Ranking the Factors Affecting Financial Flexibility Using Artificial Neural Networks and Machine Learning

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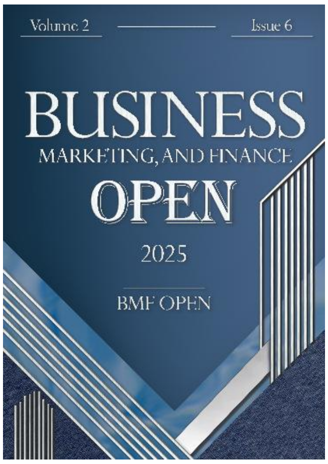

Citation: Lotfinia, E., Khodadadi, V., Jorjor Zadeh, A., & Nasiri, S. (2027). Ranking the Factors Affecting Financial Flexibility Using Artificial Neural Networks and Machine Learning. *Business, Marketing, and Finance Open*, 4(5), 1-24.

Received: 16 April 2026
Revised: 15 July 2026
Accepted: 22 July 2026
Initial Publication: 23 July 2026
Final Publication: 01 September 2027

Abstract: This study aimed to identify and rank the factors affecting the financial flexibility of companies listed on the Tehran Stock Exchange and Iran Fara Bourse using artificial neural network and XGBoost machine-learning models. This applied, quantitative, retrospective, and correlational study used longitudinal firm-level data from companies listed on the Tehran Stock Exchange and Iran Fara Bourse during 2020–2024. Following the application of the inclusion and exclusion criteria, 143 companies were selected through a census approach. Financial flexibility was assessed based on cash holdings and debt capacity. The predictors included default risk, political connections, market power, managerial ability, environmental uncertainty, managerial overconfidence, chief executive officer power, management turnover, and board financial expertise. After data screening and preprocessing, an artificial neural network and the XGBoost algorithm were trained and evaluated. Model performance was assessed using the coefficient of determination and root mean squared error, while variable importance and the direction of predictor effects were interpreted through normalized importance scores and SHAP values. Both algorithms successfully ranked the determinants of financial flexibility, although the artificial neural network demonstrated superior predictive performance. The neural network achieved an (R^2) of 0.499 and an RMSE of 0.179, whereas XGBoost produced an (R^2) of 0.413 and an RMSE of 0.194. Default risk was the most influential predictor in both models, and lower default risk was associated with greater predicted financial flexibility. In the neural network, managerial ability, market power, political connections, and environmental uncertainty followed default risk in importance. In XGBoost, political connections, environmental uncertainty, managerial ability, and market power received the next highest rankings. Managerial overconfidence had moderate importance, whereas chief executive officer power, management turnover, and board financial expertise made comparatively limited predictive contributions. Training and validation errors converged satisfactorily, indicating acceptable model stability and no severe overfitting. Financial flexibility is primarily determined by credit quality, managerial competence, competitive position, institutional access, and environmental conditions, and artificial neural networks provide a more accurate framework than XGBoost for predicting and ranking these nonlinear determinants.

Keywords: Financial flexibility, default risk, managerial ability, political connections, market power, environmental uncertainty, artificial neural network, XGBoost.

1. Introduction

Financial flexibility has become a central concern in corporate finance because firms increasingly operate in environments characterized by economic volatility, restricted access to capital, technological transformation, regulatory change, and unexpected disruptions. In such conditions, corporate survival and sustainable growth depend not merely on current profitability but also on the ability to obtain financial resources, preserve borrowing capacity, maintain sufficient liquidity, and rapidly reallocate capital when opportunities or threats emerge. Financial flexibility therefore represents a firm's capacity to respond effectively to unanticipated changes in financing and investment conditions without incurring excessive adjustment costs or jeopardizing its long-term financial stability. It allows firms to continue profitable investments during periods of financial stress, absorb adverse shocks, and avoid forced asset sales or inefficient reductions in operating activities. From this perspective, financial flexibility is not simply a short-term liquidity position but a strategic organizational capability that connects capital-structure decisions, cash-management policies, investment behavior, and risk management [1]. Accordingly, identifying the factors that create or weaken this capability has become increasingly important for managers, investors, creditors, regulators, and other capital-market participants.

In the capital-structure literature, financial flexibility is commonly associated with the preservation of unused debt capacity and the maintenance of adequate cash reserves. Firms with lower leverage and greater cash availability can access financial resources more rapidly when attractive investment opportunities arise or when operating cash flows decline unexpectedly. Conversely, companies that have already exhausted their debt capacity or maintain insufficient liquidity may be forced to abandon profitable projects, accept unfavorable financing conditions, or reduce investment during economic downturns. Financial flexibility thus reflects a deliberate balance between the current use of financing resources and the preservation of future financing capacity. Research on capital structure has emphasized that companies do not necessarily minimize debt because borrowing is undesirable; rather, they may maintain conservative leverage to protect their capacity to borrow in the future [2]. Similarly, the relationship between financial flexibility and firm performance may depend on whether available financial capacity is used to expand investment scale or to improve investment efficiency, indicating that the value of flexibility arises from the quality and timing of subsequent corporate decisions [3].

The strategic importance of financial flexibility becomes particularly visible during periods of crisis. When revenues decline sharply, firms with stronger balance sheets, larger cash buffers, and lower pre-crisis leverage are generally better positioned to maintain operations and continue investment. Evidence from the COVID-19 crisis showed that firms entering the disruption with greater financial flexibility experienced comparatively better market and operating outcomes when revenue streams were suddenly interrupted [4]. Cross-country evidence regarding debt-free and low-debt firms during the same crisis similarly suggests that preserving debt capacity can reduce the severity of financing constraints and enable companies to use borrowing capacity when external shocks occur [5]. These findings demonstrate that financial flexibility generates value not only during ordinary business conditions but especially when access to finance becomes costly or uncertain. Consequently, financial flexibility can be regarded as a form of organizational insurance that enables companies to withstand temporary disruptions while preserving their strategic investment options.

The demand for financial flexibility is not uniform across firms. Companies with extensive growth opportunities, volatile cash flows, uncertain investment requirements, or greater exposure to financing constraints may place greater value on maintaining liquidity and unused borrowing capacity. Corporate financing choices therefore reflect managers' expectations regarding future investment opportunities and the anticipated need for external funds. Firms may reduce leverage, accumulate internal resources, or postpone debt-financed distributions when they expect that future financial capacity will be valuable. The demand-based perspective indicates that financial flexibility is shaped by the interaction between anticipated financing needs, investment opportunities, and managerial choices concerning cash holdings and debt policy [6]. Firm-specific evidence also shows that profitability, tangible assets, cash holdings, and capital structure contribute to explaining differences in financial flexibility among listed companies, although not all internal financial indicators exert equally strong effects [7]. These results imply that financial flexibility is multidimensional and cannot be explained adequately by a single accounting ratio or isolated organizational characteristic.

Liquidity is among the most immediate foundations of financial flexibility because it provides firms with resources that can be used without lengthy negotiations or dependence on external capital providers. Adequate liquidity allows a company to meet current obligations, finance short-term operating needs, and respond to emerging investment opportunities. It can also moderate the adverse consequences of high leverage by reducing the probability that debt commitments will translate into operational or financial distress. Evidence concerning the relationships among liquidity, leverage, firm size, and profitability indicates that liquidity can change the way capital structure affects corporate outcomes and can strengthen the firm's capacity to manage financing pressures [8]. Nevertheless, excessive cash accumulation may involve opportunity costs, weaken investment discipline, and create agency problems. Financial flexibility therefore requires not the maximum possible amount of liquidity but an efficient liquidity position consistent with the firm's risk exposure, financing constraints, and investment requirements.

Default risk constitutes another major determinant of financial flexibility because it directly affects a firm's access to credit and the cost of external finance. Companies with a high probability of default are likely to face stricter lending conditions, higher interest rates, reduced maturity options, and greater demands for collateral. As default risk rises, creditors and investors become less willing to supply additional capital, thereby narrowing the firm's financing alternatives precisely when additional resources may be most necessary. High default risk also indicates that a substantial share of future cash flows may already be committed to debt servicing, leaving limited capacity for discretionary investment or emergency expenditures. Research focusing on default risk and corporate access to credit has emphasized that deterioration in creditworthiness restricts new financing and weakens the ability of firms to react to financial shocks [9]. Accordingly, default risk is expected to be closely associated with financial flexibility, but its influence may be nonlinear because moderate changes in credit conditions may have limited consequences until a critical threshold of financial distress is approached.

