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Research article

INTEGRATING MULTI-CRITERIA METHODOLOGY WITH SYMBOLIC REGRESSION ON LOAN MODELLING IN BANKING SECTOR

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Abstract: Forecasting loans accurately is essential for the banking sector as it underpins effective risk management, capital allocation, and portfolio optimization. This study aims to model loans in the Turkish banking sector by integrating symbolic regression with multi-criteria decision-making methodologies. Monthly data from January 2004 to September 2024, derived from banks' financial statements, are utilized for the analysis. The optimal parameter configuration for symbolic regression is determined using the TODIM (an acronym in Portuguese for Interative Multi-criteria Decision Making) methodology. The forecasting performance of symbolic regression is evaluated against established models, including Autoregressive Integrated Moving Average (ARIMA), Gaussian Process Regression (GPR), Support Vector Machines (SVM), Neural Networks (NN), Regression Trees (RT), and Long Short-Term Memory (LSTM) network models. The proposed approach is applied across private, public, and foreign banks, as well as the overall banking sector. A significant finding of this study is the identification of a robust relationship between loans and two critical variables: assets and deposits. These results underscore the

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importance of strengthening deposit mobilization strategies and enhancing asset utilization to effectively grow banks' loan portfolios.

Keywords: Loan modelling, symbolic regression, multi-criteria methodology, banking sector.

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1. INTRODUCTION

Funds are transferred to the financial system through banks and the transferred funds are distributed to sectors in the conomy through loans [1], [2]. It is possible to create the desired effects on macroeconomic variables by transferring idle funds to the real sector through banking sector by acting as a bridge in the financial system [3], [4], [5].

Central banks use monetary policy instruments to achieve their goals on macroeconomic variables such as national income, employment and price stability. Banks play an important role in the economy in the use of these policy instruments. For example, a central bank that wants to fight inflation will implement a contractionary monetary policy and consequently will want to reduce the volume of credit [6], [7], [8], [9].

A central bank that uses interest rates as a monetary policy tool to reduce the volume of credit will achieve this objective through banks. An increase in interest rates will reduce the liquidity of the banking sector [10], [11] and as a result of the decrease in the resources disbursed, a contraction in credits will be experienced and thus, inflation can be reduced. At the same time, this decrease in loans will lead to a decrease in the debt resources of the real sector, which will lead to a decrease in economic growth [12], [13], [14] and an increase in unemployment [15].

Achieving the targeted values in macroeconomic variables in the economic sense will also prevent the financial fragility of countries [16], [17]. The formation of a healthy financial structure is of great importance especially in times of crisis. In countries that are financially fragile, crises will tend to have a more severe and negative impact [2], [18]. Central banks work together with the banking sector to prevent financial fragilities and to create a sound macroeconomic structure.

The reserve requirement ratios used by central banks as a monetary policy tool have a significant impact on both crisis periods and credit volumes [19], [20], [21]. In case the actual inflation rate is below the targeted level, central banks reduce reserve requirement ratios and thus the volume of loans extended by banks increases. Increased credit volume, in turn, increases the money supply [22] and brings inflation to the targeted level.

The loans extended by banks have a significant impact on national economies [23], [24], [25]. From this point of view, it is of great importance to determine the factors affecting the loans extended by the banking sector [26]. In addition to macroeconomic factors, the loans extended by banks are thought to depend on bank assets [27], deposits [28] and profitability ratios [29], [30], which can be considered as micro factors of banks. Panel regression analysis is generally applied in the studies to determine which variables are effective on the loans extended by the banks [31], [32], [33], [34]. At the same time, studies in which the effects of variables are measured by symbolic regression analysis have recently gained importance [35], [36], [37], [38].

Multi-Criteria Decision-Making (MCDM) provides a systematic framework for evaluating and comparing alternatives when numerous, often interdependent, criteria must be considered [39]. In essence, it facilitates the selection, ranking, or sorting of options in situations where criteria are multiple and frequently conflicting, thereby offering decision-makers a transparent basis for trade-off analysis [40]. Modern extensions—such as Grey MCDM—enhance this framework's robustness by accommodating ambiguous or incomplete information, allowing large sets of complex criteria to be assessed under uncertainty [41]. Furthermore, newly developed utility-function–based techniques like CRADIS illustrate the field's versatility, showing how different weighting schemes and distance-to-ideal concepts can be synthesized to generate interpretable rankings when criterion weights are predetermined [42]. Collectively, these developments underscore MCDM's pivotal role as an adaptable decision-support paradigm across diverse domains ranging from healthcare technology adoption to sustainable resource management.

In this study, the factors influencing loan disbursements in the Turkish banking sector are analyzed by integrating multi-criteria decision-making methodologies with symbolic regression, using monthly data from January 2004 to September 2024. While existing literature predominantly evaluates factors affecting banking sector profitability using panel regression analysis [43], [44], [45], this study distinguishes itself by employing symbolic regression to assess the factors influencing loans. This novel approach is expected to make a significant contribution to the literature by offering an alternative, data-driven methodology for understanding loan dynamics.

This study proposes a novel integration of the TODIM method into the parameter tuning process of Symbolic Regression (SR), specifically tailored to the context of loan modeling. While both TODIM and SR are established techniques individually, their combined application remains underexplored, particularly as a means of embedding decision-maker preferences into model selection. Traditional optimization approaches such as grid search or Bayesian optimization focus solely on algorithmic performance metrics (e.g., error minimization), often overlooking domain-specific priorities such as model interpretability, parsimony, or alignment with financial policy logic. In contrast, TODIM—rooted in Prospect Theory—offers a preference-sensitive mechanism that accounts for perceived gains and losses, enabling more nuanced multi-criteria evaluation.

In our framework, TODIM is employed to evaluate SR-generated models based on a combination of predictive accuracy, model complexity, and inclusion of structurally meaningful variables (e.g., loans, deposits, and assets). While the TODIM algorithm itself is not modified, its implementation is context-specific: the criteria matrix reflects trade-offs relevant to banking and financial modeling, and the scoring process allows for value-informed selection rather than purely statistical optimization.

Moreover, this work addresses key limitations of symbolic regression—namely, overfitting and interpretational ambiguity—by constraining the function set (as shown in Table 4), applying multiple error metrics (MAE, MAPE, RMSE), and filtering model candidates through a behaviorally grounded decision framework. This results in symbolic models that are both accurate and interpretable, enhancing their practical relevance in regulatory or strategic financial contexts.

Although the discovered relationships between loans, assets, and deposits may appear intuitive, their symbolic derivation reveals non-linear patterns and interactions that are not captured through standard econometric modeling. Unlike black-box machine learning models, the expressions derived through this approach maintain transparency, facilitating inspection and validation by domain experts. By embedding preference-based evaluation directly into the parameter optimization process, this study contributes a decision-aware methodology that advances the interpretability and usability of symbolic modeling in financial applications.

The formation of the study is as follows. After the introduction section, a summary of the literature is presented in Section 2. In Section 3, the methodologies used in this study are summarized. Section 4 is devoted to the conceptual framework and dataset of the study. In Section 5, the models in the study are analyzed and the results are presented. Section 6 is dedicated to the conclusions, limitations, and future research directions.

2. LITERATURE REVIEW

Although the loan volumes disbursed by banks and the factors affecting them are very important, the studies on this subject in the literature are quite limited. The factors affecting the loan disbursement of banks have been evaluated by many authors from two perspectives and they have generally evaluated their studies on non-performing loans ratio variable. At the same time, when the literature is examined, it is observed that the variables affecting the loans are generally analysed by using panel regression and multiple regression analyses. In this respect, the literature is constructed by two seperate section as the studies investigate the factors that affect the bank loans and the studies used the the symbolic regression analysis as a methodology.

2.1. Literature on Bank Loans

Mitku evaluated the lending behaviour of banks and stated that loan volume was based on factors such as bank asset size, capital adequacy ratio, liquidity, interest rate, credit risk and economic growth [46]. Birhanu et al. applied panel regression analysis with the idea that loans and advances may be affected by factors such as capital adequacy, asset size, liquidity, credit risk and deposit rate, and as a result, they found that there is a positive relationship between variables other than liquidity ratio and loan volume [47].

A review of the literature reveals that non-performing loan ratios are analysed as macroeconomic and bank-specific factors. For example, Said and Mahyoub examined macro factors such as unemployment, inflation and economic growth, and micro factors such as bank size, profitability and capital adequacy separately and tried to determine which variable or variables affect non-performing loans more [48]. Cucinelli explained the variables affecting non-performing loans with unemployment, economic growth and inflation rate on a macro and micro level, with deposit ratio and the ratio of equity to assets [49]. Radivojevic and Jovoni [50] and Kjosevski and Petkovski [51] determined the inflation rate as the most important variable affecting banks' non-performing loans and stated that if the inflation rate is high, the ratio of non-performing loans to total loans is high.

The unemployment rate, which is another important macroeconomic variable affecting non-performing loan ratios, is thought to have a negative impact on the performance of loans as a result of falling incomes. For example, Messai and Jouini [52] and Makri et al. [53] concluded that there was a significant positive relationship between unemployment rate and non-performing loans. Jimenez and Saurina [54] and Abid et al. [55] stated that there was a negative relationship between economic growth and non-performing loans.

The authors ,who set out with the expectation that the rate of non-performing loans decreases when economic growth increases, supported this with their findings. Micro factors affecting banks' non-performing loans are generally evaluated as capital adequacy, mismanagement and bank size (assets). Berger and DeYoung [56] and Stern and Feldman

[57] argued that a high capital adequacy ratio would reduce banks' non-performing loans and their findings supported this argument. Podpiera and Weill [58] and Salas and Saurina [59] concluded that there was a positive significant relationship between mismanagement and non-performing loans. The ratio of operating losses to operating revenues and ROE are used as the mismanagement variable. Similarly, Louzis et al. stated that there was a negative relationship between ROA and non-performing loans [60]. Ranjan and Dhal [61], Elshaday et al.[62] and Karadima and Louri [63] concluded that there was a negative significant relationship between bank asset size and non-performing loan ratios. However, unlike others, Mensah and Adjei found a positive significant relationship between asset size and non-performing loans [64].

