



## Assessing AI and Decision-Making Impacts on GCC Bank Efficiency through a Neutrosophic Lens

Aya Merhi<sup>1,\*</sup>, Chadi Baalbaki<sup>2</sup>

<sup>1</sup>Faculty of Business and Economics, Lebanese University, Beirut, Lebanon

<sup>2</sup>College of Business Administration, American University of the Middle East, Kuwait

Emails: [a.merhi.2@st.ul.edu.lb](mailto:a.merhi.2@st.ul.edu.lb); [chadi.baalbaki@aum.edu.kw](mailto:chadi.baalbaki@aum.edu.kw)

### Abstract

The Gulf Cooperation Council (GCC) banking sector has experienced rapid digital transformation, regulatory shifts, and disruptions in recent years, especially during periods of crisis and recovery. Despite extensive studies on banking efficiency, there remains uncertainty and inconsistency regarding which bank-specific factors most influence performance. Traditional models often assume deterministic relationships, overlooking the indeterminate and ambiguous nature of real-world decision environments. Guided by Neutrosophic theory, this study reinterprets efficiency as a state influenced simultaneously by degrees of truth, falsity, and indeterminacy, acknowledging that the impact of Artificial Intelligence (AI) and Data-Driven Decision Making (DDDM) on efficiency may vary across contexts and times. The study analyzes 43 banks from six GCC countries between 2010 and 2024. In the first stage, efficiency is estimated using Data Envelopment Analysis (DEA). In the second stage, panel regression models are applied to examine the influence of bank-specific factors, including AI adoption, capital adequacy (CAR), asset quality (NPL), returns (ROA, ROI), branch footprint, and bank age. Within a Neutrosophic theoretical lens, these relationships are interpreted not as fixed or absolute but as having degrees of certainty and uncertainty that coexist within the decision environment. Findings reveal significant variation in efficiency across countries and banks. AI adoption, CAR, and ROA show strong positive associations with efficiency (high truth-values), while NPLs exhibit negative effects (high falsity values). ROI and branch footprint demonstrate mixed or indeterminate influences, suggesting that their roles depend on contextual and temporal factors. This perspective highlights how efficiency drivers in the GCC banking sector cannot be fully captured by binary or crisp evaluations. By applying Neutrosophic theory, this study provides a novel conceptual understanding of banking efficiency under uncertainty. It recognizes managerial and policy decisions are often made in environments where information is incomplete, contradictory, or evolving. The Neutrosophic interpretation enhances the explanatory depth of traditional efficiency analyses and offers a more flexible lens for understanding how digital transformation and AI adoption contribute to organizational performance amid indeterminacy.

**Keywords:** Neutrosophic Theory; Data Envelopment Analysis (DEA); Artificial Intelligence (AI); Data-Driven Decision Making (DDDM); Efficiency; GCC Banking Sector; Uncertainty; Indeterminacy

### 1. Introduction

Assessing an organization's capacity to transform inputs into desired outputs has long been a cornerstone of performance evaluation in economics and management. In the banking sector, such assessments typically benchmark institutions against a best practice frontier, highlighting efficiency gaps that reflect variations in technology, managerial behavior, and resource utilization. Among the established tools for this purpose, Data Envelopment

Analysis (DEA) remains widely used for its ability to handle multiple inputs and outputs without imposing restrictive assumptions on production functions [28] [42] [51]. Its nonparametric nature makes it especially relevant in services such as banking, where outputs are often intangible, production and consumption occur simultaneously, and uncertainty is intrinsic [23] [30] [33].

While DEA and related frontier techniques have been extensively applied to banking systems in Europe, Asia, and the Americas, their application to Gulf Cooperation Council (GCC) contexts remains limited particularly in relation to the role of digital technologies and artificial intelligence (AI) in shaping efficiency outcomes [25]. The GCC, comprising Bahrain, Kuwait, Oman, Qatar, Saudi Arabia, and the United Arab Emirates, shares structural characteristics such as high resource dependence, fixed exchange regimes, and concentrated banking markets [20]. Despite ongoing diversification into non-oil sectors, banking remains the cornerstone of financial intermediation, with Islamic finance and state linked institutions playing major roles [56].

The structure of GCC banking marked by limited competition, concentrated loan portfolios, and close state corporate ties creates a context where efficiency is not purely technical but also influenced by institutional and informational factors [12]. Recent national initiatives, including the UAE AI Strategy, the Emirates Blockchain Strategy, and Smart Qatar, demonstrate a growing emphasis on embedding AI, cloud computing, and advanced analytics into financial systems [7] [10]. Saudi Arabia's large-scale investment in AI exemplifies a broader regional agenda to enhance competitiveness, reduce costs, and strengthen financial resilience [20].

