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An Optimal Model for Managing Assets, Liabilities, and Equity in Commercial Banks under the Supervisory Regulations of the Central Bank of Iran

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ABSTRACT

This study aimed to develop an optimal model for managing assets, liabilities, and equity in Iranian commercial banks in compliance with Central Bank supervisory regulations. This applied research used audited financial statements of ten listed commercial banks (Mellat, Tejarat, Saderat, Parsian, Pasargad, Eghtesad Novin, Sina, Dey, Karafarin, and Middle East) during 2019–2023. Data were collected from CODAL, the Central Bank of Iran, and related financial databases. The methodology integrated the Best-Worst Method (BWM) for weighting decision variables and a fuzzy goal programming approach to manage uncertainty and set realistic target ranges. Six key decision criteria were evaluated: return on assets (ROA), return on equity (ROE), liquidity risk ratio (LRR), capital adequacy ratio (CAR), non-performing assets (NPA), and market share of deposits and credits (MSDL). The findings revealed that "capital adequacy ratio" ranked as the most critical criterion (average weight 0.4699), followed by liquidity risk ratio and reduction of non-performing assets. In contrast, market share of deposits and credits had the lowest priority. Results of the optimization model indicated that all banks achieved full compliance with Central Bank requirements after modest adjustments. The most recurrent deviations were observed in return on equity, which consistently required reduction across banks, averaging 1.1 percentage points below optimal values. Liquidity ratios and capital adequacy remained within acceptable ranges across institutions, while non-performing assets showed only minor deviations. Banks such as Mellat and Sina required minimal reforms, whereas Parsian, Middle East, and Eghtesad Novin demanded more extensive adjustments to balance their financial structures. The proposed fuzzy goal programming model provides a robust framework for balancing profitability, risk, and compliance.

Keywords: *Optimal model; Asset management; Liability management; Equity management; Central Bank regulations; Commercial banks; Fuzzy goal programming*

1. Introduction

The stability and efficiency of banking systems are heavily dependent on their ability to effectively manage the balance between assets and liabilities. Asset–liability management (ALM) represents a central pillar of risk management and financial sustainability within banks, serving as both a strategic and operational tool for aligning liquidity, profitability, and solvency requirements (Taheri et al., 2025). The increasing complexity of modern financial markets, alongside the expansion of financial innovation, has further intensified the importance of robust ALM frameworks. Contemporary banking systems face a multi-layered challenge: they must remain resilient in the face of credit and liquidity shocks, comply with strict regulatory frameworks, and maintain competitiveness in markets characterized by rapid technological and structural shifts (Buchak et al., 2024; Kashyap et al., 2024).

At its core, ALM enables banks to balance conflicting objectives such as maximizing profitability while minimizing exposure to risks associated with mismatches in maturities and interest rate structures (Islam, 2024). Traditional ALM approaches that relied primarily on static models have proven inadequate in dealing with volatile financial environments. Consequently, more advanced models incorporating system dynamics, multi-objective optimization, and data-driven techniques have been developed to increase resilience (Gholami et al., 2024; Taheri et al., 2025). These developments underscore a wider academic and professional consensus: without adaptive and dynamic approaches to ALM, banks may expose themselves to systemic vulnerabilities that could undermine both institutional stability and wider financial market confidence.

The historical development of ALM demonstrates a progressive shift from simple liquidity management toward complex multi-dimensional frameworks. Early models prioritized ensuring that banks had sufficient liquid assets to cover short-term obligations. Over time, however, attention expanded toward incorporating measures of credit, capital adequacy, and long-term sustainability (Basheer et al., 2021). The introduction of international regulatory standards, such as the Basel Accords, placed further emphasis on the role of capital adequacy ratios and liquidity requirements in shaping balance sheet strategies (Lysiak et al., 2022). These frameworks compelled banks to not only adopt risk-sensitive models of capital allocation but also to implement integrated approaches that consider both micro- and macroprudential dimensions (Khosravianni et al., 2023).

More recently, researchers have highlighted the endogeneity between credit risk, liquidity risk, and off-balance sheet activities. For example, in South Asian economies, it was shown that banks' operational risks are not independent but interlinked in ways that complicate regulatory oversight and ALM strategies (Basheer et al., 2021). Such findings highlight the need for banks to employ models that recognize the interconnected nature of financial risks, rather than treating them in isolation. This approach also resonates with the arguments of (Bakkar et al., 2023), who found that banks' systemic importance influences both their capital structures and their ability to adjust balance sheets effectively in times of stress.

The increasing interconnectedness of global finance has made regulation an inseparable aspect of ALM. Studies indicate that optimal regulation in the presence of credit and run risks is crucial to ensuring stability while preventing regulatory arbitrage (Kashyap et al., 2024). At the same time, regulatory requirements can also act as constraints that limit banks' ability to engage in certain profitable activities. This tension between compliance and profitability has shaped a significant portion of modern ALM research.

For instance, (Albanese et al., 2021) introduced the concept of XVA analysis from the balance sheet perspective, highlighting how valuation adjustments have become integral to understanding a bank's exposure to counterparty and funding risks. Similarly, (Mahdavi Panah et al., 2023) analyzed the impact of central bank regulatory laws on financial inclusion within Iran's Islamic banking system, emphasizing that regulatory compliance not only ensures stability but also directly influences inclusivity and the role of banks in supporting broader socio-economic goals. This dual role of regulation—both as a safeguard and as a developmental tool—has become central to debates surrounding ALM.

Meanwhile, research shows that the removal of fictional assets from bank balance sheets alters money supply dynamics and broader macroeconomic conditions, reinforcing the fact that balance sheet composition has systemic implications beyond the institutions themselves (Samsami et al., 2023). In a similar vein, (Reisi et al., 2023) explored how money creation processes within banks, shaped by accounting practices, affect both accrual and cash-basis systems, thereby influencing the interpretation of bank balance sheets and their regulatory oversight.

Technological advances are transforming the practice of ALM by enabling more accurate forecasting, data integration, and scenario simulation. The emergence of reinforcement learning models, for example, has opened pathways for intelligent decision-making in financial asset risk assessment (Ju & Zhu, 2024). Such models are particularly suited to environments characterized by uncertainty and dynamic feedback loops, making them valuable tools for banks seeking to optimize ALM under volatile market conditions.

Similarly, system dynamics approaches have been employed to model the complex interplay of risks and objectives within ALM systems. (Taheri et al., 2025) proposed an ALM model based on system dynamics that integrates risk management into a holistic structure, demonstrating the potential for dynamic simulations to inform long-term decision-making. Complementing this, (Peykani et al., 2023) emphasized the role of optimization techniques in achieving ALM goals with minimal disruption to existing structures, showcasing how mathematical tools can support incremental yet impactful improvements in balance sheet management.

Data-driven methods have also gained prominence. For example, (Gholami et al., 2024) examined ALM mechanisms in investment funds, illustrating how data-driven approaches can enhance adaptability and precision. Likewise, (Ghodrzi et al., 2024) applied advanced techniques such as copula functions and value-at-risk analysis to optimize investment portfolios, demonstrating methodological crossovers that enrich ALM practices in both banking and insurance sectors.