The studies investigated loan volumes disbursed by banks and the factors affecting them positively and negatively are summarized at Table 1.

Table 1: Literature review summary

Bank credit volume	***Bank related factors***						***Macro factors***		
	S	CA	P	DR	CR	L	GDP	IR	UR
Malede (2014) [46]	+	+			-	-	+		
Birhanu et al. (2021) [47]	+	+	+	+		-		+	
Cucinelli (2015) [49]					-				
Non performance loans	***Bank related factors***						***Macro factors***		
	S	CA	P	DR	CR	L	GDP	IR	UR
Said and Mahyoub (2021) [48]	-	-	-				-	+	+
Radivojevic and Jovoni (2017)[50]		-	-					+	+
Kjosevski and Petkovski (2017) [51]		-	- **(ROE)**				-	-	+
Messai and Jouini (2013) [52]			-				-		+
Makri et al. (2014) [53]		-	- **(ROE)**				-		+
Jimenez and Saurina (2006) [54]					+				
Berger and DeYoung (1997) [56]		-							
Stern and Feldman (2004) [57]		-							
Podpiera and Weill (2008) [58]			- **(ROE)**						
Salas and Saurina (2002) [59]			- **(ROE)**						
Louzis et al. (2012) [60]			- **(ROA)**				-		+
Ranjan and Dhal (2003) [61]	-								
Elshaday et al. (2018) [62]	-								
Mensah and Adjei (2015) [64]	+								

S (size), CA (capital adequacy), P (profitability), DR (deposit rate), CR (credit risk), L(liquidity), GDP (economic growth rate), IR (inflation rate), UR (unemployment rate)

2.2. Literature on Symbolic Regression Analysis

As mentioned earlier, it has been observed that panel regression analysis is used to determine the factors affecting loan volumes, non-performing loan ratios or bank profitability in the banking sector or multiple regression analysis is used in sectoral studies. In this respect, in this part of the study, studies conducted with symbolic regression analysis used in the model of the research is evaluated.

Yang et al. [65] used symbolic regression analysis to predict the future trend of oil production and results revealed that oil production will peak in 2021 and will decrease by 4% in about 12 years after its peak. Pan et al. [66] researched the most important factors on emission base on the importance of reducing carbon emissions by using symbolic regression analysis. In their study of 34 OECD countries, it was concluded that the factors affecting carbon emissions differed according to countries and it was seen that GDP was the most important factor in 17 countries. While for four countries industrial and technological factors are effective, for three countries total population, urbanisation and foreign direct investment are effective.

Li et al. [67] evaluated the main factors affecting energy consumption in Hennan town of China by symbolic regression analysis method and concluded that the critical factors are effectively irrigated area, total labour force of agricultural machinery, per capita rural income and total agricultural value. A similar study was conducted by Liu et al. [68] and aimed to find the variables affecting China's sulphur dioxide level. For this purpose, data for the years 2001-2020 were taken and as a result of the data evaluated by symbolic regression analysis, it was seen that GDP, total energy consumption, thermal installed power capacity and population were effective respectively. Stajic et al. [69] presented a forecast of future natural gas spot prices in the global international market. They applied symbolic regression analysis method with sensitivity analysis to determine the most important parameter and concluded that global natural gas prices are highly dependent on crude oil prices. The authors also evaluated the differences between the forecasting methods and concluded that the best forecasting method is the symbolic regression analysis method.

There are also studies comparing symbolic regression analysis with other methods and finding that symbolic regression has a significant predictive power within the models. Sheta et al. [70] investigated the most effective method in predicting stock returns by using SandP 500 index data. In their study, symbolic regression method was compared with traditional multiple regression analysis and the index with potential impact using multinomial symbolic regression genetic programming gave the best prediction result. Orzechowski et al. [71] compared the symbolic regression method with other machine learning approaches in their research. They used a set of about 100 regression benchmark problems collected from open-source repositories on the web and evaluated nine machine learning approaches from scikit-learn. They found that the symbolic regression analysis method was effective but performed slowly. Wilstrup and Kasak [72] tested the effectiveness of symbolic regression analysis method on small data sets and worked with 250 data. They concluded that this method has the highest explanatory power in 132 out-of-sample data out of 240 observations and also shows the best explanatory performance compared to other models in 184 out of 240 data.

Although symbolic regression has proven highly effective in domains as diverse as energy forecasting, environmental impact assessment, and financial-market prediction, the technique has yet to be employed in modelling bank-level outcomes - such as loan volumes, non-performing loan ratios, or profitability - highlighting a clear gap that the present study seeks to fill.

3. METHODOLOGY

In this methodology section, firstly symbolic regression will be explained, and then followed by an explanation of TODIM, one of the multi-criteria methodologies. Finally, performance evaluation metrics will be presented.

3.1. Symbolic Regression

Symbolic Regression (SR) aims to discover mathematical expressions that accurately describe a given dataset by searching the space of possible mathematical expressions to find the best model that fits the data [73], [74], [75], [76]. Unlike traditional regression methods that assume a fixed model structure and only adjust parameters, SR allows for flexibility in both model structure and parameters [74], [77].

The process of symbolic regression is as follows:

- Define a set of basic mathematical building blocks: These blocks, called primitives, include operators (e.g., +, −, ×, /, sin, cos, exp, log) and operands (variables, constants) [35], [76].
- Generate candidate expressions: These expressions are often represented as tree structures, where internal nodes represent operators and leaf nodes represent operands [35], [78].
- Evaluate the fitness of each candidate expression: The fitness measures how well the expression fits the data, typically using metrics like root mean squared error (RMSE) [35], [78], [79].
- Evolve the population of candidate expressions: This evolution involves selecting the best-fitting expressions and applying genetic operators like crossover (combining parts of different expressions) and mutation (randomly modifying an expression) to create new candidate expressions [35], [74], [79].
- Repeat the evaluation and evolution process: This process continues for a predetermined number of generations or until a satisfactory solution is found [35].
- Select the best-fitting expression: The final output is a human-readable mathematical equation that represents the relationship between the input and output variables [76].

Advantages of symbolic regression can be summarized as follows:

- Automatic Equation Discovery: Symbolic regression algorithms automatically search for mathematical expressions that describe relationships in data without relying on pre-defined model structures [73], [79], [80], [81]. This data-driven approach allows for the discovery of complex and potentially novel equations that might not be apparent through manual analysis or traditional statistical methods. Symbolic regression can handle various model forms and coefficient determination automatically [79].
- Interpretability: The resulting mathematical expressions from symbolic regression are typically human-readable and interpretable [73], [78], [79], [80], [81]. Unlike black-box models like neural networks, symbolic regression provides insights into the underlying relationships between variables. This interpretability is crucial for understanding the discovered equations and gaining scientific insights from the data.
- Potential for Extrapolation: Symbolic regression models, if they accurately capture the underlying physical laws, have the potential to extrapolate well outside of the training

data domain [76]. This ability to predict beyond the observed data is valuable for forecasting and making inferences about unobserved phenomena. Symbolic regression can converge to the true model and its parameters when working with synthetic data [81].

• Versatility and Wide Applicability: Symbolic regression can be applied to a variety of problems across different domains [78], [79], [80], [81]. Its ability to discover equations from data makes it a powerful tool for scientific discovery, engineering design, financial modeling, and other fields where underlying relationships is essential. Examples of its use include discovering natural laws, simplifying expressions, and assisting domain experts in energy policy making.

Limitations of symbolic regression can be summarized as follows:

• Search Space Complexity: The search space of potential mathematical expressions grows exponentially with the complexity of the target equation and the number of input variables [74], [78], [79]. This vast search space can make symbolic regression computationally challenging, especially for high-dimensional problems. While methods like problem decomposition [79] and exhaustive search with simplification procedures [78] have been proposed to address this issue, it remains a fundamental challenge.

• Overfitting: Symbolic regression models, like other machine learning models, can be prone to overfitting, especially when dealing with noisy data [73], [74], [78], [79], [81]. Overfitting occurs when the model learns the specific details of the training data too well, leading to poor performance on unseen data. Techniques like complexity control, regularization, and using appropriate fitness metrics [78], [79], [81] are essential to mitigate overfitting.

• Sensitivity to Input Parameters: Symbolic regression results can be sensitive to the choice of input parameters like the set of mathematical operators, function set, and hyperparameters [69], [73], [79], [81]. Careful selection of these parameters based on domain knowledge or using techniques like sensitivity analysis can improve the quality and interpretability of the discovered equations. The sources mention experimenting with different iterations, population sizes, and mathematical operators to achieve better results [69]. Another study found that the choice of operators, especially for non-linear effects, did not significantly influence the results because the algorithm itself could evolve functions into sufficiently complex forms [73].

• Bloating: Some symbolic regression algorithms, particularly those based on genetic programming, can suffer from bloating, where the generated expressions become unnecessarily large and complex [35], [73], [79]. This issue can affect both the interpretability and computational efficiency of the algorithm. Techniques like parsimony pressure, simplification procedures, and multi-objective optimization [35], [73], [79] have been developed to control bloating.

• Limited Exploration of Complex Operators: While symbolic regression algorithms can theoretically incorporate complex mathematical operators, practical limitations like computational resources and search space complexity restrict the use of such operators [73], [81]. This limitation might prevent the discovery of equations involving complex mathematical relationships. However, several studies suggest that using simpler operators can still be effective in discovering useful models [81], especially when combined with techniques like linear transformation of variables [73], [81].

