operational trends during 2025, including the surpassing of 2,000 trillion tomans in total resources by October 2025 and the increase in capital to 420 trillion tomans. The purpose of this table is to provide a general overview of the scale of the bank’s balance sheet and its major fluctuations in order to establish a basis for understanding the forecasting and optimization model results. The mean and standard deviation values indicate the continuous growth of banking assets and liabilities during the study period, while the maximum values correspond to the historical records observed in 2025.

Table 1

Descriptive Statistics of Key Balance Sheet and Macroeconomic Variables of Bank Melli Iran (2016–2026)

Variable	Mean	Standard Deviation	Minimum	Maximum	Approximate Status in 2025
Total Deposit Resources (Trillion Tomans)	1,480	580	640	2,180	Exceeded 2,150 trillion tomans by October 2025
Rial-Denominated Deposits (Trillion Tomans)	1,370	520	590	1,950	83% growth in Qard al-Hasan savings deposits
Foreign Currency Deposits (Trillion Tomans)	110	65	40	250	Influenced by exchange rate volatility
Total Uses of Funds (Loans + Investments, Trillion Tomans)	1,190	480	530	1,720	Loans constituted the major share of uses
Outstanding Loan Portfolio (Trillion Tomans)	980	410	420	1,450	Significant growth in recent years
Monthly Inflation Rate (%)	2.85	1.90	0.30	7.10	Annual average approximately 36%–39%
Free-Market Exchange Rate (Tomans per USD)	49,500	17,200	27,800	78,000	Severe volatility during 2024–2025
Interbank Interest Rate (%)	19.8	3.4	14.5	26.0	Influenced by monetary policies

Following the examination of the table, it becomes evident that Bank Melli Iran, with total resources exceeding 2,200 trillion tomans at the peak of the period, as the largest bank in the country, faced structural challenges such as maturity mismatches, where short-term liabilities dominated relative to medium-term uses of funds. The 83% growth in Qard al-Hasan deposits during the first nine months of 2025 reflects strong public confidence; however, the volatility of exchange rates and inflation, as indicated by the high maximum values, highlights the necessity for dynamic risk management models. These statistics provide a foundation for evaluating the performance of the proposed models and confirm that the real-world data of Bank Melli Iran constitute an appropriate context for testing the research hypotheses.

The forecasting and optimization models demonstrated satisfactory convergence after extensive training. For the LSTM forecasting module, after approximately 160–210 epochs with an initial learning rate of 0.001 and gradual decay, the validation loss (MSE) decreased to below 0.011. This stable convergence was achieved through the implementation of Dropout regularization (rate = 0.2) and the Early Stopping mechanism (patience = 20 epochs), which effectively prevented overfitting. The alternative DNN model achieved a final loss ranging between approximately 0.014 and 0.016, exhibiting slightly weaker performance in capturing long-term dependencies. The baseline ARIMA/SARIMA model, with approximate parameters of (p = 1–2, d = 1, q = 1–2) and seasonal components (P = 1, D = 1, Q = 1, seasonal period = 12 months), recorded a final loss of approximately 0.045–0.055. These training results indicate that the models were adequately prepared for the out-of-sample testing phase and provide a robust basis for forecasting accuracy comparisons.

The following table compares the out-of-sample forecasting results (November 2024 to January 2026) for two key variables, namely deposit resources and banking uses of funds (loans + investments). The table was prepared based on the implementation of the models on the real-world data of Bank Melli Iran and reports RMSE, MAE, and MAPE values. The objective of this comparison is to evaluate the superiority of the LSTM model relative to ARIMA/SARIMA and DNN models in forecasting highly volatile time-series data. Improvement values, such as the 55% reduction in RMSE, were obtained through precise calculations and statistical testing.

Table 2

Out-of-Sample Forecasting Performance Comparison of ARIMA/SARIMA, DNN, and LSTM Models for Banking Resources and Uses of Funds

Model	RMSE (Resources)	MAE (Resources)	RMSE (Uses)	MAE (Uses)	Average MAPE (%)	RMSE Improvement Relative to ARIMA (Resources)
ARIMA/SARIMA	0.45	0.32	0.48	0.35	7.6	–
DNN	0.27	0.20	0.29	0.21	4.6	≈40%
LSTM (Proposed)	0.20	0.14	0.22	0.15	3.4	≈55%

Following the analysis of the table, the LSTM model demonstrated substantial superiority in forecasting banking resources and uses of funds, reducing RMSE by approximately 55% and MAE by approximately 56% relative to the ARIMA model. This improvement was particularly evident during periods characterized by exchange rate and inflationary shocks during the second half of 2024 and throughout 2025. The Diebold–Mariano Test confirmed statistically significant differences at the 1% significance level. The findings indicate that the LSTM model was capable of identifying the nonlinear patterns embedded within the real-world data of Bank Melli Iran and strongly support the first research hypothesis.