The scope of ALM has extended beyond traditional banking into other sectors and contexts. For instance, debt management frameworks have been applied in public sector organizations, such as municipalities, highlighting the adaptability of ALM principles in managing diverse financial structures (Shahrabi Farahani et al., 2023). Similarly, blockchain and metaverse technologies are reshaping digital asset management, offering innovative ways of conceptualizing assets and liabilities in increasingly virtual environments (Truong et al., 2023). These broader applications underscore that ALM is not confined to banking but rather is a versatile tool for financial governance across multiple domains.

At the same time, empirical research continues to show the significance of ALM for bank performance specifically. For example, (Kaviani & Fakhrhosseini, 2023) demonstrated that duration-based metrics can significantly influence bank performance, reinforcing the central role of balance sheet composition. Complementary studies, such as (Mhejir et al., 2024), showed how the shadow economy impacts banking sector asset management, further stressing the interconnected nature of financial environments and the need for adaptable ALM frameworks.

Risk management remains a cornerstone of ALM, particularly in the context of banking risks such as liquidity, credit, and capital adequacy. According to (Lysiak et al., 2022), banking risks in ALM systems require integrated responses that acknowledge the interdependency of risk categories. This has been echoed by (Hao & Lixia, 2023), who examined the influence of equity pledges by major shareholders on investment efficiency, pointing to the risks of ownership structures and governance practices on balance sheet health.

The relationship between ALM and systemic stability also remains a subject of great importance. (Malloy et al., 2022) analyzed retail central bank digital currencies (CBDCs) and their impact on U.S. monetary policy implementation, illustrating how new instruments reshape balance sheet dynamics at both micro and macro levels. Furthermore, (Mahdawi et al., 2021) employed a modified DuPont method to analyze banks' performance through financial statements, showing how granular accounting insights can be leveraged for better ALM practices.

Synthesizing these contributions, it is clear that modern ALM must operate at the intersection of regulation, risk management, and technological innovation. Models that combine multi-objective optimization (Khosravianni et al., 2023), system dynamics (Taheri et al., 2025), and data-driven intelligence (Gholami et al., 2024; Ju & Zhu, 2024) provide promising pathways for addressing the dual challenges of financial stability and profitability. At the same time, attention must be given to the structural realities of banking systems, including ownership structures, shadow economies, and regulatory environments (Mahdavi Panah et al., 2023; Mhejir et al., 2024).

The convergence of these perspectives suggests that banks must move beyond static ALM strategies and adopt dynamic, integrated models that balance quantitative analysis with regulatory and market realities. Such models can serve as tools not only for optimizing financial performance but also for enhancing systemic resilience and aligning with broader socio-economic objectives (Buchak et al., 2024; Kashyap et al., 2024).

In light of the reviewed literature, this study aims to present a comprehensive model for asset and liability management in banks that integrates optimization, regulatory compliance, and systemic resilience.

2. Methods and Materials

This study is an applied research in which an attempt has been made to present the optimal values of assets, liabilities, and equity in accordance with the structure of the balance sheet. Considering the wide range of financial data, it is possible to introduce many other variables in addition to the balance sheet variables for this research. However, it should be noted that, first, balance sheet variables themselves are numerous, and second, the inclusion of more variables leads both to the need for extensive data collection and to increased complexity in modeling. Therefore, except for a few specific cases, the balance sheet has been considered as the main basis for calculations. Accordingly, the internal relationships between balance sheet variables and the relationship of balance sheet items with other bank data will be identified. Then, considering the objectives, limitations, and requirements governing the banking system, the constraints and goals of the model were defined in the form of a fuzzy goal programming model. In this model, fuzzy theory was used to eliminate the uncertainty of upper and lower bounds of figures and to provide better results compared to the crisp state. The prioritization and importance level of objectives were also determined through the Best-Worst Method (BWM). The objective function of this research is as follows:

z = Min ∑ (from i=1 to n) (w_i D_i^+ + w_i D_i^-)

Where:

Z: weighted sum of deviations from the defined objectives.

w_i: weight of the i-th objective, indicating its relative importance (determined by BWM).

D_i^-: negative deviation from the i-th target (value lower than the defined level).

D_i^+: positive deviation from the i-th target (value higher than the defined level).

This objective function attempts to minimize deviations from the goals (both upward and downward). The weights w_i are determined according to the priority and importance of each goal.

Decision variables:

- Increase in return on assets (ROA): maximize the overall return on assets.
- Increase in return on equity (ROE): increase return relative to shareholders’ investment.
- Reduction of liquidity risk (LRR): ensure the bank’s ability to finance short-term obligations.
- Improvement of capital adequacy ratio (CAR): maintain the capital required to mitigate risk.
- Reduction of non-performing assets (NPA): reduce overdue claims and low-yield assets. Non-performing assets in banks refer to those that do not generate direct or useful returns and do not play a role in creating profit or cash flow. These assets include non-performing or overdue loans, surplus real estate, inefficient investments, and doubtful receivables. An increase in such assets can reduce bank profitability and liquidity and increase financial risks. Effective management of these assets is essential for improving efficiency and reducing bank costs.
- Increase in market share of deposits and loans (MSDL): increase the share of the financial market. Market share of deposits and loans indicates how much of the total loans granted or deposits available in the financial market belong to the bank. This index is obtained by dividing the amount of the bank’s loans or deposits by the total loans or deposits available in the market and then expressing the result as a percentage. In simple terms, this criterion shows the extent to which the bank has attracted deposits and provided loans to clients compared to competitors. Increasing this share improves the bank’s position in the market and indicates its competitiveness.

The stages of model implementation are explained as follows.

Step One: Weighting analysis using BWM

Objective: determine the weight of importance of decision variables using BWM.

- Selecting the best and worst objective: first, decision-makers or experts are asked to select the best and worst objectives from among all goals.
- Comparing the best objective with other objectives: for each objective, a comparison between the best and the others is made, and their relative importance is determined.
- Comparing the worst objective with other objectives: then, for each objective, a comparison with the worst objective is conducted, and their relative importance is also calculated.
- Calculating weights: using these comparisons, the weights are accurately calculated with BWM-specific formulas.

Step Two: Fuzzy goal programming model

Objective: manage uncertainty in the data using fuzzy numbers.

The fuzzy goal programming model is employed to manage uncertainty in data. The research objectives are defined as fuzzy intervals to provide more flexibility in modeling real data. These objectives are defined using triangular fuzzy numbers and include a lower bound (L_i), an upper bound (U_i), and the actual value of the decision variable (g_i (X)). Thus, the model is capable of better performance under uncertainty and data fluctuations and can provide more optimal decision-making. This method allows the consideration of different scenarios for more effective management of assets, liabilities, and equity.

Definition of fuzzy values: the objectives are defined as ranges of fuzzy values.