3.2. TODIM

The TODIM steps can be summarized as follows [82]. A decision matrix is structured as an $m \times n$ grid, where m represents the number of alternatives and n denotes the criteria. It serves as a tool for evaluating and comparing alternatives across multiple criteria. To ensure meaningful analysis, the matrix should be carefully populated with relevant data for each alternative, using the criteria established during the initial Let the decision matrix be defined as follows:

$$X = \begin{bmatrix} x_{11} & x_{12} & \dots & x_{1n} \\ x_{21} & x_{22} & \dots & x_{2n} \\ \dots & \dots & \dots & \dots \\ x_{m1} & x_{m2} & \dots & x_{mn} \end{bmatrix} \tag{1}$$

In the second step, the decision matrix is normalized. If the criterion j is beneficial:

$$r_{ij} = \frac{x_{ij}}{\max\limits_{i}(x_{ij})} \tag{2}$$

If the criterion j is non-beneficial:

$$r_{ij} = \frac{\min\limits_{i}(x_{ij})}{x_{ij}} \tag{3}$$

In step 3, calculate the measurement of the dominance of alternatives with the following equations:

$$\delta(A_i, A_j) = \sum_{c=1}^{m} \phi\_c(A_i, A_j), \qquad \forall(i,j)$$

$$\phi_c(A_i, A_j) = \begin{cases} \sqrt{\dfrac{w_{cr}(r_{ic} - r_{jc})}{\sum_{c=1}^{n} w_{cr}}}, & if\ (r_{ic} - r_{jc}) > 0 \\ 0, & if\ (r_{ic} - r_{jc}) = 0 \\ -\dfrac{1}{\theta}\sqrt{\dfrac{(\sum_{c=1}^{n} w_{cr})(r_{jc} - r_{ic})}{w_{cr}}}, & if\ (r_{ic} - r_{jc}) < 0 \end{cases} \tag{4}$$

where θ is the attenuation factor of the losses, in this study, θ is set equal to 1. w_{cr} represents relative criteria weight and calculated with $w_{cr} = \frac{w_c}{w_r}$, where w_c represents criteria weight and w_r represents the maximum of the criteria weights ($w_r = \max\ (w_c | c = 1,2, \dots, n)$).

Step 4, the overall value of alternative i is calculated by normalizing its corresponding measurements. This process ensures that the criteria are evaluated on a comparable scale, and the calculation is performed using the following equation.

$$\tau_i = \frac{\sum_{j=1}^{n} \delta(A_i, A_j) - min \sum_{j=1}^{n} \delta(A_i, A_j)}{\max \sum_{j=1}^{n} \delta(A_i, A_j) - \min \sum_{j=1}^{n} \delta(A_i, A_j)} \tag{5}$$

The best alternative has the highest τ score.

The TODIM scores were normalized by dividing each score by the total sum of all scores. This normalization was conducted to ensure comparability and maintain consistency within the decision-making process. Since TODIM generates scores on an unbounded scale that can vary significantly depending on the criteria and alternatives, normalization was deemed necessary. By transforming the raw scores into relative values, their proportionality and comparability were enhanced, allowing for a clearer interpretation of the alternatives' performance. This approach is recognized as standard practice in multi-criteria decision-making, ensuring that the results remain robust and interpretable. To normalize the values, following equation is employed:

$$n\tau_i = \frac{\tau_i}{\sum(\tau_i)} \tag{6}$$

Given that TODIM produces relative dominance scores that are not inherently bounded or normalized, a post-processing normalization was applied to transform these scores into a standardized format. Specifically, the raw TODIM scores were rescaled to the [0,1] interval such that their sum equals 1. This approach ensures that the scores can be interpreted as relative performance weights, making them more suitable for comparative evaluation of parameter configurations.

In the context of parameter tuning, where multiple criteria (e.g., model accuracy, complexity, interpretability) are in conflict, normalization offers several benefits. It simplifies downstream analysis, enhances interpretability, and allows for seamless integration with other optimization or selection frameworks. The method employed—min-shift followed by proportioning—preserves the ordinal structure of the TODIM rankings, ensuring that the most preferred parameter configurations remain dominant after transformation.

However, it is important to acknowledge that normalization alters the original scale of TODIM's dominance values, which may reduce the visibility of the magnitude differences among competing parameter sets. While this may not be critical in optimization tasks focused primarily on ranking or selection, it could be a limitation in contexts where understanding the strength of preference is necessary. Nonetheless, in the practical setting of parameter optimization, where interpretability and comparability are key, the normalization of TODIM scores is both methodologically sound and functionally appropriate.

TODIM has some advantages. TODIM's structure allows for flexibility in handling various criteria, decision, contexts, and investor prefenernces [83], [84]. The easiness of the calculation steps of the TODIM, make it accessible for practitioners and researchers [83]. TODIM has demonstrated the potential to produce stable, consistent, and more informed decisions [84]. TODIM combines elements of the multi-attribute utility theory from the AHP method with features of the ELECTRE methods. Another distinguishing feature of the TODIM method is its incorporation of psychological behavioural factors of decision-makers in situations involving risk and uncertainty, grounded in the principles of prospect theory.

TODIM also has some disadvantages. Determining the most effective TODIM configurations can be challenging [83]. The method's performance is influenced by various parameters like the attenuation factor, weighting allocation method, and input criteria transformation method. The optimal choice for these parameters often depends on the specific decision context, requiring careful consideration and experimentation.

In this study, the TODIM (Interactive and Multicriteria Decision Making) method was employed for parameter selection in Symbolic Regression due to its ability to model decision-maker preferences under risk and uncertainty. Grounded in Prospect Theory, TODIM accounts for perceived gains and losses in a nonlinear fashion, making it well-suited for trade-off-intensive tasks such as balancing model accuracy, complexity, and interpretability [82]. Unlike purely compensatory methods, TODIM's value function enables more realistic prioritization among conflicting objectives, a common challenge in model tuning. Its successful application in engineering design, machine learning, and decision support systems further supports its reliability in multi-criteria optimization contexts [85], [86]. These properties make TODIM an appropriate and interpretable tool for identifying robust parameter configurations in Symbolic Regression tasks

In this study, the TODIM method was selected due to its distinctive strengths compared to more commonly used multi-criteria decision-making techniques. While traditional methods such as AHP, TOPSIS, and PROMETHEE primarily focus on structured criteria analysis, TODIM uniquely incorporates behavioral nuances and risk attitudes of decision-makers, providing a more realistic representation of human decision-making processes. Additionally, TODIM's flexibility allows it to adapt effectively to diverse decision scenarios and integrate smoothly with other analytical methods, potentially leading to more robust and context-sensitive outcomes [76], [83], [84], [87], [88]. Thus, TODIM's capability to model psychological factors and uncertainty offers distinct advantages, justifying its selection for handling the complex decision-making challenges addressed in this research.

3.3. Performance Evaluation Metrics

The performance evaluation metrics frequently used in forecasting studies in the literature are presented in Table 2. In a successful forecasting study, lower values of MAE, RMSE, and MAPE are desired, while a higher adjusted R² value is preferred.

Table 2: Performance evaluation metrics

Name of the Metric	***Equation of the Metric***
Mean Absolute Error (MAE)	$\frac{1}{n}\sum_{i=1}^{n}\lvert d_i\rvert$
Square-root of MSE (RMSE)	$\sqrt{\frac{1}{n}\sum_{i=1}^{n} d_i^2}$
Mean Absolute Percentage Error (MAPE)	$\frac{1}{n}\sum_{i=1}^{n}\left\lvert\frac{d_i}{p_i}\right\rvert \times 100$
Adjusted $\boldsymbol{R^2}$	$1-\frac{(1-R^2)(n-1)}{(n-w-1)}$
$\boldsymbol{d_i = p_i - \hat{p}_i}$ $\boldsymbol{p_i}$: *actual price for day* $\boldsymbol{i}$ $\boldsymbol{\hat{p}_i}$: *predicted price for day* $\boldsymbol{i}$ $\boldsymbol{n}$: *number of days* $\boldsymbol{w}$: *number of independent variable.*	

4. FRAMEWORK AND DATASET

4.1. Conceptual framework

In this study, the factors that affect the loans extended by the banks in the Turkish banking sector are investigated by integrating multi-criteria methodologies with symbolic regression using monthly data of the period of January 2004-September 2024. In essence, this study aims to determine an equation that models the relationship between loans (credits) and key financial variables of banks, such as assets, deposits, equity, and profit. This relationship can be expressed as:

$$Loan = f(asset, deposit, equity, profit)$$

Here, f represents a functional form or equation that mathematically captures how changes in these explanatory variables (inputs) affect loan (output) and it is discovered with symbolic regression procedure.

Figure 1 presents the conceptual framework of this study and summarized as follows:

- This study conducts distinct analysis across four segments of the Turkish banking sector: the overall banking sector, private banks, public banks, and foreign banks.
- Initially, the dataset's descriptive profile is outlined, and the data is divided into training and testing subsets. The testing set comprises data from 33 months post-2022, while the training set includes data from 216 months, used for model training and parameter selection.
- Within the training set, a symbolic regression model is trained individually for each parameter combination, and performance metrics are calculated.
- A decision matrix based on four distinct performance metrics undergoes TODIM analysis to identify the optimal parameter configuration.
- The selected parameter configuration is then applied to train the model, and its performance is evaluated using the test set.
- Forecasting is conducted using ARIMA, Gaussian Process Regression, Support Vector Machines, Neural Networks, Regression Trees, and LSTM models. The results are subsequently compared with the predictive performance of symbolic regression.
- The findings of the analysis by using the overall banking sector data are presented in the study and findings of the private banks, public banks, and foreign banks are presented in the online appendix.

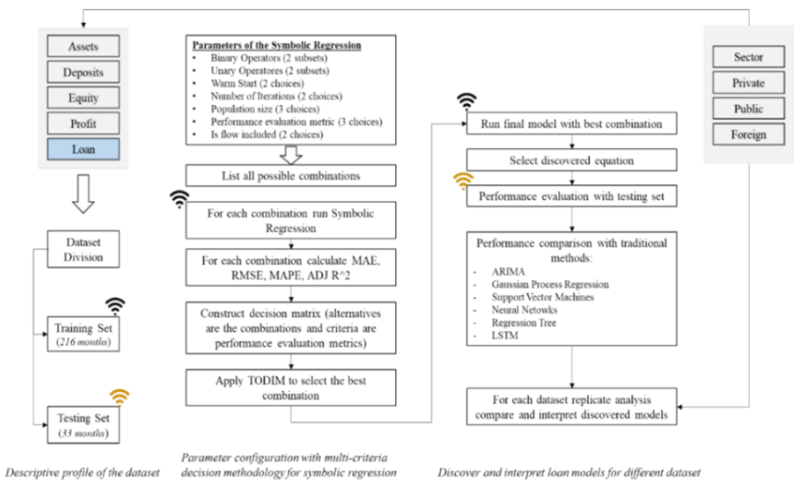

Figure 1: Outline of the study

4.2. Dataset

In this study, the factors that affect the loans extended by the banks in the Turkish banking sector are investigated by using monthly data of the period of January 2004-September 2024. Dataset of the study is extracted from the monthly bulletin of the Banking Regulation and Supervision Agency of Turkiye, the watchdog of the Turkish banking sector, which is responsible for the supervision of the banking sector.