Market power may also influence financial flexibility by shaping the stability and predictability of corporate revenues. Firms with stronger competitive positions may possess greater pricing discretion, more stable customer relationships, higher profit margins, and improved capacity to pass cost increases to consumers. These advantages can support internal cash generation and reduce dependence on costly external financing. Research on market power and corporate financial stability suggests that firms with stronger market positions tend to enjoy more stable financial resources and greater resilience against changes in demand or input prices [10]. However, the relationship may not be uniformly positive. Strong market power may encourage organizational complacency, inefficient resource allocation, or reduced innovation, while firms in highly competitive markets may develop superior adaptive capabilities. The financial consequences of market power may therefore depend on managerial quality, industry conditions, and the company's capacity to transform competitive advantages into sustainable cash flows.

Managerial ability is particularly relevant because financial flexibility is ultimately created and used through managerial decisions. Managers determine liquidity targets, debt maturity structures, investment priorities, dividend distributions, and the timing of external financing. Highly capable managers may generate greater revenue from available resources, forecast financing requirements more accurately, negotiate more favorable funding arrangements, and respond more efficiently to environmental changes. A widely used approach to managerial ability separates firm efficiency attributable to managerial competence from efficiency arising from firm size, market share, age, or other organizational characteristics [11]. Studies of managerial characteristics in emerging markets further indicate that managerial experience, analytical capability, strategic orientation, and risk-management competence can substantially influence financial flexibility [12]. Managers with a long-term orientation may also design capital structures that sacrifice some immediate financing benefits in order to maintain resilience and strategic capacity over time [13].

Although managerial ability can strengthen financial flexibility, managerial behavioral biases may produce different outcomes. Overconfident executives may overestimate future cash flows, underestimate project risk, and believe that their investment decisions are more accurate than external assessments suggest. Such managers may undertake excessive investment, avoid issuing equity they perceive as undervalued, or rely heavily on internal funds and debt. The classic evidence on chief executive overconfidence demonstrates that managerial beliefs can significantly affect corporate investment behavior, particularly when firms possess substantial internal financial resources [14]. Overconfidence may occasionally support decisive action and encourage the exploitation of valuable opportunities, but it may also lead to overinvestment, excessive risk-taking, and depletion of cash reserves. Its relationship with financial flexibility is therefore likely to be complex and potentially nonlinear, making it difficult to capture through models that assume a constant marginal effect.

Corporate-governance characteristics may further affect financial flexibility by influencing the quality of financial oversight and strategic decision-making. Financially knowledgeable directors can evaluate complex financing alternatives, monitor liquidity and leverage policies, and identify financial risks before they become critical. Research on accounting expertise within governance structures has shown that the specific nature of directors' financial knowledge can influence reporting quality and conservative financial practices [15]. Nevertheless, the existence of financial expertise does not automatically guarantee stronger financial flexibility. Its practical effect may depend on the authority of expert directors, board independence, access to reliable information, and the extent to which professional recommendations influence executive decisions. Consequently, financial expertise may have a weaker direct predictive role when broader managerial, institutional, and market factors dominate financing outcomes.

Political connections represent another potentially influential institutional factor, particularly in emerging economies where government agencies, public-sector banks, regulatory bodies, and politically connected organizations play substantial roles in resource allocation. Politically connected firms may obtain easier access to loans, government contracts, regulatory concessions, tax advantages, or informal information. Political relationships can therefore reduce external financing constraints and provide support during periods of financial pressure. Evidence regarding political connections and control structures indicates that firms may actively establish such connections because of the economic advantages and rent-seeking opportunities associated with access to government institutions [16]. Political ties may also improve firm performance under uncertainty by providing institutional protection and facilitating access to scarce resources [17]. However, political connections may create dependency, weaken market discipline, encourage inefficient investment, and expose firms to changes in political power. Their effect on financial flexibility may thus vary according to the quality of institutions and the stability of the political environment.

Environmental uncertainty adds another layer of complexity to corporate financial decision-making. Firms operating under unstable demand, inflationary pressures, exchange-rate volatility, regulatory changes, technological disruption, or unpredictable government policies face greater difficulty in forecasting sales, costs, and financing needs. Environmental uncertainty may encourage companies to accumulate cash and reduce leverage as precautionary measures, thereby increasing observable financial flexibility. At the same time, severe uncertainty may reduce profitability, limit access to credit, and increase the likelihood of financial distress. Research examining managerial responses to environmental uncertainty demonstrates that uncertain conditions influence managerial discretion and organizational reporting behavior [18]. Therefore, uncertainty may both increase the demand for flexibility and weaken the resources required to create it. The net effect is likely to depend on firm-specific adaptive capacity, managerial competence, market position, and institutional support.

The growing importance of digital transformation has further expanded the meaning of organizational and financial flexibility. Companies increasingly require digital infrastructures, integrated financial systems, real-time information, and innovative financing mechanisms to respond rapidly to market changes. Organizational readiness can facilitate digital financial innovation, which may strengthen financial performance, resilience, and adaptability [19]. Digital financial capabilities can improve cash-flow monitoring, risk assessment, financing decisions, and communication with capital providers. Nevertheless, technology alone does not guarantee flexibility; its value depends on strategic alignment, organizational culture, managerial competence, and effective implementation. Digital readiness should therefore be considered part of a broader system of internal capabilities that interacts with financial, managerial, market, and environmental determinants.

Despite the extensive literature on financial flexibility, several important limitations remain. A substantial proportion of earlier studies has examined individual determinants through conventional regression techniques, often assuming linear, additive, and relatively stable relationships. Such models are valuable for testing specified hypotheses and estimating average effects, but they may be less effective in detecting complex interactions, threshold effects, asymmetric relationships, and nonlinear patterns. For example, managerial overconfidence may be beneficial at moderate levels but harmful at extreme levels; political connections may improve financing access in one institutional setting while increasing dependency in another; and environmental uncertainty may encourage precautionary liquidity until declining performance begins to erode financial capacity. The simultaneous presence of these mechanisms makes the determinants of financial flexibility particularly suitable for advanced predictive methods.

Artificial neural networks and machine-learning algorithms provide a complementary analytical perspective because they can learn complex relationships from multidimensional data without requiring the researcher to specify every functional form in advance. Artificial neural networks can approximate nonlinear relationships through interconnected processing units, while gradient-boosting algorithms such as XGBoost can capture interactions, discontinuities, and threshold-dependent effects through sequential decision trees. More importantly, contemporary interpretation methods can rank the relative importance of predictors and clarify their contribution to model outputs. The use of more than one machine-learning model also makes it possible to assess whether the identified rankings are robust across algorithms with different computational structures. This is important because predictive importance does not necessarily correspond to the magnitude of a linear coefficient, and the ranking of determinants may vary according to the way interactions and nonlinearities are represented.

The need for such an analysis is especially pronounced in the Iranian capital market. Listed companies operate under substantial inflation, financing constraints, exchange-rate volatility, regulatory uncertainty, restricted access to international capital, and significant government involvement in economic activity. Under these conditions, the factors influencing financial flexibility may differ from those identified in developed capital markets. Default risk, political connections, managerial ability, market power, and environmental uncertainty may interact in ways that cannot be fully represented through isolated linear relationships. Moreover, comparing artificial neural networks with XGBoost can provide evidence regarding which analytical architecture offers stronger predictive accuracy and which variables remain influential regardless of the selected algorithm. Such evidence can assist managers in prioritizing financial policies, help creditors improve risk evaluation, support investors in assessing corporate resilience, and enable policymakers to better understand the institutional conditions affecting firms' financing capacity.

Accordingly, the aim of this study is to identify and rank the factors affecting the financial flexibility of companies listed on the Tehran Stock Exchange and Iran Fara Bourse by applying and comparing artificial neural network and XGBoost machine-learning models.

2. Methodology

This study employed a quantitative, applied, longitudinal, and retrospective research design to identify and rank the factors affecting corporate financial flexibility through artificial neural networks and machine-learning algorithms. The study population consisted of all companies listed on the Tehran Stock Exchange and Iran Fara Bourse. These capital-market companies were selected because their audited financial statements, board reports, ownership information, and market data are publicly available and prepared according to relatively consistent accounting and disclosure standards. The availability of standardized longitudinal data also provided a sufficiently large dataset for training, validating, and evaluating machine-learning models. The unit of analysis was the firm-year observation, and the study covered the five-year period from 2020 to 2024, corresponding to the Iranian fiscal years 1399–1403. A census approach was used because the study required longitudinal panel data and because excluding eligible companies through probabilistic sampling could reduce the amount of information available for model training. Accordingly, all active companies meeting the inclusion criteria during the study period were considered. Companies were excluded when they underwent a major structural transformation, such as a merger, acquisition, dissolution, or substantial reorganization; were awaiting approval or formal decisions from the board of directors or the Securities and Exchange Organization in a manner that affected the comparability of their information; published incomplete, irregular, or unavailable financial reports; or followed a fiscal year that was not aligned with the calendar commonly used by the majority of listed companies. These restrictions were applied to improve temporal comparability, reduce measurement inconsistency, and prevent structural breaks from distorting the learned relationships. Following the application of these criteria, 143 companies were retained as the final research sample. Given the five-year observation period, the initial balanced panel could contain up to 715 firm-year observations, although the final number of usable observations depended on the availability of complete data for all variables and the procedures used to manage missing values and outliers.