The COVID-19 pandemic intensified these transitions, compelling banks to accelerate digitization, automate processes, and integrate data driven decision-making (DDDM) into areas such as risk management, fraud detection, and customer service [16]. AI adoption in this environment represents both an opportunity and a source of uncertainty it may enhance efficiency by reallocating resources toward digital channels, yet challenges related to data quality, governance, and capability development persist [45].

However, the influence of AI and DDDM on efficiency remains indeterminate. In complex systems such as banking, causal relationships are rarely crisp or binary. Factors that enhance performance in one context may hinder it in another. This study introduces Neutrosophic theory as a conceptual lens for interpreting efficiency under such conditions of uncertainty. Neutrosophic thinking posits that any statement or outcome can be characterized by simultaneous degrees of truth, falsity, and indeterminacy—reflecting the coexistence of known, unknown, and contradictory information. In the context of GCC banking, the effects of AI, capital adequacy, and other bank characteristics can therefore be viewed as having varying degrees of certainty and ambiguity rather than fixed outcomes.

By adopting this perspective, the study extends the conventional efficiency framework to acknowledge that decision environments in banking are inherently uncertain and often governed by incomplete knowledge. It examines 43 GCC banks over the period 2010–2024, estimating DEA based efficiency scores and then explaining these through a second stage panel regression including AI adoption, capital adequacy (CAR), asset quality (NPL), profitability (ROA, ROI), bank age, and branch footprint. The analysis distinguishes between the COVID era and post pandemic periods to capture potential shifts in the strength or direction of relationships during crisis and recovery phases.

This study contributes to the literature by (i) providing the first longitudinal evidence on AI's relationship with efficiency in GCC banking, (ii) situating efficiency drivers within the region's structural and technological context, and (iii) introducing Neutrosophic theory as a framework to interpret performance outcomes under indeterminacy. Through this integration, the research recognizes managerial and policy decisions are rarely made under complete certainty; instead, they involve navigating partial truths, conflicting evidence, and evolving information.

Accordingly, two research questions guide the study:

**RQ1.** How do artificial intelligence (AI) adoption and data driven decision-making (DDDM) influence the technical efficiency of GCC banks during crisis and recovery periods?

**RQ2.** Which bank specific characteristics most significantly determine efficiency when interpreted through the lens of Neutrosophic uncertainty?

## 2. Related Work

### An Overview of the GCC Banking Sector

The Gulf Cooperation Council (GCC) is a union of six oil-exporting countries: Bahrain, Kuwait, Oman, Qatar, Saudi Arabia, and the United Arab Emirates linked by strong political and economic ties. Their fixed exchange rate systems keep domestic financial conditions closely tied to global oil market dynamics [20]. Since the discovery of oil, the region has undergone rapid transformation. While petroleum revenues remain the primary source of external income and fiscal revenue, GCC members have diversified toward finance, manufacturing, healthcare, tourism, and technology sectors.

Maintaining financial stability and supporting sustainable growth depend heavily on effective reforms within the banking sector. Europe's post crisis banking union experience, with its centralized supervision, resolution mechanisms, and deposit insurance framework, offers instructive parallels for improving resilience and efficiency [31] [54]. Although the GCC's structural configuration differs, it faces a similar challenge: achieving efficient transformation of inputs into outputs under pervasive uncertainty and partial information. The banking system in the GCC remains dominated by locally owned institutions, with Islamic banks accounting for about one quarter of total banking assets and non-bank financial intermediaries still modest in scale [56]. Entry barriers, public ownership, and implicit guarantees have fostered stability but also limited competition, leading to concentrated loan portfolios and significant exposures to government-linked entities [12].

These structural characteristics influence traditional efficiency drivers: capital adequacy reflects public ownership and regulatory policies; asset quality is shaped by industrial concentration; size and branch networks signal consolidation; and profitability indicators such as ROA and ROI mirror both operational strategy and government participation. Over the past decade, however, technological change has added a new layer of complexity. The GCC has shifted from fragmented IT systems to integrated digital ecosystems encompassing artificial intelligence (AI), analytics, cloud computing, the Internet of Things (IoT), and smart technologies [7] [10] [14]. Governments have launched ambitious initiatives such as Dubai Internet City, the UAE AI Strategy, the Emirates Blockchain Strategy, and Smart Qatar, embedding digital infrastructure in both public and private sectors. Saudi Arabia has made especially large-scale investments in AI, expecting cost savings and efficiency gains through automation and data driven decision-making [20].