Using balance sheet and income statement items to model loans in the banking sector is a well-founded approach for several reasons. The balance sheet and income statement of the banks, as standardized and comparable across banks, reflects the financial position of banks, which are critical for assessing their ability to manage credit risk and potential defaults in the context of loan modeling and risk management. Various studies in finance and economics also use balance sheet and income statement data to build predictive models for loans by estimating default probabilities, loan growth, and credit risk, which is highlighting the practical and empirical validity of such approach. By leveraging these financial statements, the loan modeling process captures both the operational strengths and risk factors of banks, ensuring a robust and data-driven analysis. This method aligns with sector best practices and regulatory requirements, making it a reliable framework for evaluating credit behavior and performance.

In this study, we deliberately did not use interest rates as a variable for credit modeling. Interest rates are macroeconomic variables influenced by central bank policies, inflation, and global economic conditions, which may not directly reflect the unique financial dynamics of individual banks, in other word, we prioritize bank-specific characteristics over broader macro economic indicators. By relying on financial statement items, which are relatively stable and regularly reported, we reduce variability and improve the reliability of the analysis due to the volatily in the interest rates over time, which cause noise into models. Additionaly, since the study's objective is to explore how bank-specific variables relate to credit allocation and performance, incorporating interest rates could divert attention from understanding the intrinsic financial health and operational efficiency of banks. By excluding interest rates, the study ensures a sharper focus on bank-specific financial indicators, enabling a robust and granular analysis of loan modeling. This approach aligns with the research aim of understanding internal banking factors that drive loan performance.

There are total of 249 observations in this study between January 2004-September 2024. Observations from the last two years (post-2022) are used for testing, while the remaining observations are utilized for training purposes. The descriptive profile of the training and testing set for the banking sector data is given in Table 3.

Table 3: Descriptive profile of the training and testing set for sector

		Min	*Max*	*Mean*	*%25*	*Median*	*%75*	*Std*	*Skewness*	*Kurtosis*
Trainin	***Assets***	247132.00	9215463.00	2112062.00	650339.30	1368968.00	2980968.00	1898387.00	1.34	4.28
	Deposits	154160.20	5303348.00	1177349.00	401785.10	772974.90	1586710.00	1061720.00	1.53	4.94
	Equity	35602.97	713945.90	228910.30	78763.75	182552.60	333334.90	176298.30	0.95	2.89
	Profit	341.18	92942.32	16498.94	5512.92	12279.27	21467.24	15224.05	1.74	6.74
	Credits	64291.77	4897731.00	1239108.00	342064.30	796938.10	1930648.00	1139504.00	1.08	3.30
Testing	***Assets***	9221105.00	30518692.00	18593596.00	12999778.00	16846448.00	24083025.00	6585821.00	0.27	1.76
	Deposits	5381075.00	17835273.00	11321793.00	7974255.00	10355711.00	14995934.00	3945513.00	0.08	1.63
	Equity	751947.30	2643632.00	1679270.00	1177723.00	1606765.00	2188717.00	568957.10	0.07	1.78
	Profit	20089.47	620494.80	246832.80	104117.20	233649.30	358634.40	162016.40	0.41	2.26
	Credits	4962284.00	15006409.00	9544952.00	6788060.00	9232818.00	12039085.00	3077734.00	0.19	1.76

Number of observation in training set = 216; number of observation in testing set = 33

The financial time series is presented in Figure 2. The values of the financial time series are denominated in Turkish Lira. Due to economic issues and high inflation in the Turkish economy in the recent period, the values of recent observations exhibit higher volumes. Therefore, the time series has been scaled by taking the logarithm of the data in the graph. Since the profit data is quarterly and has the character of flow data, the profit series in the Figure 2 is seen as volitile.

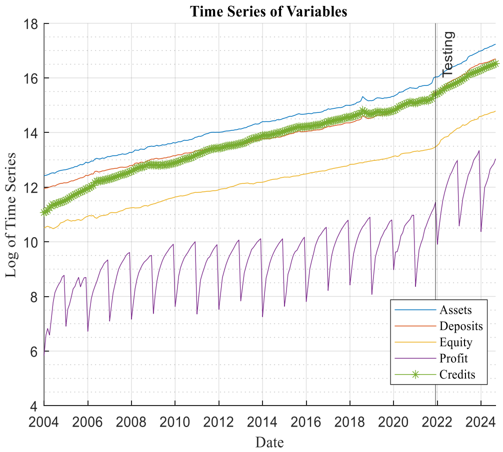

Figure 2: Time series plot of financial time series for sector

Figure 3 presents the correlation graph for loans, assets, deposits, equity, and three monthly-period profits in the Turkish banking sector. A positive relationship is observed between loans and assets, as well as equity. Additionally, a positive correlation is also evident with profits, though the strength of this relationship is comparatively weaker than the others.

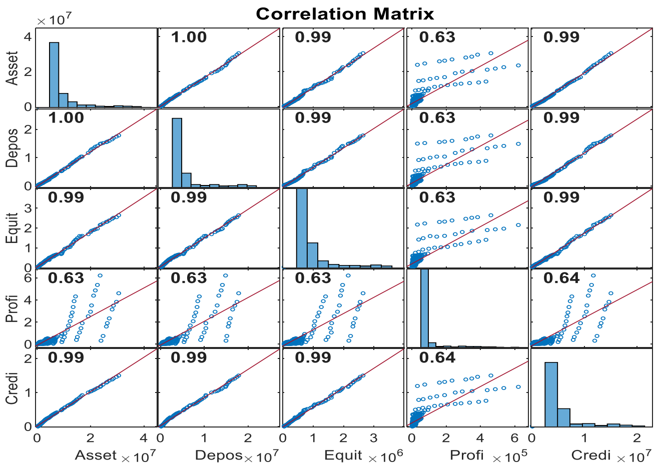

Figure 3: Correlation plot of the input set

Figure 4 displays third-degree polynomial curves and their equations for the relationships between loans and other variables (assets, deposits, equity, and period profits). In the relationships between loans and assets, deposits, and equity, the coefficients of the non-linear terms are close to zero.

This finding suggests that the relationships between these variables are nearly linear, despite the use of a higher-order polynomial model. In other words, while the model allows for non-linear relationships, the data indicates that a linear model would adequately capture the interactions between these variables. This could imply that changes in loans are proportionally associated with changes in assets, deposits, and equity, without significant curvature or complexity in their relationships.

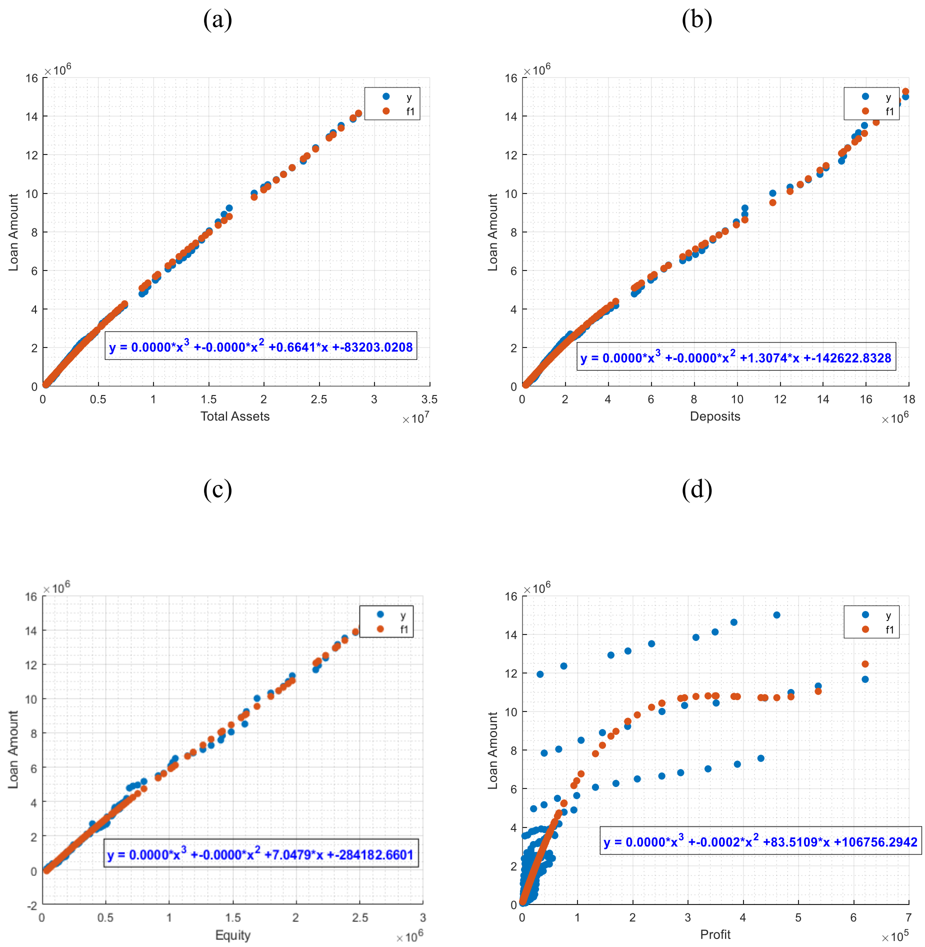

Figure 4: Sensitivity of loans on (a) assets, (b) deposits, (c) equity, (d) profit

5. ANALYSIS

5.1. Selecting parameters for PySR with TODIM

PySR provides a range of configurable parameters to tailor the symbolic regression (SR) process. Key parameters include binary and unary operations, the number of iterations, population size, and the warm start option, which enables PySR to resume from its previous state rather than starting a new search with each execution. Additionally, a performance evaluation criterion was specified, guiding PySR to optimize based on user-defined metrics. In this study, three distinct performance metrics were employed, as detailed in Table 4.