The use of artificial intelligence and machine learning was appropriate because financial flexibility may be influenced by nonlinear, interactive, and threshold-dependent relationships that cannot be fully captured by conventional linear regression models. Traditional statistical methods generally estimate average marginal effects under assumptions concerning functional form, error distribution, and independence or limited dependence among observations. In contrast, artificial neural networks and tree-based ensemble algorithms can learn complex patterns directly from data, approximate nonlinear functions, and identify interactions among financial, managerial, governance, market, and environmental characteristics. The study therefore used an artificial neural network as a nonlinear predictive model and Extreme Gradient Boosting, or XGBoost, as the principal machine-learning algorithm for ranking the explanatory variables. The two approaches were used comparatively so that the robustness of the predictive results and the relative importance of the determinants could be assessed across algorithms with different learning structures. The artificial neural network modeled financial flexibility through interconnected computational nodes and nonlinear activation functions, whereas XGBoost developed an ensemble of sequential decision trees in which each new tree attempted to reduce the prediction errors of the preceding trees. This combined analytical strategy made it possible to determine not only whether the selected variables were associated with financial flexibility but also which variables contributed most strongly to its prediction.

The required information was collected through a structured researcher-developed data-extraction checklist. The checklist was designed according to the operational definitions of the study variables and was completed using audited annual financial statements, explanatory notes accompanying the financial statements, reports of the board of directors to the annual general meeting, corporate-governance disclosures, ownership reports, and stock-market information. Financial and market data were obtained from the official disclosure and trading databases of the Iranian capital market, including the Comprehensive Database of All Listed Companies, commonly known as the CODAL system, and the Tehran Securities Exchange Technology Management database. Information regarding the professional background of directors, chief executive officers, major shareholders, political connections, financial expertise of board members, and changes in senior management was extracted from corporate disclosures, board reports, official company announcements, and other publicly available organizational records. To increase data accuracy, financial figures were cross-checked across annual reports, explanatory notes, and market databases whenever more than one source was available. All monetary data were reviewed for consistency of scale and reporting unit before analysis. Variables with substantially different measurement ranges were subsequently standardized or normalized when required by the learning algorithm, particularly for the artificial neural network.

Financial flexibility was the dependent variable and represented a company’s ability to obtain financing, preserve unused borrowing capacity, maintain liquidity, and respond effectively to investment opportunities or adverse financial shocks. It was operationalized through the company’s cash-holding position and debt capacity. Higher cash reserves combined with lower financial leverage were interpreted as indicating greater financial flexibility because such companies have more internally available resources and a greater capacity to raise additional debt when necessary. The relevant cash and leverage components were derived from balance-sheet and cash-flow-statement information and combined in a consistent direction so that higher values of the resulting measure represented stronger financial flexibility. This operationalization reflects the view that financially flexible firms simultaneously preserve liquid resources and avoid exhausting their borrowing capacity.

Default risk was defined as the probability that a company would be unable to meet its financial obligations when due. It was calculated using a firm-level default-probability measure based on accounting and market indicators of financial distress. The measure incorporated relevant information concerning profitability, leverage, liquidity, market performance, and other indicators associated with corporate failure. Higher values represented a greater probability of default, weaker debt-repayment capacity, and greater exposure to financial distress. Because an increase in default risk can restrict access to external financing and reduce unused debt capacity, the variable was expected to have an inverse predictive relationship with financial flexibility.

Political connections referred to direct or identifiable relationships between the company and governmental or political institutions through its chief executive officer, board members, or major shareholders. This construct was measured as a binary variable. A value of one was assigned when at least one chief executive officer, board member, or major shareholder had previously held or currently held a governmental, political, parliamentary, ministerial, military, regulatory, or senior public-sector position, and a value of zero was assigned when no such connection was identified. This operational definition was intended to capture whether the company possessed relational access that could potentially facilitate financing, regulatory support, government contracts, or preferential treatment.

Market power represented the company's ability to influence product prices, sustain margins, and protect its competitive position. It was measured using the Lerner index, which reflects the extent to which a firm's price or operating margin exceeds its marginal cost. Because marginal cost is generally not directly observable from published financial statements, the index was estimated using available sales, operating-cost, and profitability information. Higher values indicated stronger market power, greater pricing discretion, and a potentially stronger capacity to generate stable internal funds. The measure was calculated consistently across companies and years to ensure comparability within the panel dataset.

Managerial ability referred to managers' capacity to use corporate resources efficiently in generating revenue and improving operating performance. It was measured using the approach developed by Demerjian and colleagues. In the first stage, data envelopment analysis was used to estimate firm efficiency by comparing the revenue generated by each company with the resources used in its operations. Relevant inputs included operating assets and expenses that contribute to revenue generation. In the second stage, the estimated efficiency score was separated from firm-specific characteristics such as company size, market share, age, business complexity, and other structural attributes. The residual component, after removing the effects of these organizational characteristics, was interpreted as the portion of efficiency attributable to managerial ability. Higher residual scores therefore represented greater managerial competence in converting resources into corporate revenues.

Environmental uncertainty referred to instability and unpredictability in the company's operating environment. It was measured using the variability of sales over the preceding five-year period. Specifically, the standard deviation of company sales was calculated over a rolling historical window, with sales values adjusted or scaled when necessary to prevent company size from dominating the measure. Greater variation in sales indicated that the company operated in a more unstable environment in which demand, revenue generation, and future cash flows were less predictable. Where a complete five-year historical series was required for the calculation, financial information preceding the main study period was used only to construct the uncertainty measure and was not treated as part of the primary analysis period.

Managerial overconfidence was defined as the tendency of managers to overestimate their capabilities, the quality of their decisions, and the company's future investment returns. It was measured through an overinvestment-based indicator. First, expected corporate investment was estimated on the basis of observable economic determinants such as growth opportunities, cash flow, leverage, company size, prior investment, and other relevant firm characteristics. The difference between actual investment and expected investment was then calculated. A positive and materially high residual, indicating investment above the level justified by the company's observable economic conditions, was treated as evidence of managerial overconfidence. Depending on the analytical specification, the residual could be retained as a continuous measure or converted into a binary indicator distinguishing overconfident from non-overconfident management. Higher values represented a stronger tendency toward managerial overconfidence.

The financial expertise of board members represented the extent to which the board possessed relevant educational qualifications, employment experience, or professional credentials in accounting, auditing, banking, finance, financial management, investment, or related disciplines. It was calculated as the number of board members possessing at least one qualifying form of financial expertise divided by the total number of board members. The resulting ratio ranged from zero to one, with higher values indicating a greater concentration of financial knowledge on the board. Board members' qualifications and professional backgrounds were identified from company reports, corporate websites, official disclosures, and biographical information accompanying board appointments.

Management turnover referred to a change in the company's chief executive officer during a financial year. It was measured as a binary variable, with a value of one assigned when the chief executive officer changed during the relevant year and a value of zero assigned when the same chief executive officer remained in office. Temporary appointments were examined using official company announcements to determine whether they constituted a substantive management change. This variable was included because a change in senior management may alter financing policies, liquidity preferences, risk tolerance, investment decisions, and relationships with capital providers. All variables were aligned by company and fiscal year before model development so that the predictor information corresponded to the financial-flexibility outcome for the appropriate observation period.

Data analysis was conducted in several sequential stages, including data screening, preprocessing, model development, model validation, performance comparison, and factor ranking. Initially, the extracted dataset was examined for duplicate observations, coding inconsistencies, impossible values, missing information, and extreme observations. Records with irrecoverably incomplete information for the dependent variable or essential predictors were excluded. Where limited missingness occurred in continuous predictors, imputation was performed using information derived exclusively from the training data to prevent information leakage into the validation or test datasets. Continuous financial variables were winsorized at appropriate lower and upper percentiles to reduce the disproportionate influence of extreme accounting values while preserving the observations in the dataset. Binary variables were retained in their original zero-and-one format. Continuous predictors were standardized using the mean and standard deviation of the training sample before they were entered into the artificial neural network. The same transformation parameters were then applied to the validation and test observations. Because the data had a panel structure, company and year identifiers were retained for data management and sensitivity analyses but were not treated as ordinary continuous predictors unless theoretically justified.