$L\_i \leq g\_i\ (X) \leq U\_i$

Where:

L_i: lower bound of the objective.

U_i: upper bound of the objective.

g_i (X): actual value of the decision variable.

The objectives are expressed with triangular fuzzy numbers.

Step Three: Construction of the mathematical model

1. Objective function: minimize the weighted sum of positive and negative deviations from the objectives:

$z = \text{Min} \sum \text{(from i=1 to n)} (w\_i\ D\_i\text{^+} + w\_i\ D\_i\text{^-})$

Constraints:

First constraint: Balance sheet equilibrium

This constraint ensures that the bank's balance sheet remains balanced. That is, total assets must equal total liabilities plus equity. This constraint is expressed as:

Assets = Liabilities + Equity

This constraint is a fundamental relationship that must always be satisfied.

Second constraint: Legal requirements

Banks must comply with certain legal ratios that help maintain financial health and reduce risk. These ratios include:

CRR: cash reserve ratio, which is the proportion of deposits that banks must keep as reserves relative to total deposits.

SLR: statutory liquidity ratio, which refers to the liquidity banks must hold to settle their short-term liabilities. In Iran, banks are required to hold a percentage of their deposits as legal reserves with the Central Bank. This ratio, known as the "statutory reserve ratio," must not be less than 10 percent and not more than 30 percent according to the Monetary and Banking Law. However, the Central Bank can determine different ratios depending on the type of activity and the composition of each bank's deposits. For example, in September 2020, the Central Bank set the reserve ratio between 10 and 13 percent. This ratio is used as a tool to control liquidity and inflation in the economy.

CAR: capital adequacy ratio. This is a key measure of a bank's ability to manage financial risks and withstand potential losses. It is calculated by dividing regulatory capital by risk-weighted assets. Regulatory capital includes Tier 1 capital (core resources such as common stock and retained earnings) and Tier 2 capital (general reserves and subordinated debt). Risk-weighted assets include all the bank's assets.

The legal constraints are expressed as follows:

CLR ≤ CRR

CAR ≤ CRR_min

CAR_min ≤ CLR_min

Where: CRR_min, C_min, and CLR_min are the minimum legal values of these ratios.

The legal constraints such as CRR, SLR, and CAR that banks must comply with are specified in the circulars and instructions of the Central Bank of the Islamic Republic of Iran. To access these regulations, one may refer to the official website of the Central Bank at www.cbi.ir, under the "Laws and Regulations" or "Circulars" sections, where the relevant documents are provided. These documents include detailed requirements and the minimum thresholds defined for each ratio.

Third constraint: Liquidity requirement

This constraint ensures that the bank can finance its short-term obligations. The bank must maintain sufficient liquidity to cover its short-term liabilities. It is expressed as:

LCR_min ≤ LCR

Where:

LCR: liquidity coverage ratio, which determines the proportion of high-quality liquid assets (HQLA) that the bank must hold to cover a 30-day stress period.

HQLA: includes cash, government securities, and other marketable assets.

Net cash outflows in 30 days: includes maturing liabilities and cash outflows, after deducting inflows.

LCR_min: minimum required liquidity level that must be maintained (defined by the Central Bank or other supervisory authorities).

Fourth constraint: Reduction of non-performing assets

Non-performing assets (NPA) are those that do not yield appropriate returns or are overdue claims. The bank must reduce its NPA ratio to improve profitability and reduce credit risk. This constraint is expressed as:

NPA ≤ NPA_max

Where:

NPA: the amount of non-performing assets.

NPA_max: maximum allowable level of non-performing assets that must be observed (defined by the Central Bank or supervisory financial authorities).

For conducting this research, audited financial statements of Mellat, Tejarat, Saderat, Parsian, Pasargad, Eghtesad Novin, Sina, Dey, Karafarin, and Middle East banks during 2019–2023, along with CODAL data and statistical resources of the Central Bank of the Islamic Republic of Iran, were used.

3. Findings and Results

In this section, to collect expert opinions for determining the weights of decision variables in the BWM model, a set of specialists in banking, finance, and supervisory regulations was first identified by precisely defining the study objectives and relevant criteria. The selected experts included senior bank managers, risk assessment specialists, faculty members in finance, and several officials at the Central Bank. A standard Best–Worst Method (BWM) questionnaire with instructions on how to perform pairwise comparisons was prepared and sent to them. Before distribution, briefing sessions were held to improve the correct understanding of the criteria and comparison scales. Then, the experts identified the best and the worst objective among the decision criteria and performed the required comparisons. The collected data were reviewed, and any potential inconsistency in the comparisons was controlled through feedback and revision. Finally, by solving the BWM mathematical model, the optimal weights of the criteria were extracted. Careful selection of and interaction with experts played an important role in the validity of the results. The questionnaire results for pairwise comparisons of all variables with the most important variable, the questionnaire results for pairwise comparisons of all variables with the least important variable, and, ultimately, the weight of each decision variable are reported in Table 1.

Table 1

Questionnaire for pairwise comparisons of all variables with the most important variable

Description	Increase in ROA	Increase in ROE	Reduction of LRR	Improvement of CAR	Reduction of NPA	Increase in MSDL
Expert 1	7	7	4	1	6	9
Expert 2	8	8	3	1	6	8
Expert 3	7	6	4	1	5	8
Expert 4	8	7	3	1	5	8
Expert 5	9	7	4	1	4	8
Expert 6	7	7	3	1	6	8
Expert 7	7	6	3	1	4	9
Expert 8	9	6	3	1	4	8
Expert 9	8	8	3	1	6	8
Expert 10	8	6	3	1	5	9
Expert 11	8	7	3	1	6	8
Expert 12	7	7	4	1	5	7
Expert 13	8	7	3	1	4	7
Expert 14	8	6	4	1	5	9
Expert 15	9	7	2	1	4	8
Expert 16	8	8	2	1	4	9

Table 1 shows the results of the pairwise comparison questionnaire between all decision variables and the most important decision variable (i.e., improvement of the capital adequacy ratio or CAR) for sixteen experts. In this stage, using the Best–Worst Method (BWM), the experts were asked to evaluate each decision variable relative to the most important variable based on its importance. As observed, for all experts, the value related to the "improvement of the capital adequacy ratio (CAR)" variable is recorded as 1. This means that all experts identified this variable as the most important or best variable among the other objectives. In other words, the improvement of CAR was considered the reference or benchmark for comparison, and all other variables were judged against it. Values greater than 1 for other variables indicate lower priority compared to the improvement of CAR. Complete consensus among respondents about the high importance of this variable indicates the key role of CAR in the optimal management of assets, liabilities, and equity in commercial banks under Central Bank regulations. Hence, the results of this table serve as the basis for computing the final weights in the BWM model.