The parameters and their respective search spaces used in the analysis, as presented in Table 4, were selected to balance computational feasibility with exploratory flexibility in Symbolic Regression. Binary and unary operations were categorized into narrow and extended sets to investigate the trade-off between model simplicity and expressive capacity. Narrow sets contain basic arithmetic and functional operators commonly used in symbolic modeling, while extended sets include more complex mathematical functions to allow richer symbolic structures. The inclusion of a warm start option enables the evaluation of potential gains in convergence efficiency through reuse of previously optimized models. Varying the number of iterations and population sizes allows the assessment of optimization depth and diversity in solution search, both of which can significantly affect the performance of evolutionary algorithms. Multiple performance metrics—MAE, MAPE, and RMSE—were included to reflect different perspectives on error sensitivity and practical relevance. Lastly, the inclusion of the flow variable was tested to determine its explanatory power and necessity within the model structure. Collectively, these parameter settings were chosen to enable a multi-faceted, criteria-driven evaluation using the TODIM method, ensuring that both model quality and user-defined preferences could be systematically integrated into the optimization process.

Table 4: Parameters and values for banking sector

Parameters	***Search Length***	***Search values***
Binary operations	2	Narrow: [‘+’ , ‘*’ ,’ –’ , ‘/’] Extended: [‘+’ , ‘*’ , ‘-’ , ‘/’ , ‘^’]
Unary operations	2	Narrow: [‘abs’, ‘exp’, ‘sqrt’, ‘inv’] Extended: [‘abs’, ‘exp’, ‘sqrt’, ‘inv’, ‘sin’, ‘cos’, ‘tan’, ‘log’]
Warm start	2	True false
Number of iterations	2	1000 2000
Population size	3	500 800 1000
Performance Evaluation Metric	3	MAE MAPE RMSE
Is flow included	2	True false

Considering the parameter search values, a total of $2\ x\ 2\ x\ 2\ x\ 2\ x\ 3\ x\ 3\ x\ 2\ = 288$ combinations emerge. An exhaustive search was conducted to test each parameter combination, and the prices predicted by the best model selected by PySR were recorded. Subsequently, these predicted prices were compared with the actual prices, and the MAE, MAPE, RMSE, and adjusted R^2 values were calculated. This raises the question of which parameter combination demonstrates the best performance. Different combinations yield the best results for different performance metrics. Moreover, while the first three performance metrics aim to be minimized, the adjusted R^2 value is expected to be maximized. This situation can be considered a typical multi-criteria decision-making problem. The alternatives are the parameter combinations tested during the exhaustive search, while the criteria are the performance evaluation metrics.

Figure 5 presents a scatter plot depicting the values of performance metrics for the unary operations group among the 288 performance metrics tested during the parameter selection process. It can be observed that adjusted R^2 values exhibit an inverse relationship with the other performance metrics, while a positive correlation is noted among the other metrics. No significant difference is apparent between the use of the unary narrow subset and the unary extended subset.

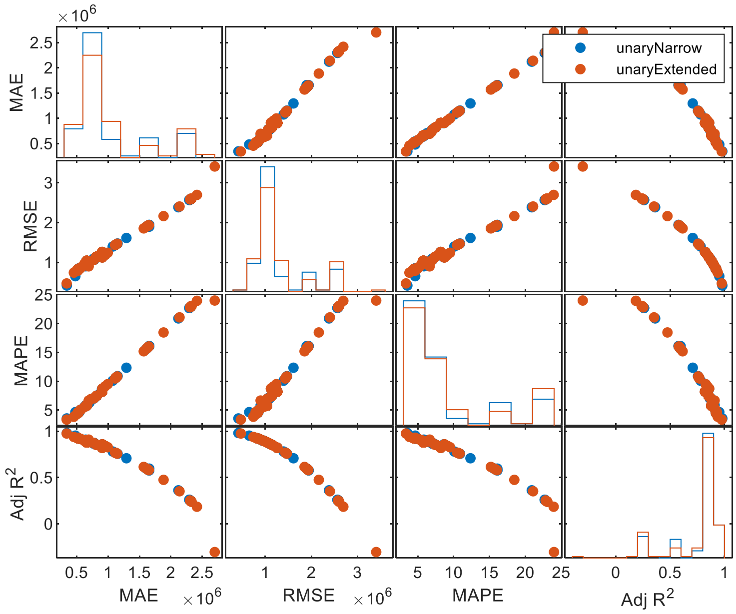

Figure 5: Performance metrices in hyperparameter optimization process

When examining the performance of parameter sets, it becomes evident that no single parameter configuration yields the best results across all performance metrics. For instance, when rankings are based on MAE, the parameter set that produces the lowest MAE value may not necessarily perform best in terms of MAPE (or other performance evaluation metrics). Consequently, selecting the optimal parameter set emerges as a multi-criteria decision-making problem.

Table 5 represents a segment of the decision matrix. It was assumed that the criteria have equal weights.

Table 5: A segment from decision matrix that will be used in multi-criteria methodology

Criteria characteristics	***Minimum (Cost)***	***Minimum (Cost)***	***Minimum (Cost)***	***Maximum (Benefit)***
Parameter set	***MAE***	***RMSE***	***MAPE***	***Adjusted R^2***
Binary subset = extended *Unary subset = narrow* *Warm start = false* *Iteration Number = 1000* *Population size = 500* *perf metric = MAE* *include Flow = false*	660063.2	1037631.0	5.7782	0.879
Binary subset = extended *Unary subset = narrow* *Warm start = false* *Iteration Number = 1000* *Population size = 500* *perf metric = MAE* *include Flow = true*	1655025.0	1939241.0	16.0852	0.5774
Binary subset = extended *Unary subset = narrow* *Warm start = false* *Iteration Number = 1000* *Population size = 500* *perf metric = MAPE* *include Flow = false*	659486.6	1036788.0	5.7728	0.8792
Binary subset = extended *Unary subset = narrow* *Warm start = false* *Iteration Number = 1000* *Population size = 500* *perf metric = MAPE* *include Flow = true*	2325368.0	2597783.0	23.0056	0.2416
Binary subset = narrow *Unary subset = extended* *Warm start = true* *Iteration number = 2000* *Population size = 1000* *Performance metric = MAPE* *Include flow = true*	561064.3	857481.1	5.0157	0.9174
Binary subset = narrow *Unary subset = extended* *Warm start = true* *Iteration number = 2000* *Population size = 1000* *Performance metric = RMSE* *Include flow = false*	1884658.0	2160914.0	18.4565	0.4752
Binary subset = narrow *Unary subset = extended* *Warm start = true* *Iteration number = 2000* *Population size = 1000* *Performance metric = RMSE* *Include flow = true*	523587.8	828692.8	4.4972	0.9228

The TODIM computation steps were performed, taking into account the decision matrix and the characteristics of the criteria, and 288 TODIM scores were visualized in Figure 6. The highest TODIM score, 0.995, was achieved by the combination that used an extended subset for binary operations, a narrow subset for unary operations, a true value for warm start, 2000 iterations, a population size of 800, MAPE as the performance evaluation metric, and included the profit value in the input set. This combination was selected as the best-performing configuration.

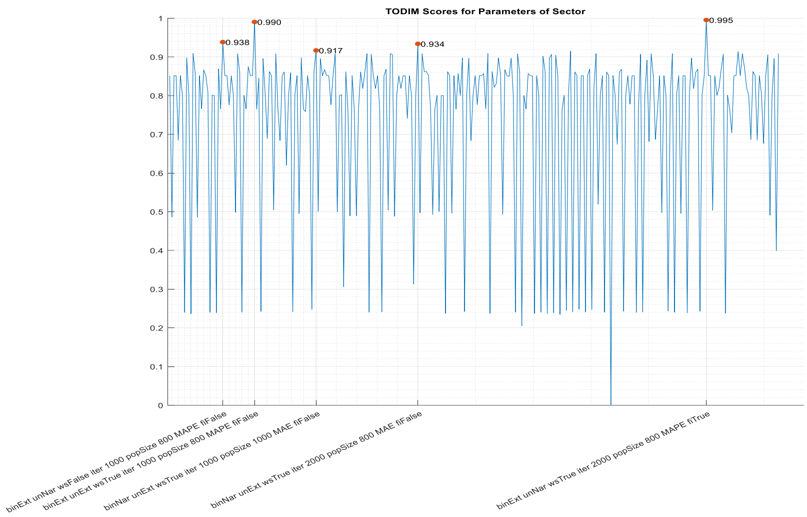

Figure 6: Rescaled TODIM scores for the exhaustive search

5.2. Discovered equations

Discovered equations are listed in Table 6. The symbolic regression study yields a progression of equations of increasing complexity, demonstrating how different combinations of financial predictors impact credit prediction accuracy. Initial models, such as simple linear relationships with deposits or assets, show limited predictive accuracy. As the models incorporate non-linear transformations and additional variables like equity and profit, the accuracy (measured by MAPE) improves significantly. The more complex models reveal intricate interactions where assets are scaled by deposits and modulated by profit or equity through non-linear and inverse relationships, indicating that credit prediction benefits from multifactorial, non-linear equations. The top-performing model highlights that the optimal prediction involves a sophisticated balance of these variables, yielding the lowest forecasting error.

Table 6 highlights a clear—but non-linear—trade-off between symbolic-model complexity and predictive accuracy (measured by mean absolute percentage error, MAPE). Moving from the baseline linear specification (Eq 1, complexity = 1, MAPE ≈ 24.8 %) to a modestly non-linear form (Eq 3, complexity = 5) cuts the error by more than 80 %. Subsequent refinements yield progressively smaller marginal improvements: increasing complexity from 7 to 11 trims MAPE by only ≈0.003 percentage-points and, even at the highest tested complexity (Eq 15, complexity = 20), the gain relative to Eq 6 (complexity = 9) is a modest 0.20 pp. This pattern suggests diminishing returns once key non-linear interactions—particularly between Assets (x_1) and Deposits (x_2) raised to fractional powers—are captured.