The dataset was divided into training and testing subsets to evaluate the models on observations not used during model estimation. Model tuning was performed within the training data using cross-validation. To reduce the risk that observations from the same company would appear simultaneously in both training and testing subsets and thereby produce overly optimistic estimates of predictive performance, data partitioning was conducted at the company level or through a grouped cross-validation procedure. Under this approach, all observations belonging to a selected company remained within the same analytical subset. As an additional robustness procedure, a time-oriented validation strategy could be used in which earlier years were employed for model development and later observations were reserved for out-of-time testing. Hyperparameters were selected according to cross-validated predictive performance rather than in-sample fit. All preprocessing operations, including imputation, scaling, and feature selection, were performed separately within each resampling cycle to prevent test information from influencing the trained models.

The artificial neural network was specified as a multilayer feedforward network in which the study predictors formed the input layer, one or more hidden layers learned nonlinear combinations of the predictors, and a single output node estimated the financial-flexibility score. The number of hidden layers, number of neurons in each layer, activation functions, learning rate, batch size, and regularization parameters were determined through systematic hyperparameter tuning. Nonlinear activation functions were used in the hidden layers, while a linear activation function was used in the output layer because financial flexibility was modeled as a continuous outcome. Network weights were optimized through backpropagation using an adaptive gradient-based optimizer. To reduce overfitting, the modeling procedure incorporated regularization techniques such as dropout, weight penalties, early stopping, or a combination of these procedures. Training was terminated when validation error no longer improved over a predefined sequence of iterations. Because neural-network results may vary according to random initialization, the model was estimated repeatedly with controlled random seeds, and its average out-of-sample performance was considered in the final evaluation.

XGBoost was used as the principal tree-based machine-learning model. The algorithm sequentially generated regression trees, with each tree focusing on residual errors that remained after the preceding trees had been fitted. The final prediction was obtained by aggregating the contributions of all trees. The principal XGBoost hyperparameters included the number of boosting rounds, maximum tree depth, learning rate, minimum child weight, subsampling ratio, proportion of predictors sampled for each tree, and the L1 and L2 regularization parameters. These parameters were optimized through cross-validation within the training set. Early stopping was applied to terminate the boosting process when additional trees did not improve validation performance. This procedure limited unnecessary model complexity and reduced the likelihood of overfitting. XGBoost was particularly suitable for the study because it could accommodate nonlinear effects, complex interactions, mixed measurement scales, and potentially asymmetric relationships between the predictors and financial flexibility.

Predictive performance was assessed using regression evaluation criteria calculated for the independent test data. The principal indices included the root mean squared error, mean absolute error, mean squared error, and coefficient of determination. Root mean squared error assigned relatively greater penalties to large prediction errors, while mean absolute error provided an interpretable estimate of the average absolute difference between observed and predicted financial-flexibility values. The coefficient of determination indicated the proportion of out-of-sample variation in financial flexibility explained by each model. Model selection was based primarily on lower prediction errors and a higher out-of-sample coefficient of determination. Cross-validation results were also considered to determine whether predictive performance was stable across different subsets of companies. The artificial neural network and XGBoost results were compared to determine whether the ranking of predictors remained consistent across distinct modeling frameworks.

The factors affecting financial flexibility were ranked using model-interpretation techniques rather than relying exclusively on raw algorithmic coefficients. For XGBoost, initial importance measures were obtained from the reduction in prediction error attributable to splits involving each predictor. Because traditional tree-based importance measures may be biased toward variables with more potential split points, permutation importance and Shapley Additive Explanations were used to generate more reliable rankings. Permutation importance quantified the increase in test-set prediction error after the values of a predictor were randomly rearranged while all other variables were left unchanged. A larger deterioration in performance indicated that the predictor made a greater contribution to accurate prediction. Shapley Additive Explanations assigned each predictor a contribution value for every firm-year prediction and enabled both global and observation-specific interpretation. Global importance was calculated using the mean absolute SHAP value of each variable across the analyzed observations. Predictors with larger mean absolute SHAP values were ranked as more influential determinants of financial flexibility. SHAP dependence patterns were additionally examined to determine whether each factor increased or decreased predicted financial flexibility and whether its effect changed at particular threshold levels.

The importance of predictors in the artificial neural network was evaluated using model-agnostic permutation procedures and, where applicable, SHAP values adapted to neural-network models. This approach enabled the study to compare factor rankings across the neural network and XGBoost without treating the magnitude of individual network weights as a direct measure of substantive importance. A consolidated ranking was developed by comparing the normalized importance scores generated by the two models. Factors that received consistently high importance scores in both algorithms were interpreted as robust determinants of financial flexibility, whereas variables with unstable rankings were interpreted more cautiously. Partial-dependence or accumulated-local-effect analyses were used when necessary to illustrate nonlinear relationships and threshold effects. Interaction effects identified by the machine-learning models were also examined to determine whether the influence of one factor, such as managerial ability or default risk, depended on another organizational condition, such as environmental uncertainty or board financial expertise.

To assess the reliability of the findings, sensitivity analyses were conducted using alternative data partitions, repeated cross-validation, alternative specifications of financial flexibility, and different treatments of extreme values. Model performance and variable rankings were compared across these specifications. The conclusions were regarded as robust when the principal predictors retained similar positions and directional patterns across the artificial neural network, XGBoost, and alternative analytical settings. Statistical programming environments capable of implementing machine-learning and explainable-artificial-intelligence procedures were used for data preprocessing, model estimation, hyperparameter optimization, evaluation, and interpretation. Throughout the analytical process, particular attention was given to preventing data leakage, controlling overfitting, preserving the longitudinal structure of the observations, and distinguishing predictive importance from conventional statistical causality.

3. Findings and Results

Descriptive statistics were first examined to determine the central tendency, dispersion, range, skewness, and kurtosis of the research variables. Because the number of valid observations differed across variables, the analyses were based on all available firm-year observations for each measure.

Table 1. Descriptive Statistics of the Research Variables

Variable	N	Mean	Median	SD	Minimum	Maximum	Skewness	Kurtosis
Market power	2,025	0.173	0.149	0.260	−2.796	3.715	−0.658	37.020
Political connections	1,485	0.344	0.000	0.475	0.000	1.000	0.656	−1.569
Default risk	2,025	0.958	0.792	0.854	0.031	14.239	6.624	69.432
Environmental uncertainty	2,025	0.141	0.136	0.681	−15.460	6.853	−13.236	294.033
Managerial ability	2,025	0.140	0.116	0.182	−1.189	2.101	0.563	8.745
CEO power	1,547	0.484	0.000	0.500	0.000	1.000	0.063	−1.996
Management turnover	1,759	0.076	0.000	0.264	0.000	1.000	3.211	8.307
Managerial overconfidence	1,491	0.717	1.000	0.451	0.000	1.000	−0.963	−1.072
Board financial expertise	1,755	0.002	0.000	0.048	0.000	1.000	20.875	433.752
Liquidity	1,487	0.074	0.041	0.090	0.000	0.609	2.512	7.652
Return on assets	1,487	0.147	0.125	0.189	−1.189	0.709	−0.355	3.995
Firm size	1,487	14.849	14.566	1.745	10.492	21.572	0.764	0.764
Financial leverage	1,487	0.624	0.577	0.389	0.025	3.852	3.963	24.529
Market-to-book ratio	1,390	5.311	3.942	4.918	−4.795	25.582	1.598	2.821

Default risk had a mean of 0.958 and a median of 0.792. Its pronounced positive skewness of 6.624 and kurtosis of 69.432 indicate that most observations were concentrated at relatively low or moderate levels, whereas a limited number of firms had exceptionally high default-risk values. Political connections had a mean of 0.344, indicating that approximately 34.4% of the observations were associated with politically connected companies. Because this variable was binary, its median of zero shows that the majority of the observations did not involve an identified political connection.

Environmental uncertainty had a mean of 0.141 but exhibited a particularly broad range, from −15.460 to 6.853. Its skewness of −13.236 and kurtosis of 294.033 indicate extreme asymmetry and heavy tails, consistent with substantial instability and the presence of unusual observations in firms' operating environments. Managerial ability had a mean of 0.140, a median of 0.116, and a standard deviation of 0.182. Its comparatively moderate skewness suggested a more balanced distribution than default risk or environmental uncertainty.