Table 2

Questionnaire for pairwise comparisons of all variables with the least important variable

Description	Increase in ROA	Increase in ROE	Reduction of LRR	Improvement of CAR	Reduction of NPA	Increase in MSDL
Expert 1	3	5	7	9	4	1
Expert 2	2	3	8	9	5	1
Expert 3	4	3	6	7	4	1
Expert 4	3	3	8	7	4	1
Expert 5	4	3	7	8	5	1
Expert 6	4	3	8	9	5	1
Expert 7	3	4	8	9	6	1
Expert 8	3	4	8	8	4	1
Expert 9	3	5	7	8	4	1
Expert 10	2	4	7	9	5	1
Expert 11	4	3	6	8	4	1
Expert 12	3	5	7	7	4	1
Expert 13	3	3	8	9	5	1
Expert 14	4	5	8	7	6	1
Expert 15	4	4	7	9	6	1
Expert 16	2	5	7	8	6	1

Table 2 shows the results of pairwise comparisons of all decision variables against the least important variable from the experts' viewpoint. In this part of the weighting process using the BWM, experts were asked to evaluate each variable relative to the weakest or least important decision variable. As seen, the variable "increase in market share of deposits and loans (MSDL)" was identified by all experts as the least important variable. This is inferred from the fact that, in all rows of the table, the value for MSDL equals 1; in this method, 1 indicates the lowest level of importance compared to other options. The other variables are evaluated with higher values relative to MSDL, indicating their greater relative priority. This complete alignment in opinions lends high credibility to the model's results and shows that, from the experts' perspective, "increase in market share of deposits and loans" has the least impact on achieving macro banking objectives compared to other indicators. Together with the table of comparisons against the most important variable, this table is a primary input for solving the BWM and deriving the final optimal weights of the decision variables. Based on these two tables, Table 3 reports the final weight of each decision variable.

Table 3

Weights of decision variables

Description	Increase in ROA	Increase in ROE	Reduction of LRR	Improvement of CAR	Reduction of NPA	Increase in MSDL	Objective value	Consistency ratio
Expert 1	0.0915	0.0915	0.1601	0.5083	0.1068	0.0418	0.0132	0.0615
Expert 2	0.0783	0.0783	0.2087	0.4870	0.1043	0.0435	0.0139	0.0647
Expert 3	0.0885	0.1032	0.1548	0.4808	0.1239	0.0489	0.0139	0.0644
Expert 4	0.0768	0.0878	0.2048	0.4631	0.1229	0.0445	0.0151	0.0704
Expert 5	0.0697	0.0896	0.1568	0.4845	0.1568	0.0428	0.0143	0.0663
Expert 6	0.0875	0.0875	0.2041	0.4763	0.1021	0.0425	0.0136	0.0633
Expert 7	0.0812	0.0947	0.1894	0.4547	0.1421	0.0379	0.0114	0.0529
Expert 8	0.0650	0.0976	0.1951	0.4553	0.1463	0.0407	0.0130	0.0605
Expert 9	0.0783	0.0783	0.2087	0.4870	0.1043	0.0435	0.0139	0.0647
Expert 10	0.0725	0.0967	0.1934	0.4793	0.1160	0.0420	0.0101	0.0469
Expert 11	0.0754	0.0861	0.2010	0.4899	0.1005	0.0471	0.0113	0.0526
Expert 12	0.0917	0.0917	0.1606	0.4817	0.1284	0.0459	0.0161	0.0747
Expert 13	0.0745	0.0852	0.1987	0.4493	0.1491	0.0432	0.0147	0.0683

Expert 14	0.0814	0.1086	0.1629	0.4744	0.1303	0.0425	0.0177	0.0823
Expert 15	0.0591	0.0760	0.2661	0.4258	0.1331	0.0399	0.0106	0.0495
Expert 16	0.0677	0.0677	0.2707	0.4211	0.1353	0.0376	0.0120	0.0560
Average	0.0774	0.0888	0.1960	0.4699	0.1251	0.0428	0.0134	0.0624
Rank	5	4	2	1	3	6	—	—

Table 3 presents the final weighting results of the decision criteria based on the Best–Worst Method from the perspective of 16 banking experts. For each expert, the table reports the criterion weights, the objective function value, and the inconsistency (consistency ratio, CR). It also provides the average weights and the final rank of each criterion. A close analysis of this table offers a comprehensive view of decision-making priorities in the banking system. According to the averages, the criterion "improvement of the capital adequacy ratio (CAR)" ranks first with a weight of 0.4699. This indicates that, for most experts, it is the most important factor in evaluating bank performance. Its high importance can be attributed to its vital role in assessing financial soundness and a bank's capacity to face credit and financial risks. As the key indicator of a bank's ability to absorb unexpected losses, capital adequacy is also a core requirement under Basel regulations. The second rank belongs to "reduction of liquidity risk (LRR)" with an average weight of 0.1960, reflecting experts' significant concern about banks' liquidity. Reducing liquidity risk is crucial for preventing insolvency and maintaining depositors' confidence. The third rank goes to "reduction of non-performing assets (NPA)" with an average weight of 0.1251. This variable is also highly important, as NPAs can reduce profitability and increase credit risk. Next are "increase in ROE" with a weight of 0.0888 and "increase in ROA" with a weight of 0.0774. Although these two indicators are important for financial analysis, they appear to have lower priority relative to risk- and soundness-related indicators. Finally, "increase in MSDL" has the lowest average weight of 0.0428 in sixth (last) place. Its low weight may be because experts regard increased market share as a result—not a cause—of improvement in other indicators; that is, with stronger capital adequacy, better risk management, and lower NPAs, market share naturally increases. In other words, this indicator is more a consequence of desirable performance in other indicators than an independent driver. The average inconsistency ratio equals 0.0624, which is at an acceptable level and indicates that the experts' responses are logically coherent. The low objective function values also indicate the model's good performance in fitting the priorities. Overall, the results of this table can guide banking policymakers to focus more on higher-priority indicators when evaluating and improving bank performance.

Given the availability of real time-series data for banks' key performance indicators—including return on assets (ROA), return on equity (ROE), liquidity risk ratio (LRR), capital adequacy ratio (CAR), the level of non-performing assets (NPA), and market share of deposits and loans (MSDL)—for 10 banks over a five-year period, this study employed a data-driven analytical approach to determine the aspiration bounds of the fuzzy goal programming model. First, the values of each indicator were extracted and recorded by year and by bank. To ensure full coverage of annual fluctuations and to reduce the influence of outliers or unusual values, statistical quartiles were used to set the lower (L) and upper (U) bounds. Specifically, for each indicator, the values recorded over five years across the 10 banks were pooled, and the first quartile (lowest 25 percent) was calculated as the lower aspiration bound (L), while the third quartile (highest 25 percent) was calculated as the upper aspiration bound (U). This approach allowed the aspiration ranges to be defined not subjectively but based on the reality of bank performance and the historical trend of the data, while the use of quartiles mitigated the effects of outliers and abnormal volatility. Furthermore, using real data helps the optimization model to run scenarios in line with the operating conditions of domestic banks, thereby enhancing the scientific and practical validity of the results with respect to market realities and existing regulations. The derived ranges were also compared with the Central Bank's regulations and the expectations of international supervisory standards to ensure that the suggested ranges are acceptable both in terms of optimal performance and legal compliance. Accordingly, the aspiration bounds obtained from this analytical procedure were entered into the fuzzy goal programming model as fuzzy intervals (L and U) and served as the basis for optimizing the banks' key indicators in this study. This process enabled deviations from the goals to be computed realistically and in proportion to the banks' historical performance, and it provided scientific remedies for improving banks' assets, liabilities, and equity within supervisory requirements. Table 4 reports the first-quartile (L) and third-quartile (U) values for each indicator, which were used as aspiration bounds in the final model.