Table 6: Discovered equations for banking sector dataset

Equation No	*Complexity*	*Loss (MAPE)*	*Equation*
Eq 1	1	24.796047	$y = x(2)$
Eq 2	3	10.844897	$y = -88359.52 + x(2)$
Eq 3	5	4.0206600	$y = -110618.91 + x(1)^{0.9702452}$
Eq 4 *	7	2.6828744	$y = \frac{\left(-93972.54 + x(1)\right)^{1.930602}}{x(2)}$
Eq 5	8	2.6097560	$y = \sqrt{\frac{(x(1) + -120274.63)^{2.9009972}}{x(2)}}$
Eq 6	9	2.4049678	$y = \left(\frac{\left(-106886.61 + x(1)\right)^{2.2965987}}{x(2)}\right)^{0.7261495}$
Eq 7	11	2.4014368	$y = \left(\left(\frac{(x(1) + -106435.04)^{2.2966063}}{x(2)}\right) - x(3)\right)^{0.7261663}$
Eq 8	12	2.3845274	$y = \left(\frac{(x(1) + -106435.04)^{2.2966063 - \frac{1}{x(4)}}}{x(2)}\right)^{0.7262075}$
Eq 9	13	2.3843850	$y = \left(\frac{(x(1) + -106435.04)^{2.2966003 - \left(\frac{0.97288626}{x(4)}\right)}}{x(2)}\right)^{0.7262075}$
Eq 10	14	2.3656528	$y = \left(x(1) + \left(-85611.6 + \left(\frac{x(2)}{-1.5960371}\right)\right)\right) - \sqrt{\sqrt{e^{\left(\sqrt{\sqrt{x(1)}}\right)}}}$
Eq 11	15	2.3634660	$y = \left(\frac{(x(1) + -106886.61)^{2.2966003 + \left(-\frac{2.1301699}{x(3) + -110618.91}\right)}}{x(2)}\right)^{0.7261987}$
Eq 12	16	2.3435526	$y = \left(\frac{\left(-106886.61 + x(1)\right)^{2.2966003 - abs\left(-\frac{2.1732001}{x(3) + -110618.91}\right)}}{x(2)}\right)^{0.7261987}$
Eq 13	17	2.2433395	$y = \left(\frac{\left(-106435.04 + x(1)\right)^{2.2958527 + \left(-\frac{0.28603426}{\sqrt{abs(x(3) + -112041.15)}}\right)}}{x(2)}\right)^{0.7269437}$
Eq 14	19	2.2392352	$y = \left(\left(\frac{\left(-106435.04 + x(1)\right)^{\left(-\frac{0.29594338}{\sqrt{abs(x(3) + -112041.15)}}\right) + 2.2958527}}{x(2)}\right) + x(3)\right)^{0.7269437}$
Eq 15	20	2.2021215	$y = \left(\frac{\left(x(1) + \left(-106886.61 + x(4)\right)\right)^{2.2966003 - \left(\frac{\frac{1}{(2.2965987)}}{\sqrt{abs\left(-106435.04 + x(3)\right)}}\right)}}{x(2)}\right)^{0,7261}$
y = Loans (Amount ₺)			*x(1) = Assets (Amount ₺)* *x(2) = Deposits (Amount ₺)* *x(3) = Equity (Amount ₺)* *x(4) = Profit (Amount ₺)*

From a modelling-parsimony perspective, Eq 6 (complexity = 9, MAPE = 2.40 %) appears to strike an optimal balance: it achieves nearly the lowest error while remaining substantially more interpretable than equations of complexity ≥ 15, which embed nested exponents, absolute-value operators, and cross-criterion adjustments that complicate economic interpretation. Importantly, across the best-performing equations, Assets consistently enter as a shifted power term $(x_1 + \text{constant})^{\alpha}$ divided by Deposits, underscoring the dominant, non-linear influence of bank size on loan issuance after normalising for funding capacity. Equity (x_3) and Profit (x_4) only improve fit at higher complexities, indicating that their incremental explanatory power is limited once the primary balance-sheet drivers are properly scaled.

As a result of the analysis, the equation that achieves the optimal balance between performance and complexity has been identified as Equation 4. The performance of this equation, along with that of the other equations on the training and test sets, is presented in Figure 7.

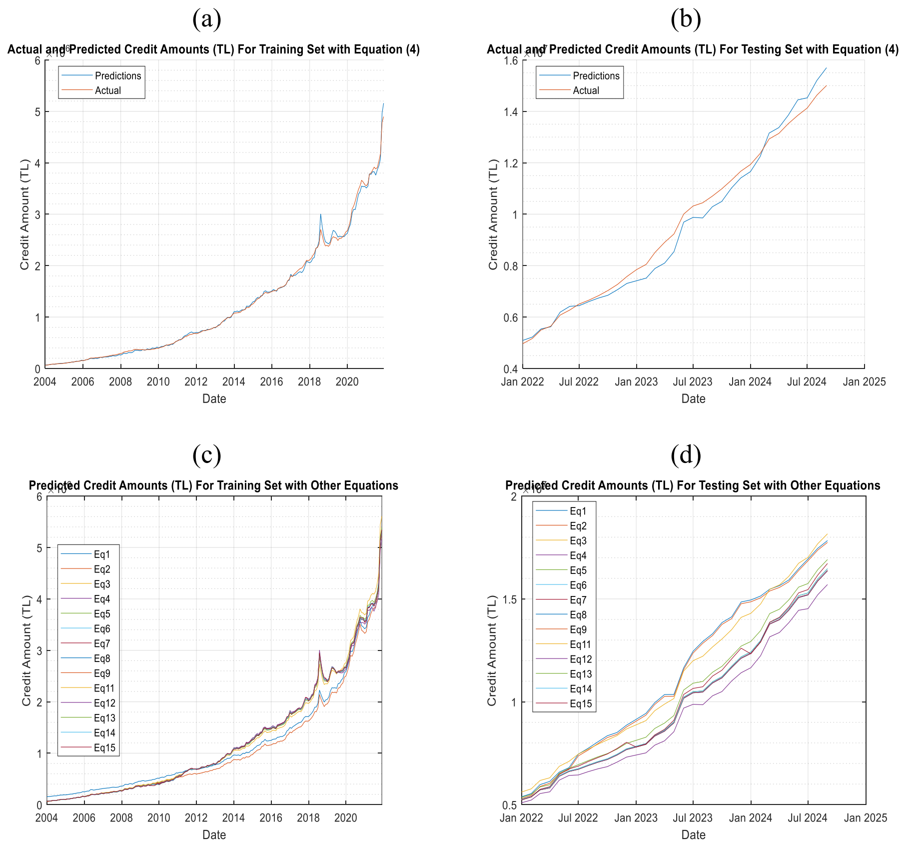

Figure 7: Performance of the equations: (a) best equation (Eq 4) in training set, (b) best equation in testing set, (c) other equations in training set, (d) other equations in testing set

The predicted values for the best-performing equation closely align with the actual values, demonstrating the model's strong predictive performance. Additionally, it is observed that the other equations do not produce predictions significantly different from one another. In other words, the models exhibit similar levels of performance.

However, due to the poor performance of Equation 10, which distorts the scale of the figure, the predicted values from Equation 10 have been omitted from the figure.

In Figure 8, the horizontal axis represents the complexity values of the equations, while the vertical axis displays the MAPE values on the test set. As evident from the figure, an increase in complexity values corresponds to a decrease in MAPE values, indicating an improvement in the predictive accuracy of the equations. However, higher complexity values also make the equations more difficult to interpret and manage, presenting a trade-off between prediction accuracy and model simplicity.

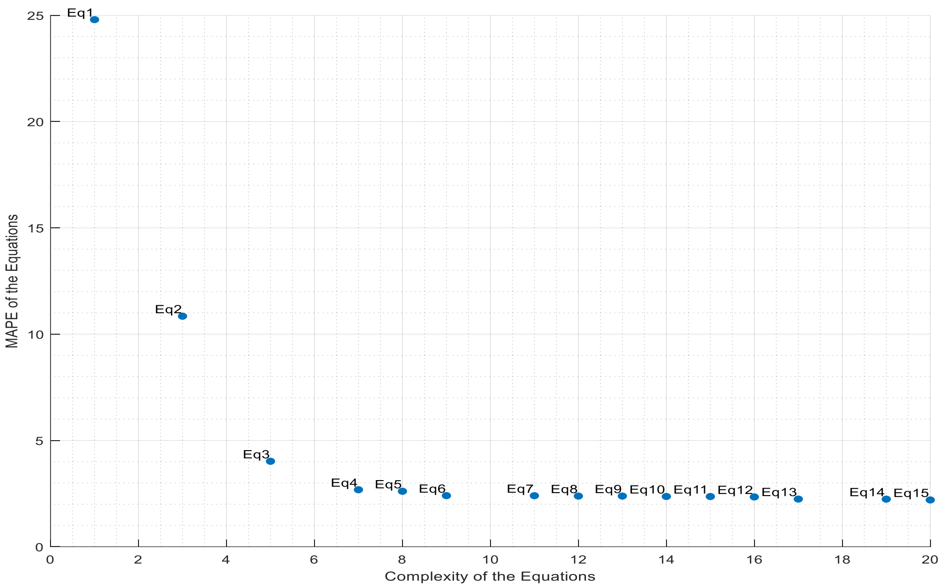

Figure 8: Complexity vs out-of-sample performance of the equations

Table 7 presents the performance of various equations on both training and test sets, evaluated using metrics such as Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), and Adjusted R^2. These results provide a comprehensive comparison of each equation's effectiveness in terms of predictive accuracy and generalizability.

Equation 4 emerges as the best-performing model, achieving an Adjusted R^2 of 1.00 on the training set and 0.98 on the testing set. It also shows notably low error rates, with a training set MAE of 29,109.28 and a testing set MAE of 324,833.4. This indicates strong predictive accuracy and excellent generalization to unseen data, suggesting it maintains the ideal balance between complexity and performance.