The mean market-power score was 0.173. Although its skewness was moderately negative, its kurtosis of 37.020 indicated that most companies were concentrated within a relatively narrow portion of the distribution, accompanied by a small number of extreme market-power observations. Managerial overconfidence had a mean of 0.717, indicating that this behavioral characteristic was present in approximately 71.7% of the relevant observations. CEO power had a mean of 0.484, suggesting that concentrated chief-executive authority characterized approximately half of the observations. Management turnover was comparatively uncommon, with a mean of 0.076, while board financial expertise had a mean of only 0.002 and extremely high skewness and kurtosis. Thus, the coded form of financial expertise was almost entirely concentrated at zero.

Among the financial control variables, average liquidity was 0.074, average return on assets was 0.147, average financial leverage was 0.624, and the average market-to-book ratio was 5.311. The positive skewness of liquidity, leverage, and the market-to-book ratio indicated that a limited number of observations had substantially higher values than the remainder of the sample.

The pairwise association between variables was evaluated through the Pearson correlation coefficient:

$$r_{XY} = \frac{\sum_{i=1}^{n}(X_i - \bar{X})(Y_i - \bar{Y})}{\sqrt{\sum_{i=1}^{n}(X_i - \bar{X})^2}\sqrt{\sum_{i=1}^{n}(Y_i - \bar{Y})^2}}$$

where r_{XY} represents the correlation between variables X and Y, and $\bar{X}$ and $\bar{Y}$ represent their respective means.

Table 2. Correlation Matrix of the Principal Research Variables

Variable	MP	PC	DR	EU	MA	CP	MT	MO	FE	FF
Market power (MP)	1.00	0.06	−0.39	0.53	0.62	−0.07	−0.23	0.39	−0.01	0.25
Political connections (PC)	0.06	1.00	−0.03	0.07	0.10	−0.05	0.02	0.01	−0.02	0.13
Default risk (DR)	−0.39	−0.03	1.00	−0.57	−0.47	0.07	0.32	−0.25	0.00	−0.22
Environmental uncertainty (EU)	0.53	0.07	−0.57	1.00	0.44	−0.01	−0.28	0.18	−0.00	0.19
Managerial ability (MA)	0.62	0.10	−0.47	0.44	1.00	−0.06	−0.26	0.43	−0.02	0.44
CEO power (CP)	−0.07	−0.05	0.07	−0.01	−0.06	1.00	0.03	−0.07	0.03	−0.05
Management turnover (MT)	−0.23	0.02	0.32	−0.28	−0.26	0.03	1.00	−0.07	−0.01	−0.08
Managerial overconfidence (MO)	0.39	0.01	−0.25	0.18	0.43	−0.07	−0.07	1.00	0.02	0.12
Board financial expertise (FE)	−0.01	−0.02	0.00	−0.00	−0.02	0.03	−0.01	0.02	1.00	−0.01
Financial flexibility (FF)	0.25	0.13	−0.22	0.19	0.44	−0.05	−0.08	0.12	−0.01	1.00

The correlation coefficients were generally low to moderate, and no coefficient exceeded the conventional thresholds of 0.70 or 0.80. The largest positive correlation was observed between market power and managerial ability, $r = 0.62$. Thus, firms characterized by greater managerial ability also tended to hold stronger market positions. Market power was also positively correlated with environmental uncertainty, $r = 0.53$, and managerial overconfidence, $r = 0.39$.

Default risk was negatively correlated with environmental uncertainty, $r = -0.57$, managerial ability, $r = -0.47$, and market power, $r = -0.39$. It was positively correlated with management turnover, $r = 0.32$, suggesting that greater financial distress risk was accompanied by a higher incidence of changes in senior management.

Financial flexibility had its strongest correlation with managerial ability, $r = 0.44$. It was also positively correlated with market power, $r = 0.25$, environmental uncertainty, $r = 0.19$, political connections, $r = 0.13$, and managerial overconfidence, $r = 0.12$. In contrast, financial flexibility was negatively correlated with default risk, $r = -0.22$, management turnover, $r = -0.08$, CEO power, $r = -0.05$, and board financial expertise, $r = -0.01$. These coefficients describe the direction and strength of the bivariate relationships and do not, by themselves, determine the nonlinear predictive importance identified by the machine-learning models.

The variance inflation factor for predictor $j$was computed as:

$$VIF_j = \frac{1}{1 - R_j^2}$$

where $R_j^2$is the coefficient of determination obtained by regressing predictor $j$on the other predictors. Values approaching one indicate limited overlap, whereas substantially larger values indicate increasing multicollinearity.

Table 3. Variance Inflation Factors for the Predictor Variables

Predictor	VIF	Assessment
Market power	1.961	Acceptable
Managerial ability	1.934	Acceptable
Environmental uncertainty	1.803	Acceptable
Default risk	1.679	Acceptable
Managerial overconfidence	1.295	Acceptable
Management turnover	1.154	Acceptable
Political connections	1.018	Acceptable
CEO power	1.014	Acceptable
Board financial expertise	1.002	Acceptable

All variance inflation factors were below 2.00. Market power had the highest value, $VIF = 1.961$, followed by managerial ability, $VIF = 1.934$, environmental uncertainty, $VIF = 1.803$, and default risk, $VIF = 1.679$. The remaining variables had values close to one. These findings were consistent with the correlation matrix and indicated that none of the variables created severe redundancy. Accordingly, all predictors were retained in the machine-learning analyses.

The XGBoost prediction for observation $i$can be expressed as the additive contribution of Msequential trees:

$$\hat{y}_i = \sum_{m=1}^{M} \eta\, f_m(\mathbf{x}_i)$$

where $f_m$is the prediction generated by tree m, and $\eta$is the learning rate. The normalized importance of predictor $j$was calculated as:

$$I_j^{XGB} = \frac{G_j}{\sum_{k=1}^{p} G_k}$$

where $G_j$is the predictive gain attributable to predictor j. Consequently, the XGBoost importance scores sum approximately to one.

Default risk received the highest normalized importance score, 0.232957, and was therefore the most influential predictor of financial flexibility. The result indicates that a firm's credit condition and its ability to meet financial obligations were central to its capacity to preserve liquidity, maintain borrowing capacity, and react to financial shocks. Greater default risk restricted access to new financing and reduced the company's capacity to respond to investment opportunities.

Political connections ranked second, with an importance score of 0.191638. Thus, access to political and governmental networks provided considerable predictive information regarding financial flexibility. Such connections may influence access to credit, institutional support, preferential facilities, informal information, and other resources, particularly in an emerging capital-market environment.

Environmental uncertainty ranked third, with an importance score of 0.155890. This result indicates that volatility in economic conditions, policies, exchange rates, sales, and other environmental conditions contributed substantially to variations in financial flexibility. Companies operating under greater uncertainty may maintain more cash, exercise greater control over debt, and avoid excessively risky investments to preserve their capacity to withstand future shocks.

Managerial ability ranked fourth, with an importance score of 0.132346, while market power ranked fifth, with a score of 0.116733. These results demonstrate that resource-allocation efficiency, cash-flow management, cost control, competitive position, pricing capacity, and the stability of operating cash flows were important predictors of financial flexibility.

Managerial overconfidence ranked sixth, with an importance score of 0.096703. Its moderate predictive importance reflects the potentially nonlinear nature of this behavioral characteristic. Overconfident managers may act decisively and exploit investment opportunities, but they may also accept unnecessary risks, overinvest, or exhaust liquid resources.

CEO power and management turnover had lower importance scores of 0.043320 and 0.030414, respectively. These characteristics therefore made relatively limited contributions when compared with credit, institutional, environmental, and competitive conditions. Board financial expertise had an XGBoost importance score of zero, indicating that it did not provide additional predictive gain after the remaining variables were considered.

The prediction generated for observation $i$was decomposed using SHAP values as:

$$\hat{f}(\mathbf{x}_i) = \phi_0 + \sum_{j=1}^{p} \phi_{ij}$$

where $\phi_0$is the baseline prediction and $\phi_{ij}$is the contribution of predictor $j$to the prediction for observation i. Global SHAP importance was calculated as:

$$I_j^{SHAP} = \frac{1}{n}\sum_{i=1}^{n} | \phi_{ij} |$$

A larger mean absolute SHAP value indicates that changes in a variable generate larger changes in model output.

The XGBoost SHAP distribution confirmed the dominant role of default risk. Low default-risk observations were predominantly positioned on the positive side of the SHAP axis and increased predicted financial flexibility, whereas high default-risk observations were concentrated around zero or on the negative side. Thus, lower default risk contributed positively to the estimated capacity of firms to retain financial flexibility.