Table 4

Fuzzy ideal (aspiration) values

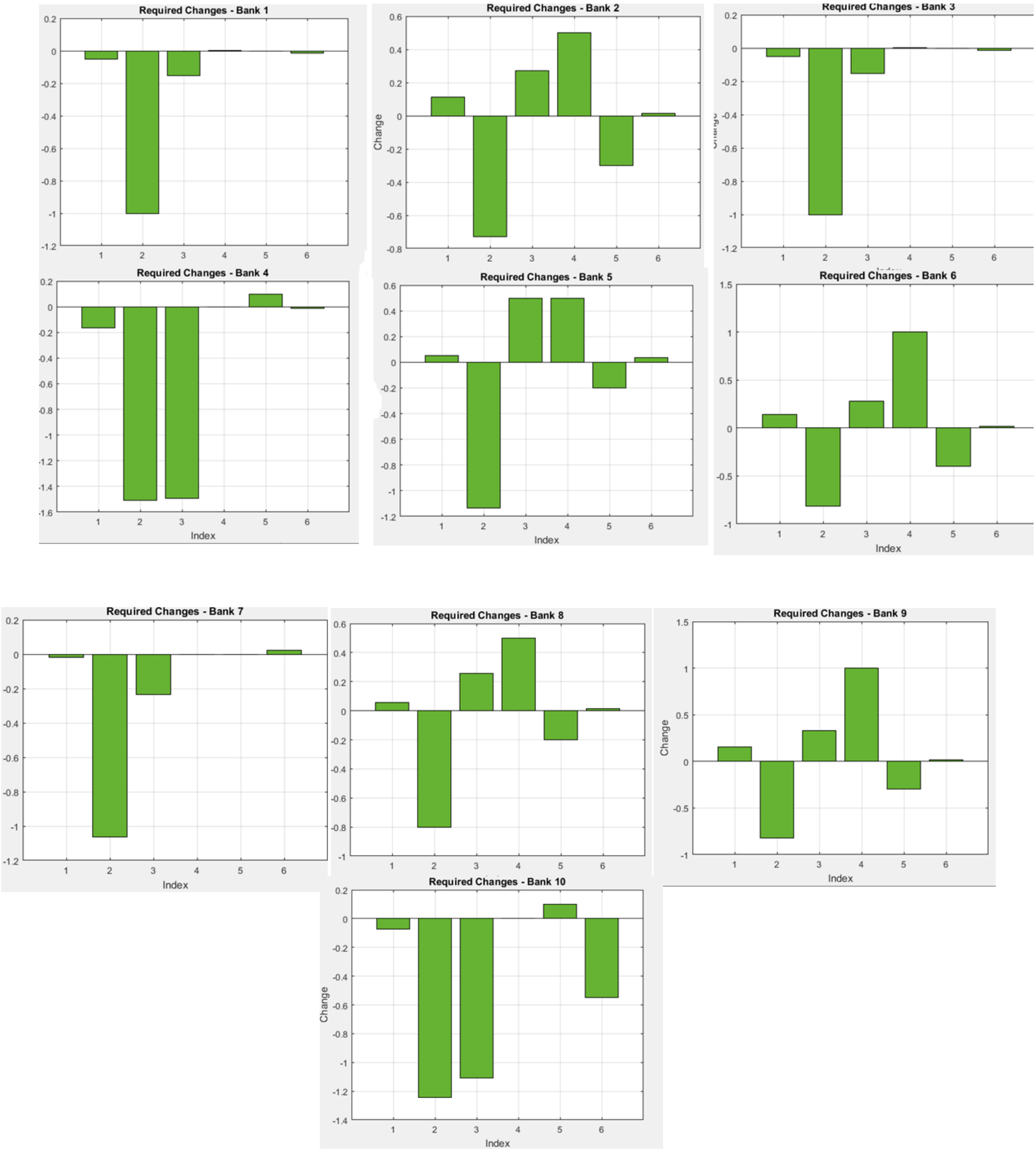
Indicator	Lower aspiration bound (L)	Upper aspiration bound (U)
Return on assets (ROA)	0.7	0.95
Return on equity (ROE)	6	7
Liquidity risk ratio (LRR)	12	14
Capital adequacy ratio (CAR)	10.5	12
Non-performing assets (NPA)	1.6	2
Market share of deposits and loans (MSDL)	7	9

In Chart 1, bar 1 shows return on assets, bar 2 shows return on equity, bar 3 shows the liquidity risk ratio, bar 4 shows the capital adequacy ratio, bar 5 shows non-performing assets, and bar 6 shows the market share of deposits and loans.

In this section, the results of the analysis of required changes in banks’ balance-sheet items are presented based on the fuzzy goal programming optimization model. Designed to reduce the gap between the current state and the optimal state, this analysis provides a framework for reforming banks’ financial structure. The ultimate aim is to steer managerial decisions toward improving efficiency, increasing financial stability, and complying with Central Bank supervisory requirements. In general, indicators such as return on assets, return on equity, capital adequacy ratio, liquidity, market share of deposits and loans, and the level of non-performing assets were examined. Positive bars in the model’s charts indicate the need to increase an indicator, while negative bars indicate the need to decrease it. The longer the bar, the greater the deviation from the desired state. For Bank Mellat (Bank 1), the model indicates that ROA should be reduced by 0.05 percent and ROE should be reduced by 1 percentage point. This reflects funding cost pressure and weaknesses in the cost of capital management. Changes in the other indicators are marginal, and performance in liquidity and capital adequacy is assessed as appropriate. For Bank Tejarat (Bank 2), there is a need to increase ROA by 0.113 percent and to improve CAR by 0.5 percentage points, while ROE should be reduced by 0.73 percentage points. This points to the need to enhance asset productivity and cut non-operating costs. For Bank Saderat (Bank 3), the model recommends reducing ROA by 0.05 percent and ROE by 1 percentage point, indicating inefficiencies in leveraging existing capital and the need to review revenue structure and cost management. Liquidity and capital adequacy appear stable. For Bank Parsian (Bank 4), the largest adjustments were observed: ROA should be reduced by 0.165 percent and ROE by 1.5 percentage points, signaling serious challenges in capital productivity. Accordingly, revising the loan portfolio and focusing on non-interest income are key remedies. For Bank Pasargad (Bank 5), ROA needs to increase by 0.05 percent, while ROE should decrease by 1.13 percentage points. Liquidity and capital adequacy are in good condition, and emphasis on improving deposit and credit market share is recommended. Bank Eghtesad Novin (Bank 6) should increase ROA by 0.14 percent and improve CAR by 1 percentage point. In addition, the required 0.8 percentage-point reduction in ROE indicates the need to adjust the cost structure and increase non-interest income. For Bank Sina (Bank 7), ROA should be reduced by 0.02 percent and ROE by 1.06 percentage points. To reach the desired state, this bank should improve loan quality and control financing costs. For Bank Dey (Bank 8), an increase in ROA by 0.058 percent and an improvement in CAR by 0.5 percentage points are necessary; however, a reduction in ROE by 0.8 percentage points remains the main challenge. Focusing on expanding the market share of deposits and loans may help improve this bank’s position. Bank Karafarin (Bank 9) needs to increase ROA by 0.155 percent and improve CAR by 1 percentage point, while also reducing ROE by 0.8 percentage points. Performance on the other indicators is relatively stable and requires only minor adjustments. Finally, Bank Middle East (Bank 10) should reduce ROA by 0.07 percent and ROE by 1.24 percentage points. Increasing the market share of deposits and loans and reducing non-performing assets are among the most important corrective actions for this bank. Overall, the model indicates that, in most banks, the principal area requiring adjustment is ROE, whose average deviation from the optimal level is about 1.1 percentage points. This reflects funding cost pressures and the need to enhance capital efficiency within the banking system. Moreover, liquidity and capital adequacy indicators are within the desired range for all banks and comply with supervisory requirements, while changes in non-performing assets are generally minor. This analysis provides a basis for designing corrective policies to achieve an optimal balance-sheet structure across banks.