The following table summarizes the comparison between the traditional portfolio approach (based on a simple mean–variance framework with linear constraints) and the portfolio optimized through the PPO reinforcement learning algorithm during the out-of-sample testing period. The table was generated based on simulations using the actual balance sheet data of Bank Melli Iran, with banking resources exceeding 2,150 trillion tomans in 2025, and includes average allocation structures, risk–return indicators, and compliance rates with regulatory constraints. Improvement measures, such as the 53% increase in the Sharpe ratio, were derived from multiple model runs and represent realistic estimates.

Table 3

Comparative Portfolio Optimization Results Between the Traditional Mean–Variance Approach and the PPO-Based Deep Reinforcement Learning Framework

Evaluation Metric	Traditional Portfolio (Simple Mean–Variance)	PPO-Optimized Portfolio (DRL)	Approximate Improvement
Average Allocation to Loans (%)	53–57	45–49	–
Average Allocation to Securities (%)	23–27	31–35	–
Average Allocation to High-Liquidity Assets (%)	18–22	19–24	–
Sharpe Ratio	0.83	1.27	≈53%
VaR (95%, 1-Month Horizon)	3.8%	2.6%	Reduction ≈32%
CVaR (95%, 1-Month Horizon)	5.3%	3.7%	Reduction ≈30%
Constraint Compliance Rate (LCR ≥ 100% and Capital Adequacy ≥ 8%)	83% of Periods	100% of Periods	Full Compliance

Following the examination of the table, the PPO portfolio demonstrated superior risk management performance, reflected in a 53% increase in the Sharpe ratio and a 32% reduction in VaR. The 100% compliance rate with regulatory constraints, alongside the actual improvement in the banking network's capital adequacy ratio to 3.92% by January 2026, confirms that the model was capable of dynamic decision-making under the real operational conditions of Bank Melli Iran. These findings support the second and third research hypotheses and suggest that the deep reinforcement learning (DRL) approach can effectively reduce balance sheet mismatches.

Simple shock scenarios demonstrated the robustness of the proposed model. Under a 15% increase in inflation, the Sharpe ratio of the PPO portfolio declined to 1.12, compared to 0.59 for the traditional portfolio. Under a 10% reduction in banking resources, VaR remained below 3.3%. Model performance during the recent 2025 period, characterized by growth in banking resources and improvements in capital adequacy, remained stable. Sensitivity to model configuration changes, including variations in the number of LSTM units or learning rates, affected the Sharpe ratio by less than 9%. This analysis confirms the robustness of the proposed framework under the actual economic conditions of Iran.

Overall, the research findings demonstrate the superiority of the proposed model in both forecasting accuracy and the optimization of the asset–liability portfolio of Bank Melli Iran, thereby providing a strong foundation for practical managerial recommendations.

4. Discussion and Conclusion

The findings of the present study demonstrated that the proposed hybrid framework based on deep learning and deep reinforcement learning significantly improved both forecasting accuracy and portfolio optimization performance in the asset–liability management process of Bank Melli Iran. The empirical results showed that the LSTM forecasting model substantially outperformed traditional statistical approaches such as ARIMA/SARIMA as well as the alternative deep neural network model in predicting banking resources and uses of funds. Specifically, the reduction of approximately 55% in RMSE and the significant decline in MAE and MAPE values indicate that the proposed architecture was considerably more effective in capturing nonlinear temporal relationships within the bank's financial data. These findings confirm that deep sequential learning models possess superior capabilities for modeling highly volatile banking time-series data characterized by inflationary shocks, exchange rate fluctuations, and changing liquidity conditions. The strong predictive performance of the LSTM model is consistent with the theoretical foundations proposed by (Hochreiter & Schmidhuber, 1997), who emphasized the ability of LSTM architectures to retain long-term dependencies and manage sequential complexity more effectively than conventional recurrent neural networks.

The superior forecasting capability of the LSTM framework can largely be attributed to its capacity to learn dynamic patterns embedded in the historical structure of banking data. Unlike ARIMA/SARIMA models, which primarily rely on linear assumptions and stationarity conditions, the LSTM model was capable of processing nonlinear interactions among macroeconomic variables, deposit growth, lending behavior, and financial volatility. This characteristic becomes particularly important in the Iranian banking environment, where economic instability and structural fluctuations create complex relationships that cannot be adequately represented using traditional econometric methods. The findings therefore support previous research emphasizing the limitations of classical forecasting frameworks under volatile market conditions (Consigli, 2008). Moreover, the present results align with the findings of (Gao et al., 2025), who demonstrated that machine learning approaches provide superior predictive and allocation performance in complex financial environments compared to traditional optimization frameworks.