After default risk, the broadest SHAP distributions were associated with managerial ability, market power, and environmental uncertainty. High managerial-ability values were predominantly associated with positive SHAP values, indicating that stronger managerial ability increased predicted financial flexibility. Market power and environmental uncertainty also generated meaningful changes in model output, although the direction and magnitude of their effects varied across observations, reflecting nonlinear and potentially threshold-dependent relationships.

Political connections, managerial overconfidence, CEO power, management turnover, and board financial expertise displayed more concentrated SHAP distributions around zero. Consequently, these variables made smaller observation-specific contributions in the SHAP interpretation than default risk, managerial ability, market power, and environmental uncertainty. The difference between the normalized XGBoost gain ranking and the SHAP distribution reflects the fact that gain measures the improvement produced by tree splits, whereas SHAP values quantify the contribution of a predictor to individual model outputs.

The output of the feedforward artificial neural network can be represented as:

$$\hat{y}_i = b_0 + \sum_{h=1}^{H} v_h \, g\left(b_h + \sum_{j=1}^{p} w_{hj} \, x_{ij}\right)$$

where x_{ij} is predictor j for observation i, w_{hj} is the weight connecting an input to hidden neuron h, v_h is the output weight, b_h and b_0 are bias terms, and $g(\cdot)$ is the hidden-layer activation function.

The loss function used to evaluate learning was the mean squared error:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2$$

The reported training histories showed substantial reductions in both training and validation errors. In the 100-epoch run, training MSE began at approximately 0.235, decreased sharply during the initial epochs, and reached approximately 0.043 at the end of training. Validation MSE decreased from approximately 0.098 to approximately 0.062. Both curves became comparatively stable after approximately 20–30 epochs.

A second recorded training trace covering 64 epochs produced a similar pattern. Training MSE decreased from approximately 0.119 to 0.045, while validation MSE declined from approximately 0.088 to 0.062. Validation loss stabilized after approximately the twentieth epoch, whereas training loss continued to decline gradually.

The small increase in the distance between the training and validation curves during the later epochs suggested mild overfitting. Nevertheless, validation loss did not exhibit a sustained upward trend, the difference between the two curves remained limited, and no substantial instability or divergence was observed. The model therefore achieved satisfactory convergence and maintained acceptable generalizability to observations not used in weight optimization.

The mean absolute SHAP results for the neural network identified default risk as the leading predictor, with a value of approximately 0.074. Managerial ability ranked second at approximately 0.045, followed by market power at approximately 0.029, political connections at approximately 0.025, and environmental uncertainty at approximately 0.019. Managerial overconfidence had a mean absolute SHAP value of approximately 0.016. Management turnover and CEO power had substantially lower values of approximately 0.007 and 0.006, respectively, while board financial expertise had an approximately zero contribution.

The neural-network decision path similarly showed that default risk produced the largest shift from the baseline prediction toward the final predicted output. Managerial ability and market power produced the next largest changes, followed by environmental uncertainty and political connections. After the inclusion of CEO power, managerial overconfidence, management turnover, and financial expertise, the predicted value changed only slightly. The decision path therefore supported the global mean absolute SHAP ranking.

Because normalized XGBoost importance and mean absolute neural-network SHAP values are measured on different scales, their magnitudes should not be directly equated. Their rankings, however, provide a meaningful comparison of the relative ordering of predictors.

Table 4. Comparison of Factor Importance and Ranking in XGBoost and the Artificial Neural Network

Factor	XGBoost Importance	XGBoost Rank	ANN Mean SHAP Value	ANN Rank
Default risk	0.232957	1	0.074	1
Political connections	0.191638	2	0.025	4
Environmental uncertainty	0.155890	3	0.019	5
Managerial ability	0.132346	4	0.045	2
Market power	0.116733	5	0.029	3
Managerial overconfidence	0.096703	6	0.016	6
CEO power	0.043320	7	0.006	8
Management turnover	0.030414	8	0.007	7
Board financial expertise	0.000000	9	0.000	9

Both algorithms placed default risk in first position and board financial expertise in ninth position. They also assigned managerial overconfidence the same sixth-place ranking. This agreement at the highest, middle, and lowest portions of the ranking supports the stability of the findings.

The principal differences occurred among the moderately influential variables. The neural network placed managerial ability second, whereas XGBoost placed it fourth. Market power was third in the neural network and fifth in XGBoost. Conversely, political connections ranked second in XGBoost but fourth in the neural network, while environmental uncertainty ranked third in XGBoost and fifth in the neural network.

The algorithms also differed slightly in their ordering of the least influential managerial variables. XGBoost placed CEO power seventh and management turnover eighth, whereas the neural network reversed these positions. Nevertheless, both methods indicated that these variables made relatively limited contributions. Collectively, the results demonstrate that default risk was the most stable and dominant predictor, while managerial ability, market power, political connections, and environmental uncertainty formed the second tier of influential factors.

The predictive accuracy of the models was evaluated through the coefficient of determination and root mean squared error:

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}$$

Higher R^2values indicate greater explanatory and predictive capacity, whereas lower RMSE values indicate smaller prediction errors.

Table 5. Ranking of the Predictive Performance of the Models

Rank	Model	$\boldsymbol{R^2}$	RMSE
1	Artificial neural network	0.499	0.179
2	XGBoost	0.413	0.194

The artificial neural network achieved the best predictive performance. Its coefficient of determination of 0.499 indicates that it accounted for approximately 49.9% of the observed variation in financial flexibility. It also produced the lowest prediction error, with an RMSE of 0.179.

XGBoost ranked second, with $R^2 = 0.413$and $RMSE = 0.194$. Although XGBoost demonstrated acceptable predictive performance, its coefficient of determination was lower and its prediction error was higher than those of the neural network. The neural network reduced RMSE by approximately 7.7% relative to XGBoost:

$$\frac{0.194 - 0.179}{0.194} \times 100 \approx 7.7\%$$

The superior performance of the artificial neural network indicates that its hidden-layer structure was more effective in learning the nonlinear relationships and interactions among the financial, managerial, institutional, and environmental predictors. Accordingly, the ANN ranking may be regarded as the principal predictive ranking, while the broad agreement between ANN and XGBoost confirms that the identification of the most and least influential factors was not dependent on a single algorithm.

Overall, the findings answered the research questions by demonstrating that both artificial neural networks and XGBoost were capable of ranking the determinants of financial flexibility. Default risk was the most important factor in both models. Managerial ability and market power were particularly prominent in the neural network, whereas political connections and environmental uncertainty received greater relative importance in XGBoost. Managerial overconfidence occupied an intermediate position, while CEO power, management turnover, and especially board financial expertise made comparatively limited predictive contributions. The artificial neural network provided the more accurate prediction of financial flexibility because it combined the highest coefficient of determination with the lowest RMSE.

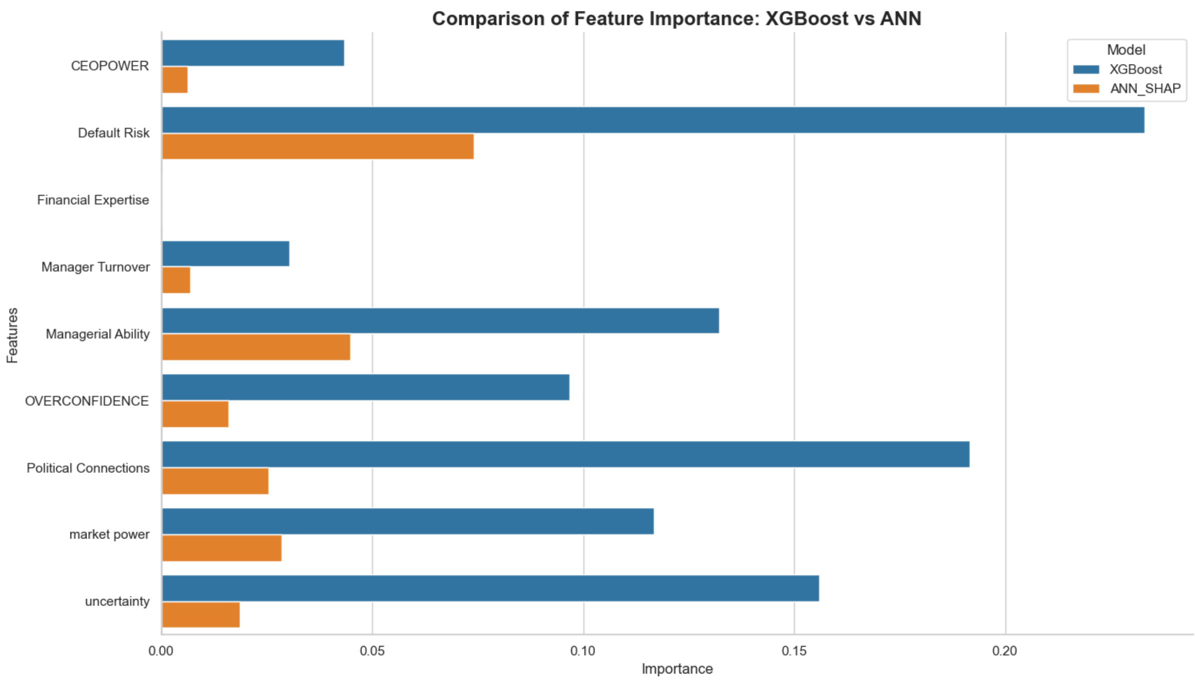

Figure 1. Comparison of Feature Importance (XGBoost vs ANN)