Figure 1

Analysis of required items across all banks



In Chart (2), bar 1 shows return on assets, bar 2 shows return on equity, bar 3 shows the liquidity ratio, bar 4 shows the capital adequacy ratio, bar 5 shows non-performing assets, and bar 6 shows the market share of deposits and loans.

In this section, the analysis of deviations from banks' aspiration levels in the framework of asset, liability, and equity management is presented. The relevant charts show that the research model demonstrates, for each bank, the distance from the defined aspiration ranges for key indicators after optimization. Each indicator has an aspiration range representing the most desirable performance level. The presence of non-zero bars in the charts indicates that even in the best-case scenario, full attainment of aspirations is not possible due to conflicting goals or legal constraints.

For Bank Mellat (Bank 1), five indicators—including ROA, liquidity ratio, capital adequacy ratio, NPA, and market share—were reported without deviation, while ROE showed a deviation of 3.5. Bank Tejarat (Bank 2) showed a similar pattern, with only ROE deviating by the same amount. This indicates a structural challenge in shareholder profitability across the banking industry. Bank Saderat (Bank 3) repeated the same pattern.

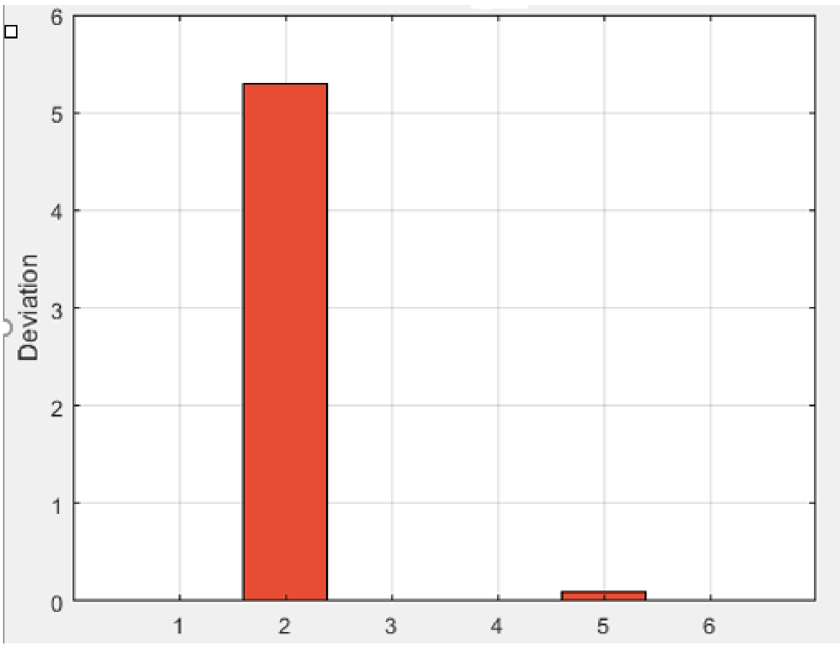
For Bank Parsian (Bank 4), in addition to ROE, NPA also showed a slight deviation (0.100). Bank Pasargad (Bank 5) similarly showed deviations in both ROE and NPA, though other indicators were satisfactory. Bank Eghtesad Novin (Bank 6) displayed the same two deviations, and Bank Sina (Bank 7) also repeated this pattern, highlighting a common issue with capital returns and low-yield asset management.

Bank Dey (Bank 8) likewise showed ROE deviation of 3.5 and NPA deviation of 0.100. Bank Karafarin (Bank 9) also deviated in these two indicators, while all other indicators matched aspiration levels. Finally, Bank Middle East (Bank 10) exhibited the same pattern with deviations only in ROE and NPA.

Overall analysis shows that all banks performed satisfactorily in five indicators—ROA, liquidity ratio, capital adequacy ratio, NPA (with minor deviations), and market share. However, ROE in all banks showed a fixed deviation of 3.5. This finding represents a recurring pattern across the banking network. The main reason for this convergence is that the model performed optimization for all banks based on a fixed set of aspirations and Central Bank legal constraints. Consequently, the algorithm converged toward a standardized optimal profile, generalizable to the entire Iranian banking system. This similarity in deviation charts demonstrates the model's success in identifying an "optimal profile" for commercial banks. The profile shows that even in the best conditions, complete attainment of all aspirations is impossible, since conflicting goals—such as profit maximization versus risk minimization—and stringent supervisory constraints prevent full realization of aspirations. Therefore, the observed deviations should be interpreted not as performance weaknesses but as a logical outcome of balancing goals and restrictions.

Figure 2

Analysis and interpretation of deviations from aspiration levels in all banks



In Chart (3), for each bank, asset, liability, and equity management is presented. In each bank, curve 1 represents ROA, curve 2 represents ROE, curve 3 represents the liquidity ratio, curve 4 represents the capital adequacy ratio, curve 5 represents NPA, and curve 6 represents the market share of deposits and loans.

In this study, the asset, liability, and equity management performance of commercial banks in Iran during the five-year period from 2019 to 2023 was examined. The plotted charts for each bank show the actual trend of the indicators (blue line) compared with the optimal values calculated by the mathematical model (red line). Comparing the two lines reflects the degree of alignment or deviation of banks' performance with the desired state.