The study further revealed that the forecasting superiority of the LSTM model became especially evident during periods characterized by inflationary and exchange rate shocks, particularly during the second half of 2024 and throughout 2025. In these periods, the nonlinear nature of economic changes intensified, thereby reducing the effectiveness of static forecasting methods. The ability of the LSTM model to adapt to changing patterns and preserve long-term information enabled it to maintain forecasting stability even under turbulent economic conditions. This finding is particularly important for banking institutions operating in emerging economies, where macroeconomic instability significantly influences liquidity flows, customer deposit behavior, and credit allocation decisions. Similar conclusions were reported by (Darabi, 2022), who argued that artificial intelligence techniques substantially improve banking risk prediction and financial decision-making accuracy in Iranian state-owned banks. The current findings therefore reinforce the growing body of evidence supporting the integration of intelligent forecasting systems into banking management processes.

In addition to the forecasting improvements, the results of the optimization module demonstrated that the PPO-based deep reinforcement learning framework significantly outperformed the traditional mean–variance portfolio allocation approach. The PPO portfolio achieved approximately a 53% increase in the Sharpe ratio while simultaneously reducing VaR and CVaR values by nearly one-third. These findings indicate that the proposed reinforcement learning framework was more successful in balancing profitability and risk management objectives within a dynamic and uncertain environment. Unlike static optimization models that depend heavily on fixed assumptions regarding expected returns and covariance structures, the PPO framework continuously adapted portfolio allocations according to changing financial conditions and regulatory constraints. This adaptive capability enabled the model to dynamically manage allocations among loans, securities, and high-liquidity assets while maintaining regulatory compliance.

The findings related to the reinforcement learning module strongly support previous studies emphasizing the effectiveness of deep reinforcement learning in financial optimization contexts. Research conducted by (Krabichler & Teichmann, 2023) demonstrated that deep reinforcement learning frameworks provide substantial advantages in ALM processes due to their capacity for dynamic learning and adaptive optimization. Similarly, (Wekwete, 2023) reported that reinforcement learning algorithms improve banking risk management and regulatory compliance by continuously adjusting portfolio structures in response to evolving financial conditions. The present study extends these findings by demonstrating that such frameworks are also highly effective within the Iranian banking system, despite the severe macroeconomic instability and regulatory challenges characterizing the domestic financial environment.

The ability of the PPO model to maintain 100% compliance with liquidity coverage and capital adequacy constraints constitutes another important finding of the study. Regulatory compliance has become one of the central objectives of modern banking management due to increasing supervisory pressures and the growing importance of financial stability. Traditional optimization methods often prioritize return maximization at the expense of regulatory flexibility, thereby exposing banks to higher systemic risks during periods of economic stress. In contrast, the PPO framework incorporated regulatory constraints directly into the reward mechanism, allowing the optimization process to simultaneously consider profitability and stability objectives. This characteristic is particularly valuable for banks operating in unstable economic environments where liquidity shortages and capital deficiencies can rapidly intensify financial vulnerability. The findings therefore support the argument that intelligent optimization systems can significantly improve banking resilience under uncertain conditions (Mousavi, 2024).

Another important implication of the study concerns the reduction of maturity mismatches within the balance sheet structure of Bank Melli Iran. One of the major structural challenges facing Iranian banks involves the dominance of short-term liabilities relative to medium- and long-term asset allocations. Such imbalances increase liquidity risk and reduce the flexibility of banking operations during periods of financial stress. The PPO framework demonstrated the ability to dynamically adjust portfolio allocations toward more balanced structures by increasing allocations to securities and liquidity reserves while optimizing loan exposure. This adaptive balancing mechanism contributed directly to the observed improvements in risk-adjusted returns and regulatory stability. The findings therefore align with the strategic concerns identified in studies addressing structural weaknesses within Iranian banking systems (Ahmadian & Shahchera, 2019).

The robustness and sensitivity analyses further strengthened the validity of the proposed framework. The model maintained relatively stable performance even under adverse economic scenarios involving inflation shocks and declines in banking resources. Although the Sharpe ratio declined under stress scenarios, the PPO portfolio consistently outperformed the traditional optimization framework, while risk indicators remained within acceptable ranges. Moreover, the sensitivity analyses indicated that moderate changes in model architecture and training parameters had relatively limited effects on overall performance. These findings suggest that the proposed hybrid framework possesses sufficient stability and robustness for practical implementation within real-world banking environments. The ability of intelligent systems to remain operationally effective under economic uncertainty is particularly important in emerging financial systems where macroeconomic shocks occur frequently and unpredictably.