Equations 5, 6, and 7 also perform well, with high Adjusted R^2 values (1.00) on the training set and high scores (0.97–0.91) on the test set. Their relatively low MAPE values further support their effectiveness, highlighting their capability to model the underlying data effectively.

Conversely, Equation 10 exhibits extreme overfitting, with an Adjusted R^2 of 1.00 on the training set but a highly negative value of -176.87 on the testing set. The MAE and

RMSE on the test set (25,001,554 and 39,784,159, respectively) indicate substantial deviations, rendering it an unreliable model for real-world predictive tasks.

Equations 1, 2, and 3 show moderate performance, with lower Adjusted R^2 values on the test set (ranging from 0.55 to 0.63) and higher error metrics compared to the top models. While they achieve reasonable results, their generalization to new data is inferior to that of Equation 4 and similar high-performing equations.

Overall, the analysis highlights the need for selecting models that balance high training performance with robust test set accuracy, as evidenced by Equation 4's superior results.

Table 7: Performance of the equations

	Training set				***Testing set***			
Equation no	*MAE*	*RMSE*	*MAPE*	*Adjusted R^2*	*MAE*	*RMSE*	*MAPE*	*Adjusted R^2*
Eq 1	146229.80	184006.90	24.80	0.97	1776841.0	1995594.0	17.42	0.55
Eq 2	161417.90	229303.20	10.84	0.96	1688482.0	1917342.0	16.39	0.59
Eq 3	53091.43	96883.17	4.02	0.99	1624152.0	1814900.0	16.11	0.63
Eq 4 *	29109.28	50518.95	2.68	1.00	324833.4	391176.9	3.28	0.98
Eq 5	29670.49	58946.83	2.61	1.00	735571.3	898790.0	7.13	0.91
Eq 6	24904.00	49142.65	2.40	1.00	405502.5	548894.4	3.86	0.97
Eq 7	24915.37	49236.86	2.40	1.00	407304.5	551046.8	3.88	0.97
Eq 8	24776.06	49559.37	2.38	1.00	415522.5	560285.3	3.96	0.96
Eq 9	24776.06	49535.33	2.38	1.00	414994.2	559679.7	3.95	0.96
Eq 10	22305.47	35680.89	2.37	1.00	25001554.0	39784159.0	198.77	-176.87
Eq 11	24774.15	49446.51	2.36	1.00	413643.8	558179.8	3.94	0.96
Eq 12	24693.24	49412.15	2.34	1.00	413641.4	558177.6	3.94	0.96
Eq 13	24470.95	50572.78	2.24	1.00	449526.8	602061.7	4.28	0.96
Eq 14	24426.10	50609.99	2.24	1.00	450816.9	603501.0	4.29	0.96
Eq 15	24438.28	52934.26	2.20	1.00	568917.2	713931.9	5.54	0.94

Figure 9 illustrates the relationship between the Mean Absolute Percentage Error (MAPE) values of equations derived from the training and test datasets. The horizontal axis represents the MAPE values obtained from the training set, while the vertical axis indicates the MAPE values calculated from the test set. Each data point is visualized as a bubble, with the size of the bubble corresponding to the complexity of the respective equation. This visualization reveals a positive correlation between performance on the training set and the test set. Equations that demonstrate strong performance (i.e., lower MAPE values) on the training set tend to also exhibit robust performance on the test set. This consistency highlights the reliability and generalizability of the equations across different datasets, affirming the validity of the modeling approach used in this study.

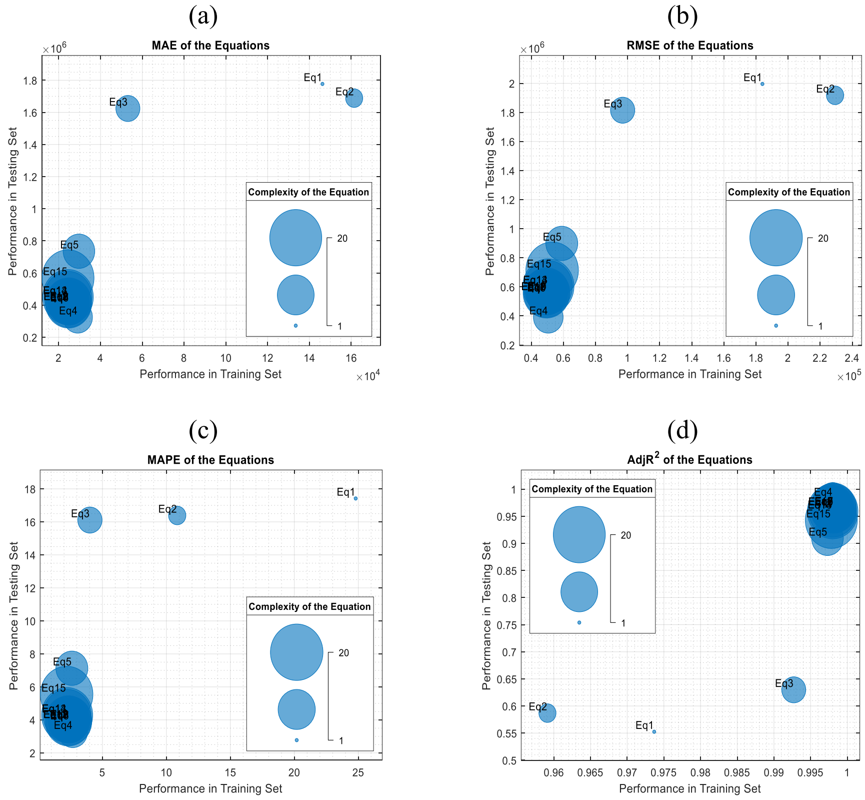

Figure 9: Performance comparison with training and testing set

5.3. Performance comparison with traditional models

Table 8 presents a comparative analysis of performance metrics for six models - Gaussian Process Regression (GPR), Support Vector Machines (SVM), Neural Network (NN), Regression Tree, ARIMA, and LSTM. Parameters of the traditional methods are optimized with Bayesian Optimization. Bayesian Optimization [89] is a sample-efficient method for parameter tuning that models the objective function probabilistically and selects the next parameter set based on expected improvement. The models were evaluated using MAE, RMSE, MAPE, and Adjusted R^2 to assess their predictive accuracy and reliability.

• NN: Among the models, the neural network stands out with favorable results (MAE: 720,597.7, RMSE: 969,718.7, MAPE: 6.48, and Adjusted R^2: 0.89). Its performance is close to that of the Gaussian Process Regression and ARIMA models. However, as a 'black box' model, the NN lacks interpretability, which could be a limitation in scenarios where understanding model behavior is essential. The optimized hyperparameters (e.g., lambda, layer weights initializer, and layer configuration) contribute to its effectiveness.

• GPR: GPR shows robust performance with an MAE of 756,326.4 and an Adjusted R^2 of 0.90. The use of a linear basis function and an ARD Matern kernel likely contributes to its balanced performance. However, GPR may be limited by computational complexity and scalability for larger datasets.

• ARIMA: The ARIMA model performs well relative to the others, with an MAE of 457,636.4 and an Adjusted R^2 of 0.95. Its simpler structure allows for clear interpretability, making it a reliable choice for time series with sufficient observations. However, its reliance on traditional time series modeling may restrict performance in more complex, non-linear scenarios.

• LSTM: The LSTM model exhibits suboptimal results, with a high MAE (2,728,681) and a negative Adjusted R^2 (-0.34), indicating overfitting or an inability to generalize. This could be due to the limited number of observations, as deep learning models like LSTM often require extensive data for optimal training. The LSTM's hyperparameters, including a large number of neurons and high learning rate, may have contributed to its inconsistent performance.

• SVM: SVM shows poor results, with a staggering MAE of 1.31E+09 and an Adjusted R^2 of -473055, reflecting severe underperformance. The polynomial kernel function and high box constraint values may have led to overfitting, particularly when combined with a limited dataset.

• RT: The regression tree has the weakest performance among non-linear models, with an MAE of 4,924,317 and an Adjusted R^2 of -2.76, indicating significant overfitting or instability. This result suggests that the chosen configuration (e.g., minimum leaf size, number of splits) might not have been suitable for the dataset or that the model struggles with generalization due to data limitations

Table 8: Performance metrics of the other models

	GPR	*SVM*	*NN*	*RT*	*ARIMA*	*LSTM*
MAE	756326.40	189797.57	720597.70	159656.34	112379.55	457636.40
RMSE	939395.90	271825.78	969718.70	196395.12	136524.76	673123.40
MAPE	6.88	6.56	6.48	6.04	4.72	5.82
Adj R^2	0.90	0.86	0.89	0.92	0.96	0.95

The parameters of the Gaussian process regression, support vector machines, neural network, and regression tree is determined with Bayesian optimization.

GPR: Sigma = 0.0011219; basis function = linear; kernel function = ardmatern32
SVM: Box constraint = 996.79; epsilon = 6733.1; kernel function = polynomial; poly ord = 4;
NN: Lambda = 4.7084; layer weights initializer = glorot; layer biases initializer = ones; layer sizes = [3 2 231]
RT: minimum leaf size = 2; maximum number of splits = 90; number of variables to sample = 4;
ARIMA: p = 1; d = 1; q = 1
LSTM: number of neurons in the lstm layer = 128; maximum epochs = 1000; minimum batch size = 64; learning rate = 0.01; solver = adam; shuffle = every epoch; gradient threshold = 10

The poor performance of some models, particularly SVM and the regression tree, may be attributed to the limited number of observations, which impacts their ability to learn patterns effectively. Bayesian optimization was employed for hyperparameter tuning of the first four models, which may explain why Gaussian Process Regression and the neural network performed relatively well. While ARIMA demonstrated solid results, its simpler, linear approach may limit its applicability for more complex, non-linear data patterns.