The analysis results indicate that for Bank Mellat, the key indicator for optimization was CAR. To reach the optimal state, a one-unit reduction in ROE and a slight reduction in NPA were necessary. Full compliance with supervisory requirements and near-zero deviation reflect this bank's precise financial management. For Bank Tejarat, CAR was also the priority, but optimization required increases in ROA, ROE, market share, and liquidity, along with a reduction in NPA. Nevertheless, deviations were eliminated after adjustments.

Bank Saderat, like Bank Mellat, focused on CAR and only required a reduction in ROE and a slight decrease in NPA, indicating financial discipline and effective management. For Bank Parsian, significant reductions in both ROE and ROA were necessary to achieve the optimal state, while control of NPA and maintenance of CAR ensured compliance with regulations. Bank Pasargad needed to increase ROA and market share while reducing NPA, and deviations were eliminated after adjustments.

Bank Eghtesad Novin required broader changes, including increases in ROA, CAR, and market share, along with a reduction in NPA. Yet, the bank's managerial flexibility enabled complete elimination of deviations. Bank Sina outperformed many peers, as only minor changes in ROE and a reduction in NPA were sufficient, with final deviation reported as very low. Bank Dey required improvements in ROA, market share, and reduction in NPA, and ultimately reached the optimal state after optimization.

For Bank Karafarin, substantial increases in ROA and CAR were mandatory to reach the optimal state, reflecting weaknesses in resource utilization in past years. However, the adjustments led to full compliance with requirements. Finally, Bank Middle East experienced the largest changes; sharp reductions in ROE and ROA were necessary to achieve the optimal state, indicating high risk or weaknesses in profitability structure. Nonetheless, after adjustments, deviations were eliminated and legal requirements were met.

The overall conclusion of this analysis shows that all banks, after optimization, managed to achieve full compliance with Central Bank regulations. However, the extent of changes required to eliminate deviations highlights differences in resource management quality and financial efficiency over past years. Banks such as Mellat and Sina achieved optimal states with limited changes, whereas Parsian, Middle East, and Eghtesad Novin required broader reforms. These results indicate that effective bank management must focus on improving CAR, controlling NPA, and enhancing capital productivity to maintain financial stability and operational efficiency in a complex competitive and regulatory environment.

Figure 3

Asset, liability, and equity management of banks for each year in all banks, showing: 1) ROA, 2) ROE, 3) liquidity ratio, 4) CAR, 5) NPA, 6) market share of deposits and loans

Based on the results obtained from the analysis and optimization of the key financial indicators of the selected banks—including return on assets (ROA), return on equity (ROE), liquidity ratio (LRR), capital adequacy ratio (CAR), non-performing assets (NPA), and market share of deposits and loans (MSDL)—the evaluation of assets, liabilities, and shareholders' equity in compliance with the Central Bank's quantitative balance sheet control regulations shows that the overall alignment of the balance sheet structures of the ten studied banks (Mellat, Tejarat, Saderat, Parsian, Pasargad, Eghtesad Novin, Sina, Dey, Karafarin, and Middle East) with the regulations of the Central Bank of the Islamic Republic of Iran has generally been maintained. The output of the optimization model indicates that, with adjustments in the six examined indicators, the deviation from the desired state after correction has reached zero or near zero. In other words, even in cases where a bank required modifications in ratios such as ROE, ROA, or liquidity, the deviations from the standards were minimized after implementing the suggested changes. This implies that the current structure of assets, liabilities, and equity of the banks is such that compliance with the Central Bank's supervisory framework is possible, and in many cases, this compliance has been fully achieved. Furthermore, the results for each bank show that four vital indicators—including statutory reserve ratio, capital adequacy, liquidity, and non-performing assets—were at appropriate levels across all banks. This means that not only from the perspective of quantitative indicators but also from the aspect of adherence to supervisory laws, banks have managed to maintain their balance sheet structures within the permitted range. It should be noted, however, that in some cases—such as Parsian, Eghtesad Novin, Karafarin, and Middle East banks—the recommended changes required to achieve full compliance were greater than in other banks, reflecting a larger initial gap with the desired framework. Nevertheless, after optimization, all banks fell within the compliance range.

From the perspective of quantitative balance sheet control regulations, which usually include restrictions on asset growth, credit concentration, liquidity levels, capital ratios, and the composition of productive and non-productive assets, the findings indicate that the model effectively identified the necessary adjustments for compliance, and implementing these adjustments led to full alignment. In some banks, such as Mellat, Saderat, and Sina, negative changes in ROE and ROA were required, reflecting the need to reduce excessive profitability in order to balance other indicators. Conversely, in banks such as Eghtesad Novin and Dey, improvements in liquidity and capital adequacy were identified as necessary.

In summary, the available analytical data demonstrate that the structure of assets, liabilities, and shareholders' equity of the examined banks, with manageable adjustments, can be fully aligned with the Central Bank's quantitative control framework. Since all banks, after optimization, were placed in compliance with the regulations and deviations were reduced to zero or near zero, it can be concluded that the Central Bank's quantitative balance sheet control is not only achievable but can also be realized under current banking system conditions with limited and targeted corrective measures. This highlights the high flexibility potential of banks' balance sheet structures and the effectiveness of a quantitative-indicator-based approach in evaluating and improving the financial performance of banking institutions in the country.

4. Discussion and Conclusion

The findings of this study indicate that the application of a fuzzy goal programming framework for asset–liability management (ALM) provides a powerful mechanism for aligning banks' financial structures with both regulatory requirements and performance optimization objectives. By integrating risk-sensitive measures such as return on assets (ROA), return on equity (ROE), liquidity risk ratio (LRR), capital adequacy ratio (CAR), non-performing assets (NPA), and market share of deposits and loans (MSDL), the results demonstrate that deviations from desired performance targets can be minimized effectively when decision variables are prioritized and weighted through the best–worst method (BWM). This approach highlights the inherent trade-offs between profitability, liquidity, and regulatory compliance, showing that balance sheet structures can be adjusted to achieve near-zero deviations from supervisory and performance benchmarks.

The outcomes of the analysis particularly emphasize the centrality of CAR as the most influential criterion across expert evaluations. This finding is consistent with prior literature, which has repeatedly highlighted the pivotal role of capital adequacy in shaping both bank resilience and systemic stability (Bakkar et al., 2023; Kashyap et al., 2024). Similar to the evidence provided by (Lysiak et al., 2022), the study confirms that CAR functions not only as a safeguard against unexpected losses but also as a benchmark for regulatory compliance under Basel frameworks. The prioritization of CAR in this research demonstrates a convergence between theoretical emphasis on solvency management and practical requirements imposed by regulators, aligning with (Taheri et al., 2025), who underscored the need for system dynamics-based ALM to focus on key solvency indicators.

Furthermore, the study finds that liquidity risk (LRR) occupies the second rank of importance, which reflects growing concerns about liquidity crises in the modern banking environment. This aligns with (Islam, 2024), who argued that duration- and convexity-based ALM models must incorporate liquidity constraints as integral elements of balance sheet strategies. Likewise, (Basheer et al., 2021) demonstrated that liquidity risk is often endogenous to credit risk and off-balance-sheet exposures, suggesting that banks' liquidity buffers cannot be analyzed independently but rather must be integrated into a holistic ALM framework. The consistency of the present findings with these studies validates the emphasis placed on liquidity management as an indispensable component of sustainable banking.