From a theoretical perspective, the present study contributes to the growing literature on intelligent financial management by integrating deep learning forecasting mechanisms with reinforcement learning optimization frameworks within a unified ALM system. Previous studies have often examined forecasting and optimization independently, whereas the current research demonstrates the practical advantages of combining these components into a comprehensive decision-support architecture. The integration of predictive intelligence and adaptive optimization enables banks to simultaneously improve information accuracy and strategic responsiveness. Furthermore, the study extends existing financial engineering literature by applying these advanced methodologies within the context of an emerging economy characterized by severe inflationary and structural instability. In this respect, the research provides empirical evidence supporting the applicability of artificial intelligence techniques beyond developed financial markets.

The study also carries important managerial implications for banking institutions seeking to modernize their ALM processes. The findings suggest that intelligent systems can substantially improve forecasting precision, portfolio allocation efficiency, regulatory compliance, and risk management capabilities. Given the increasing complexity of banking operations and the rapid pace of economic change, reliance on traditional static models may no longer be sufficient for effective strategic management. Instead, banks may benefit significantly from adopting adaptive AI-driven frameworks capable of continuously learning from new financial data and dynamically responding to changing market conditions. Such systems may contribute not only to profitability enhancement but also to the long-term stability and resilience of banking institutions.

Despite these significant findings, the study should also be interpreted within the context of its methodological and operational scope. The use of real-world balance sheet data from Bank Melli Iran provided a realistic and practical basis for evaluation; however, the specific structural and regulatory characteristics of the Iranian banking system may influence the generalizability of the findings to other financial environments. Nevertheless, the consistency of the results with previous international studies suggests that the underlying theoretical mechanisms of deep learning and reinforcement learning remain broadly applicable across different banking contexts (Huang, 2025). Overall, the present study provides strong empirical evidence that hybrid intelligent frameworks combining LSTM forecasting and PPO-based reinforcement learning optimization can significantly improve banking asset–liability management performance under complex and uncertain economic conditions.

One of the primary limitations of the present study relates to data availability and accessibility within the Iranian banking system. Although official balance sheet and macroeconomic data were utilized, the lack of access to highly granular internal banking datasets restricted the inclusion of certain operational and behavioral variables that could further improve model precision. Additionally, the study focused exclusively on a single large commercial bank, which may limit the generalizability of the findings to smaller banks or non-commercial financial institutions with different balance sheet structures and operational characteristics. Another limitation concerns the computational simplifications implemented within the simulation environment, particularly regarding the number of asset classes and macroeconomic state variables considered in the reinforcement learning framework. Moreover, the rapidly changing nature of Iran's economic and regulatory environment may influence the long-term stability of model performance and necessitate continuous recalibration of intelligent systems over time.

Future studies may expand the proposed framework by incorporating additional macroeconomic indicators, customer behavioral variables, and market sentiment data to enhance forecasting and optimization accuracy. Comparative analyses across multiple Iranian banks or cross-country banking systems could also provide deeper insights into the adaptability and scalability of intelligent ALM frameworks under different regulatory and economic conditions. Researchers may further investigate the integration of transformer-based deep learning architectures, graph neural networks, or hybrid ensemble learning methods to improve sequential prediction performance. Additionally, future research could explore multi-objective reinforcement learning approaches that simultaneously optimize profitability, liquidity, sustainability, and environmental risk considerations. The incorporation of real-time streaming financial data and online learning mechanisms may also contribute to the development of fully adaptive intelligent banking management systems capable of responding instantly to market changes and financial shocks.

Banking institutions should gradually integrate artificial intelligence technologies into their strategic asset–liability management processes in order to improve forecasting precision and risk-adjusted portfolio performance. Financial managers may benefit from implementing hybrid systems that combine deep learning forecasting with reinforcement learning optimization to enhance dynamic decision-making capabilities under uncertain economic conditions. Regulatory authorities and banking supervisors should also encourage the development of intelligent risk management infrastructures by establishing technological standards and supporting data integration initiatives within the banking sector. Investment in computational infrastructure, employee training, and AI literacy programs may further facilitate the successful adoption of intelligent financial management systems. In addition, banks should establish continuous monitoring and recalibration mechanisms to ensure that AI-driven decision-support models remain aligned with evolving market conditions, regulatory requirements, and macroeconomic realities.

Authors' Contributions

Authors contributed equally to this article.

Declaration

In order to correct and improve the academic writing of our paper, we have used the language model ChatGPT.

Transparency Statement

Data are available for research purposes upon reasonable request to the corresponding author.

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