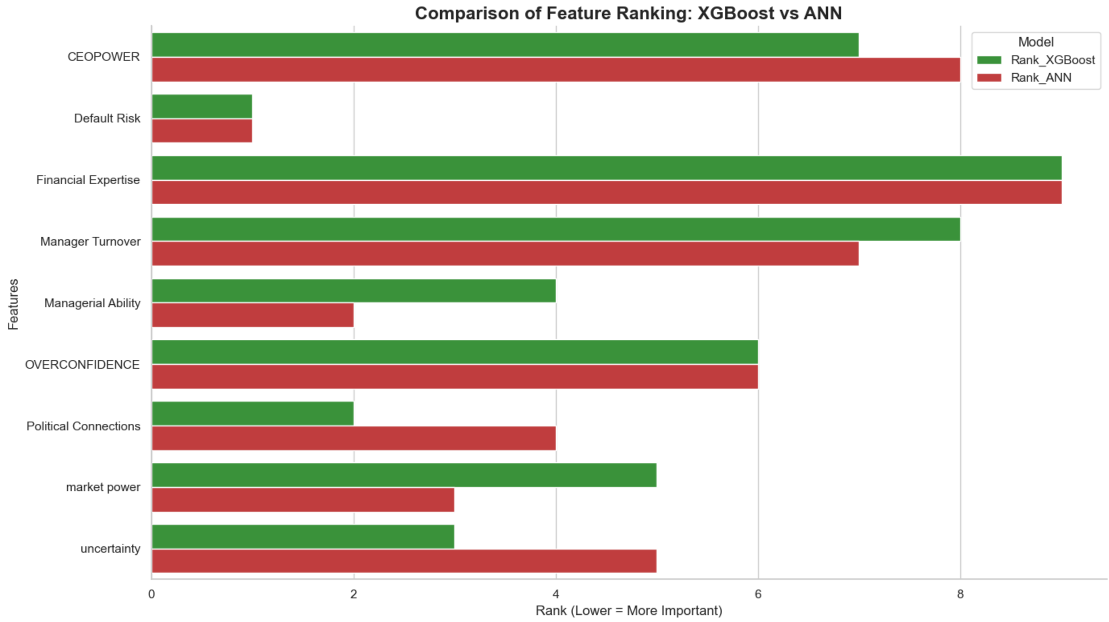

Figure 2. Comparison of Feature Ranking (XGBoost vs ANN)

4. Discussion and Conclusion

The present study aimed to identify and rank the factors affecting the financial flexibility of companies listed on the Tehran Stock Exchange and Iran Fara Bourse through artificial neural networks and the XGBoost machine-learning algorithm. The findings demonstrated that both models were capable of detecting meaningful nonlinear patterns among the financial, managerial, institutional, and environmental variables. However, the artificial neural network achieved stronger predictive performance, with a coefficient of determination of 0.499 and an RMSE of 0.179, compared with an (R^2) of 0.413 and an RMSE of 0.194 for XGBoost. The neural-network training and validation errors declined during the learning process and stabilized after the initial epochs, while the relatively limited gap between the two curves indicated that the model did not experience severe overfitting. These results suggest that financial flexibility is shaped by complex and interconnected mechanisms that are not adequately represented through purely linear relationships. This interpretation is consistent with the broader view that financial flexibility is a multidimensional strategic capability resulting from the interaction of capital structure, liquidity, managerial decision-making, market conditions, and exposure to uncertainty [1, 2].

The most important and stable finding was that default risk ranked first in both the artificial neural network and XGBoost models. In XGBoost, default risk received the highest normalized importance score, while the neural-network SHAP results similarly identified it as the variable with the largest contribution to predicted financial flexibility. The direction of the SHAP values further showed that lower default risk increased predicted financial flexibility, whereas higher levels weakened it. This result can be explained by the direct relationship between creditworthiness and access to financing. When a company faces a high probability of failing to meet its obligations, creditors tend to impose higher financing costs, more restrictive covenants, shorter maturities, and greater collateral requirements. Consequently, the company's unused debt capacity is reduced, and its ability to obtain emergency funds or finance profitable investment opportunities is weakened. This finding is consistent with evidence showing that increasing default risk restricts access to credit and reduces the range of available financing choices [9]. It also agrees with the argument that firms preserve financial flexibility partly by maintaining conservative leverage and unused borrowing capacity for future needs [6].

The dominant role of default risk also corresponds with studies conducted during periods of major economic disruption. Firms that entered the COVID-19 crisis with lower leverage, greater cash holdings, and stronger debt capacity were more capable of maintaining investment and operating performance when revenues declined abruptly [4]. Similarly, debt-free and low-debt firms experienced fewer financing constraints during the pandemic and were better able to use their available borrowing capacity in response to the shock [5]. These findings support the conclusion that default risk is not merely an indicator of current financial weakness but a constraint on future strategic action. A company with low default risk retains a wider set of financing options and can respond more effectively to unexpected investment opportunities, demand contractions, or liquidity pressures. The present findings therefore reinforce the view that preserving credit quality is central to maintaining financial flexibility.

Managerial ability was another highly influential factor, ranking second in the artificial neural network and fourth in XGBoost. The SHAP results indicated that higher managerial ability was generally associated with an increase in predicted financial flexibility. This relationship is theoretically reasonable because capable managers can allocate corporate resources more efficiently, forecast cash-flow needs more accurately, control operating and financing costs, and determine an appropriate balance between cash holdings and leverage. The measurement framework developed for managerial ability emphasizes the extent to which managers generate revenue from available resources after controlling for structural firm characteristics [11]. Accordingly, firms led by more capable managers are likely to generate stronger internal funds and make more efficient financing and investment decisions.

The finding concerning managerial ability is consistent with research indicating that managerial characteristics, strategic competence, and financial decision-making skills contribute to corporate financial flexibility, particularly in emerging economies [12]. It also supports the argument that managers with a long-term orientation are more likely to design capital structures that preserve resilience rather than maximize short-term borrowing benefits [13]. Such managers may deliberately maintain unused debt capacity, control distributions, and retain liquidity to ensure that the firm can react to future uncertainty. The higher ranking of managerial ability in the neural network than in

XGBoost may indicate that its influence operates through interactions with other variables, such as market power, environmental uncertainty, and default risk. Neural networks are particularly capable of capturing such distributed nonlinear relationships, which may explain why the importance of managerial ability was more pronounced in that model.

Market power was ranked third by the artificial neural network and fifth by XGBoost, indicating that a strong competitive position contributes substantially to financial flexibility. Firms with greater market power may generate more stable revenues, sustain higher margins, and exercise greater discretion over prices. These characteristics support internal financing and reduce dependence on external capital markets. The positive importance of market power is consistent with evidence that stronger competitive positions improve corporate financial stability and strengthen the capacity of firms to withstand changes in demand and production costs [10]. Stable cash flows also make it easier for companies to preserve creditworthiness and negotiate favorable financing terms.

The relationship between market power and financial flexibility may also operate indirectly through investment efficiency and profitability. Financial flexibility creates value when firms use available resources efficiently rather than simply maintaining excess liquidity or debt capacity [3]. Companies with stronger market positions may have more profitable investment opportunities and greater ability to finance those opportunities internally. The findings of Almomani and colleagues similarly showed that profitability, cash holdings, tangible assets, and capital structure are significant determinants of financial flexibility [7]. Therefore, market power can improve financial flexibility by stabilizing operating performance, supporting internal cash generation, and reducing the probability that temporary market disruptions will translate into financing constraints.