The third priority identified in the results—minimizing non-performing assets (NPA)—is particularly noteworthy given its direct association with credit quality and profitability. According to (Buchak et al., 2024), banks' resilience depends not only on capital and liquidity positions but also on their ability to control asset quality in the face of credit shocks. This study supports that perspective by revealing that even incremental reductions in NPAs can significantly improve financial performance, which echoes (Gholami et al., 2024), who explored ALM in investment funds and found that poor-quality assets reduce the capacity of funds to maintain stable liabilities. Similarly, (Hao & Lixia, 2023) highlighted how shareholder-level practices such as equity pledges can distort asset quality and investment efficiency, reinforcing the importance of managing NPAs at both institutional and ownership levels.

The relatively lower importance assigned to profitability indicators, specifically ROA and ROE, deserves critical interpretation. Although profitability is a fundamental objective of commercial banks, its positioning below CAR, LRR, and NPA in this study suggests that stability and compliance take precedence over short-term returns. This finding aligns with the argument of (Albanese et al., 2021), who stressed that valuation adjustments (XVA) in balance sheets reveal how profitability must often be moderated to account for funding and counterparty risks. Similarly, (Mahdawi et al., 2021) demonstrated through a modified DuPont analysis that while profitability ratios provide insights into operational efficiency, they cannot independently safeguard stability in the absence of strong capital and liquidity positions. The results of the current research therefore reinforce the literature's consensus that profitability, though essential, must be balanced against regulatory and risk-related constraints.

An additional significant finding is the consistently low priority given to MSDL. Experts indicated that market share in deposits and loans is more of a derivative outcome of improvements in capital adequacy, liquidity, and asset quality rather than an independent driver of bank performance. This aligns with (Reisi et al., 2023), who argued that balance sheet dynamics, such as money creation processes, fundamentally shape financial outcomes, whereas market share metrics simply reflect underlying structural health. Similarly, (Samsami et al., 2023) observed that eliminating fictional assets from balance sheets not only stabilized money supply but also indirectly influenced market presence. The finding also resonates with (Malloy et al., 2022), who showed that shifts in monetary instruments such as CBDCs influence bank market share not directly but through balance sheet adjustments. Thus, the study supports the conclusion that MSDL, while important, functions primarily as a secondary indicator rather than a primary determinant in ALM frameworks.

The results also highlight the utility of combining fuzzy goal programming with BWM in managing the inherent uncertainty of financial data. Unlike deterministic models, the fuzzy approach allows flexibility in defining upper and lower bounds for performance indicators, which mitigates the risks of data outliers and volatility. This methodological insight aligns with the findings of (Peykani et al., 2023), who emphasized the benefits of multi-objective optimization with minimal changes, and (Khosravianni et al., 2023), who employed similar techniques to model liquidity, credit, and capital adequacy risks simultaneously. By integrating these methods, the present study contributes to advancing methodological innovation in ALM.

Moreover, the results carry implications for understanding systemic dynamics. For instance, (Mhejir et al., 2024) highlighted the negative role of shadow economy dynamics in weakening financial market performance, thereby complicating banks' asset management. The present study's findings, which indicate that regulatory compliance and CAR are dominant factors in effective ALM, indirectly support such conclusions by demonstrating how strong governance and adherence to supervisory standards can mitigate external vulnerabilities. Similarly, (Mahdavi Panah et al., 2023) underscored the importance of regulatory frameworks for enhancing financial inclusion, which is consistent with the results here that emphasize compliance-driven indicators as top priorities.

The interplay between ALM and technological innovation also emerges as a broader theme in interpreting the findings. As (Ju & Zhu, 2024) demonstrated, reinforcement learning-based risk models can improve decision-making under uncertainty, which complements the application of fuzzy programming in this study. Likewise, (Truong et al., 2023) illustrated how blockchain and digital asset management frameworks are reshaping ALM practices in emerging domains. By situating the present results within this broader technological trajectory, it is clear that adaptive, data-driven, and digitally integrated frameworks will become increasingly critical in future ALM strategies.

Finally, the study's findings echo broader patterns in the international literature regarding the structural role of ALM in ensuring financial stability. (Shahniaei et al., 2024) designed an ALM model for Iran's Agricultural Bank, showing that localized adaptations of global models are necessary for aligning with specific institutional and regulatory contexts. Similarly, (Shahrabi Farahani et al., 2023) extended ALM principles to municipal debt management, demonstrating the versatility of ALM frameworks beyond commercial banking. Collectively, these studies support the present research's assertion that ALM frameworks must be adaptive, integrative, and context-sensitive in order to serve as effective tools for financial governance.

Despite the robustness of the fuzzy goal programming model and the integration of expert judgment through BWM, this study is not without limitations. The first limitation lies in the reliance on audited financial statements of ten selected banks, which, while representative, may not capture the full diversity of the banking sector. Regional or specialized banks may exhibit different risk profiles and balance sheet dynamics. Second, the reliance on expert judgments in weighting decision variables introduces subjectivity, even though consistency checks were applied. A larger and more diversified panel of experts could provide more balanced insights. Third, while the fuzzy framework addresses uncertainty in data, it does not fully capture macroeconomic shocks such as inflation volatility, exchange rate fluctuations, or geopolitical crises, which could significantly impact ALM outcomes. Finally, the model primarily reflects the Iranian banking context, which limits its generalizability across different legal and regulatory systems.

Future research could expand the scope of this study by incorporating macroeconomic variables, such as inflation and interest rate shocks, into the ALM optimization framework. The integration of stochastic modeling alongside fuzzy goal programming could offer a richer representation of systemic risks. Furthermore, future studies could explore the impact of emerging financial technologies, such as artificial intelligence, digital currencies, and blockchain, in refining ALM strategies. Comparative studies across countries with different regulatory frameworks would also be valuable in highlighting how contextual differences shape ALM outcomes. Finally, further research could incorporate behavioral dimensions of banking, such as managerial decision-making biases, into ALM frameworks, thereby bridging technical optimization with organizational realities.

Practitioners in the banking industry can draw several insights from this study. First, regulators and policymakers should focus on strengthening CAR and liquidity requirements, as these indicators are consistently shown to be the most influential in achieving stability. Second, banks should invest in technologies that enable adaptive and data-driven ALM, such as fuzzy modeling and reinforcement learning systems. Third, managers should treat market share metrics as outcomes of effective balance sheet management rather than as primary goals, thereby focusing resources on improving asset quality and risk management. Finally, targeted training for financial managers and risk officers in advanced optimization methods could enhance institutional capacity to navigate complex regulatory and market environments.

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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Declaration of Interest

The authors report no conflict of interest.

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Ethics Considerations

In this research, ethical standards including obtaining informed consent, ensuring privacy and confidentiality were considered.

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