The absence of a feature selection mechanism may have also contributed to the poor performance observed in some models. Feature selection plays a critical role in enhancing model accuracy and generalization by eliminating irrelevant or redundant features that can introduce noise and reduce predictive power. Without this mechanism, models like SVM, regression trees, and LSTM may have been overwhelmed by irrelevant information, leading to overfitting or inefficiency in learning meaningful patterns.

5.4. Results

The equations relate loans (y) to two key input variables:

- $x(1)$ = Assets (₺)
- (2) = Deposits (₺).

Summary of the best equations are given in Table 9. Each equation highlights how changes in assets and deposits influence loans, with coefficients and exponents capturing the complex, nonlinear relationships discovered through symbolic regression.

Banking Sector: The equation shows a nonlinear relationship where the assets ((1)) are raised to the power of 1.930602, reflecting a strong sensitivity of loans to changes in assets. The expression is offset by a negative constant (-93,972.54), which might represent a threshold or baseline adjustment. The result is divided by deposits ((2)), indicating that as deposits increase, the loans are moderated (inverse relationship with deposits). While assets have a significant positive impact on loans, an increase in deposits exerts a dampening effect on the growth of loans in the overall sector.

Private Banks: Similar to the overall sector, assets ((1)) are raised to an exponent (1.9236616), indicating a strong and nonlinear influence on loans. For private banks, assets are the dominant driver of loans, but the presence of high deposit levels introduces a moderating effect. This may reflect liquidity management practices in private banks.

Public Banks: For public banks, assets remain the primary driver of loans, while deposits contribute negatively, albeit to a smaller extent. This could reflect the public banks' focus on asset utilization and their relatively lower dependence on deposits for extending credit.

Foreign Banks: Foreign banks prioritize assets over deposits when extending loans. The negative contribution of deposits may indicate that foreign banks rely more on alternative funding sources (e.g., foreign capital) and do not depend as heavily on domestic deposit mobilization.

The graphs related to the discovered equations for different sectors are presented in Figure 10. A logarithmic scale was applied, and it can be observed that the slopes differ. When the slope differs, it suggests that the rate of change between the variables under consideration is not the same across the banking groups based on ownership. In other words, the relationship between the variables scales differently in each banking group. This difference in slope may indicate that certain factors affect the banking groups at varying intensities or growth rates, reflecting distinct underlying dynamics or patterns in how these variables interact.

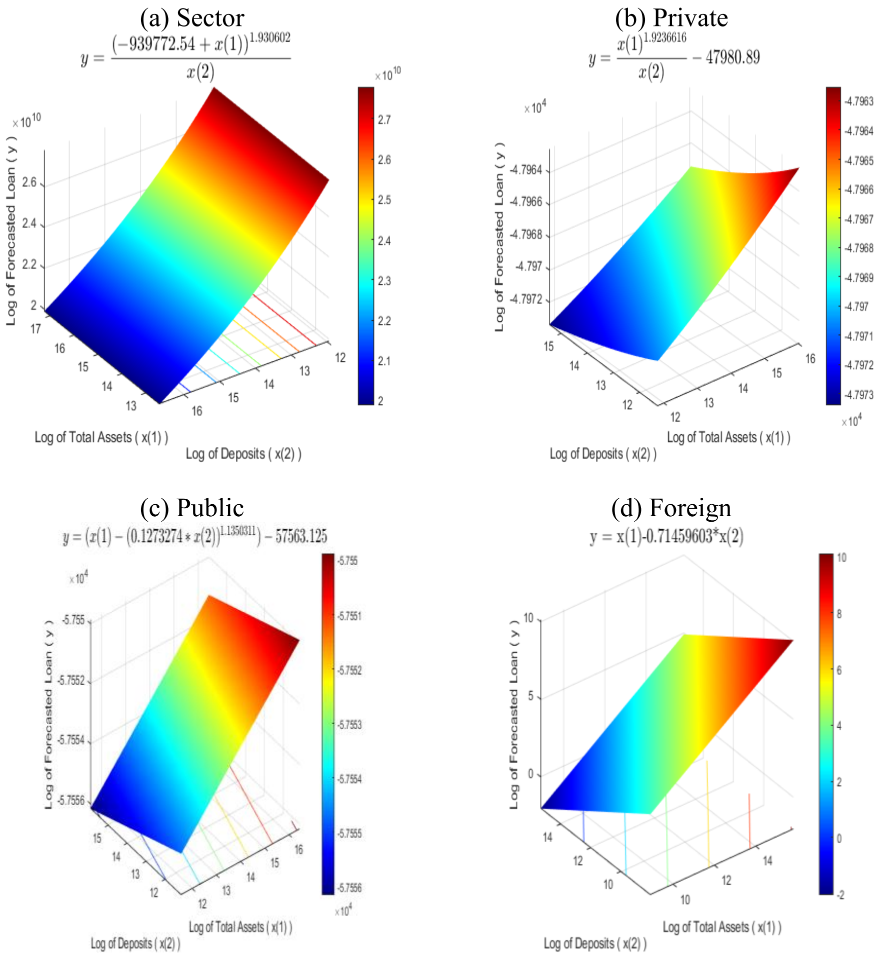

Figure 10: Discovered equations for different sectors

Table 9: Summary of the best equations

	Discovered Equations	***Economic Interpretation***
Banking Sector	$y = \frac{(-93972.54 + x(1))^{1.930602}}{x(2)}$	Lending expands at an increasing rate once total assets surpass ≈ ₺94 bn, suggesting strong scale economies. A higher deposit base dampens this expansion—consistent with regulatory or liquidity constraints linking deposit growth to loan supply.
Private Banks	$\left(\frac{x(1)^{1.9236616}}{x(2)}\right) - 47980.89$	Private institutions leverage asset growth aggressively; every 1 % rise in assets raises loans by ≈1.92 %. The fixed subtraction implies minimum internal liquidity or provisioning requirements that must be met before loans can expand.

Table 9: (continued)

	Discovered Equations	*Economic Interpretation*
Public Banks	$\left(x(1) - \left((0.1273274 * x(2))^{1.1350311}\right)\right) - 57563.152$	State-owned banks translate asset growth almost one-for-one into loans, but face a convex deposit "drag": beyond a certain deposit scale, additional deposit funding is increasingly withheld from lending—consistent with public-policy mandates (e.g., directed credit or liquidity buffers).
Foreign Banks	$x(1) - (0.71459603 * x(2))$	Foreign subsidiaries exhibit the simplest structure: loan supply equals assets minus ≈71 % of deposits. This implies a comparatively rigid internal funds-transfer pricing regime in which a fixed share of deposits is retained for liquidity or repatriation, leaving the residual asset base to support lending.
y = Loan (Amount ₺)		*x(1) = Assets (Amount ₺)* *x(2) = Deposits (Amount ₺)*

6. CONCLUSION

Forecasting loans accurately is important for the banking sector for several reasons. From the point of view of risk management, accurate loan forecasting is vital for assessing and managing lending risks for the banks, which help them to make more informed decisions about loan approvals and interest rates. Effective loan forecasting also enable banks to distribute funds in a way that maximizes profits and minimizes risk in more effective capital allocation. Since the portfolio optimization to create a balanced and diverse loan portfolio is an important factor for the banks, loans forecasting are essential for minimizing risk and maximizing return. Forecasting loan also has macro economic implications and help banks to adopt changes in the economy, which is contribute to the financial stability.

One of the significant findings of this study is that symbolic regression analysis has identified a strong relationship between loans and two key variables, namely assets and deposits in the banking sector. In other words, loans are modeled by capturing variations in these two inputs. Importantly, this relationship holds consistently across private, public, and foreign banking groups, underscoring its robustness and generalizability.

When analyzing the descriptive profile of the dataset, a positive correlation was observed between equity and loans. However, it is noteworthy that equity values did not appear in any of the derived equations generated by the symbolic regression analysis.

From a banking sector perspective, this result carries important implications. First, the exclusion of equity from the predictive equations may indicate that loan issuance is more directly influenced by readily accessible financial indicators, such as assets and deposits, rather than long-term financial stability measures like equity. This finding is aligned with the operational focus of banks, where liquidity and deposit mobilization often play a more immediate role in determining loan capacities.

Second, the observed relationship between loans, assets, and deposits highlights the fundamental role of resource mobilization in banking. Banks that effectively grow their deposit base and optimize their asset portfolios are better positioned to increase their lending capacity. This insight could inform strategic decisions in deposit mobilization campaigns or asset management policies.

The absence of equity as a significant predictor suggests that while equity remains an essential indicator of a bank's financial health, it may not directly influence lending behaviors in the short term. Instead, equity could act as a regulatory or risk-mitigation buffer, ensuring compliance with capital adequacy standards rather than driving loan decisions. This is particularly relevant in highly regulated banking environments, where equity is often treated as a safeguard against unexpected market shocks.

Overall, the findings suggest that banks should focus on enhancing their deposit mobilization strategies and optimizing asset utilization to increase their loan portfolios. Policymakers and regulators might also consider these results when designing frameworks to promote lending while maintaining financial stability. The lack of equity's influence on loan modeling could prompt further investigation into whether this dynamic shifts under different economic conditions or regulatory changes, paving the way for future research on banking sector efficiency.

Limitations of the study are as follows. In this study, while selecting the optimal parameter combination using multi-criteria decision-making (MCDM) techniques, it was assumed that all criteria have equal weights. The study is limited to the selected input set. In future research, modeling could also be conducted by incorporating different inputs specific to the banking sector. Among MCDM techniques, TODIM was chosen to represent the approach, as it is one of the most popular methods and has the simplest computational steps. In future studies, alternative MCDM techniques may be explored.

In this study, we deliberately focus exclusively on bank-specific balance sheet variables, intentionally excluding macroeconomic factors such as interest rates. This approach aims to isolate internal determinants and their direct influence on loan volumes, providing clearer insights into the banks' individual decision-making mechanisms. Although interest rates undeniably play a crucial role in shaping lending behaviors and potentially interact with internal bank characteristics, incorporating them could obscure the distinct effects attributable solely to bank-specific factors. Nevertheless, future research or robustness checks could beneficially include interest rates to empirically assess their incremental explanatory power and to validate the robustness of our primary findings.

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