Political connections were highly important in XGBoost, where they ranked second, but occupied fourth place in the artificial neural network. This difference suggests that political connections had substantial predictive relevance but that their influence may have been conditional on other institutional and company-level characteristics. Politically connected firms may obtain easier access to bank loans, government contracts, regulatory support, tax advantages, or informal information. These benefits can reduce financing constraints and increase the firm's capacity to respond to financial shocks. This interpretation is consistent with evidence showing that firms may develop political connections to obtain economic benefits and access resources controlled by governmental institutions [16]. It also agrees with findings that political connections can support firm performance under uncertainty by providing institutional protection and facilitating access to scarce resources [17].

Nevertheless, political connections may not always strengthen genuine internal financial capacity. Firms that depend heavily on institutional support may have less incentive to improve operating efficiency, risk management, or financial discipline. Political connections may also expose firms to changes in government, regulation, or the allocation of public resources. The difference between the XGBoost and neural-network rankings may therefore reflect the asymmetric nature of this variable. Political connections may produce strong predictive splits in tree-based models because the variable distinguishes connected from non-connected firms, while their broader effect in the neural network may be moderated by default risk, managerial ability, and market power. The results suggest that political connections are relevant to financial flexibility, but their contribution is less stable than the influence of default risk.

Environmental uncertainty ranked third in XGBoost and fifth in the artificial neural network. This result indicates that instability in sales, economic conditions, regulation, exchange rates, and market demand affects the financial policies adopted by firms. Under uncertain conditions, companies may increase cash holdings, limit leverage, postpone investment, and preserve unused financing capacity as precautionary responses. Research has shown that environmental uncertainty influences managerial discretion and organizational financial behavior [18]. The present findings similarly indicate that uncertainty changes the importance of liquidity, borrowing capacity, and managerial adaptation.

Environmental uncertainty may have both positive and negative implications for financial flexibility. On the one hand, it increases the demand for precautionary cash and conservative capital structures. On the other hand, persistent instability can weaken profitability, increase financing costs, and reduce access to credit. The relatively high ranking of uncertainty in XGBoost may therefore reflect threshold effects: moderate uncertainty may encourage firms to preserve flexibility, whereas extreme uncertainty may erode the resources required to maintain it. The importance of organizational readiness and digital financial innovation in improving financial adaptability further supports the view that companies require internal capabilities to respond effectively to uncertain environments [19]. Firms with effective information systems, adaptive structures, and timely financial data may convert uncertainty into precautionary preparedness, while less capable firms may experience declining flexibility.

Managerial overconfidence had a moderate level of importance and ranked sixth in both models. This convergence indicates that behavioral characteristics contribute to financial flexibility but are less influential than default risk, managerial ability, market power, political connections, and environmental uncertainty. Overconfident managers may believe that future cash flows will be stronger than external assessments suggest and may consequently undertake more investment or rely more heavily on internal financing. Prior research has shown that managerial overconfidence affects corporate investment decisions and the use of internal resources [14]. The present findings suggest that this behavior has a nonlinear influence. Moderate confidence may support decisive action and exploitation of investment opportunities, whereas excessive confidence may result in overinvestment, depletion of cash reserves, and greater financial risk. This dual effect likely explains why the variable contributed meaningfully to prediction without ranking among the dominant factors.

CEO power and management turnover were among the least influential variables in both models. Their limited importance indicates that the concentration of authority in the chief executive or a change in senior management does not independently determine financial flexibility to the same extent as credit risk, managerial efficiency, institutional access, or market conditions. CEO power may affect financial policies, but its consequences depend on governance quality, board oversight, ownership structure, and the manager's competence. Similarly, management turnover may create temporary uncertainty or lead to changes in financing strategy, but its direct contribution is likely to be limited unless it is associated with financial distress or strategic restructuring. The low ranking of these variables does not imply that they are irrelevant; rather, their effects may be indirect and embedded within broader governance and managerial mechanisms.

Board financial expertise had the lowest importance in both algorithms and produced virtually no additional predictive contribution. This finding may appear inconsistent with the expectation that directors with financial knowledge improve oversight of liquidity, leverage, and risk. Research has shown that accounting expertise among board or audit-committee members can influence reporting quality and conservative financial practices [15]. However, the effect of expertise depends on whether directors possess sufficient authority, independence, and access to reliable information. In the present sample, the very low prevalence and limited variation of the financial-expertise variable may have reduced its ability to differentiate firms. It is also possible that formal financial qualifications alone do not improve flexibility unless they are translated into effective governance and financing decisions. Therefore, the result should be interpreted as evidence of limited incremental predictive power in this dataset rather than as proof that financial knowledge has no organizational value.

The superior predictive performance of the artificial neural network indicates that the determinants of financial flexibility operate through complex nonlinear and interactive pathways. The model explained approximately 49.9% of the observed variation and generated a lower RMSE than XGBoost. This result suggests that the hidden layers of the network captured patterns that were not fully represented by sequential decision trees. Nevertheless, XGBoost also achieved acceptable performance and produced a broadly consistent ranking at the highest and lowest levels. Both models identified default risk as the leading factor and board financial expertise as the least important variable. This convergence increases confidence in the robustness of the central findings. The different rankings of political connections, environmental uncertainty, managerial ability, and market power further demonstrate the value of comparing algorithms rather than relying on a single predictive framework.

Overall, the findings are consistent with the view that financial flexibility results from a combination of credit quality, internal managerial capability, competitive strength, institutional access, and environmental adaptation. Liquidity and capital-structure decisions remain central because they determine the resources available for responding to opportunities and shocks [8]. At the same time, the results show that financial flexibility cannot be understood solely through accounting ratios. It is also influenced by managerial competence, political and institutional relationships, behavioral characteristics, and environmental instability. The results therefore extend prior work on corporate financial flexibility by demonstrating that machine-learning models can rank these factors, reveal their unequal predictive contributions, and identify nonlinear relationships that may remain hidden in conventional linear analyses.

The study was subject to several limitations. First, the sample was restricted to companies listed on the Tehran Stock Exchange and Iran Fara Bourse, and the results may not be directly generalizable to privately held firms, financial institutions, small enterprises, or companies operating in other institutional environments. Second, the measurement of some variables depended on publicly disclosed information, and characteristics such as political connections, managerial overconfidence, CEO power, and board expertise may not have been fully captured by the available indicators. Third, the study covered a limited period and may have been influenced by exceptional macroeconomic and regulatory conditions. Fourth, although machine-learning models provide strong predictive capacity, variable importance should not be interpreted as proof of causality. Finally, differences in the number of available observations across variables and the limited variation in some binary measures, particularly board financial expertise, may have affected their predictive rankings.

Future studies should examine the determinants of financial flexibility over longer time periods and compare stable, crisis, and post-crisis economic conditions. Researchers could replicate the analysis in other emerging and developed capital markets to determine whether the ranking of factors changes across institutional settings. Additional predictors such as ownership concentration, corporate governance quality, cash-flow volatility, debt maturity, financing constraints, innovation intensity, macroeconomic uncertainty, inflation, and exchange-rate exposure could be incorporated. Future research could also employ panel-aware deep-learning models, random forests, support-vector machines, and ensemble stacking methods and compare their predictive performance with the present algorithms. Causal-inference methods could be combined with machine learning to distinguish predictive importance from causal effects. More detailed measures of directors' expertise, political relationships, managerial incentives, and behavioral biases would also improve the precision of future analyses.

Corporate managers should treat default-risk control as the primary foundation of financial flexibility by maintaining sustainable leverage, preserving debt-servicing capacity, monitoring credit indicators, and avoiding the premature exhaustion of borrowing capacity. Firms should also strengthen managerial ability through executive selection, professional development, data-based financial planning, and performance evaluation focused on resource efficiency. Companies with weak market positions should improve revenue stability, product differentiation, and operating efficiency rather than relying solely on external financing. Political and institutional relationships should be used to facilitate legitimate access to resources without creating dependency or weakening financial discipline. Firms operating under high environmental uncertainty should maintain adequate liquidity, develop contingency financing plans, adopt real-time financial monitoring systems, and conduct regular stress tests. Boards should ensure that financial expertise is accompanied by genuine authority, independence, and active participation in liquidity, investment, and capital-structure decisions.

Authors' Contributions

Authors equally contributed to this article.

Ethical Considerations

All procedures performed in this study were under the ethical standards.

Acknowledgments

Authors thank all participants who participate in this study.

Conflict of Interest

The authors report no conflict of interest.

Funding/Financial Support

According to the authors, this article has no financial support.

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