The COVID-19 pandemic accelerated this digital shift, compressing adoption timelines and exposing weaknesses in legacy systems. Banks expanded digital channels and automated risk management, fraud detection, and customer verification processes [16]. Policymakers introduced measures such as liquidity injections, loan moratoriums, and fee waivers to stabilize credit flows [22] [38]. The simultaneous push for digitalization and crisis management intensified the need for tools that can handle indeterminate and conflicting information when evaluating performance.

At this point, Neutrosophic theory offers a valuable conceptual extension. Proposed by [8] and elaborated in *New Trends in Neutrosophic Theory and Applications* [9], the theory recognizes that every concept or relationship can be expressed by three independent components: truth (T), indeterminacy (I), and falsity (F), each ranging from 0 to 1. This triadic structure generalizes classical and fuzzy logic by explicitly representing uncertainty and contradiction rather than forcing outcomes into binary or probabilistic boundaries. In the GCC banking context, where efficiency is shaped by economic volatility, regulatory diversity, and rapidly evolving technology, Neutrosophic theory helps conceptualize the coexistence of reliable, uncertain, and ambiguous relationships among performance determinants.

For instance, AI adoption may have a high truth membership in improving efficiency through automation and predictive analytics, yet exhibit none zero indeterminacy due to data quality issues, skill shortages, or inconsistent policy implementation. Similarly, non-performing loans (NPLs) may display a strong falsity membership (negative effect on efficiency), but their magnitude could remain uncertain across banks or periods. Variables such as branch footprint or bank age likely carry indeterminate effects, influenced by digital substitution and differing operational models [47].

Recent literature has begun applying Neutrosophic reasoning in financial contexts to address such uncertainties. [44] used neutrosophic fuzzy numbers to model performance indicators of financial assets, while [34] explored neutrosophic modelling of covariance structures in portfolio management.

Viewed through this lens, the GCC banking sector's efficiency challenge is not merely technical but neutrosophic, its determinants operate across overlapping domains of certainty, contradiction, and ignorance. Economic shocks, oil price volatility, digital disruption, and institutional reforms continuously shift the balance among truth, falsity, and

indeterminacy in performance relationships. Recognizing this triadic reality provides a more realistic conceptual basis for evaluating how AI and data driven decision making contribute to efficiency over time, particularly through crisis and recovery phases.

Therefore, this study adopts the Neutrosophic theoretical perspective to interpret efficiency variations among GCC banks, acknowledging that financial systems rarely operate under fully known or stable conditions. Incorporating indeterminacy as a core analytical dimension complements traditional empirical approaches such as Data Envelopment Analysis (DEA) and panel regression, providing richer insight into how technological, structural, and institutional factors jointly shape efficiency under uncertainty.

### **Foundations and Applications of (DEA) in Banking Efficiency**

Banking efficiency measurement descends from [28] frontier concept and the nonparametric data envelopment analysis (DEA) developed by [42], later refined by [51]. DEA develops a piecewise linear efficiency frontier and assesses decision-making units by comparing them to their peers, using multiple inputs and outputs, without requiring strong assumptions about data distribution [28] [30] [42] [51]. DEA is well suited for cases where the functional form is unknown and can accommodate multidimensional technologies, making it particularly relevant for service sectors such as banking, where joint production and simultaneity are common. It can be integrated with second stage models to investigate efficiency determinants, although discussion continues regarding the most appropriate estimators and the necessary adjustments for bounded dependent variables and potential serial correlation [11] [17] [19] [29] [58]. Measuring outputs in services industries is challenging due to the simultaneous nature of production and consumption and the intangible aspects of quality. Efficient banks typically exhibit lower operating costs, prudent staffing, and effective IT adoption, while high non-performing loans (NPLs) and sectoral concentration reduce efficiency. Strong capital adequacy enhances resilience and can support efficiency by enabling investment across business cycles. Profitability and efficiency reinforce each other, although the direction of causality depends on the specific period and policy environment [4] [46] [52].

The broader literature points to a shared but incomplete set of factors influencing bank efficiency. Size and age are relevant, though their effects are not strictly linear. Capitalization, profitability, liquidity, and credit quality remain central determinants. Regulatory frameworks and macroeconomic cycles alter the relationship between inputs and outputs, with effects varying across regions and periods. Digitalization and AI have emerged as key drivers, shaping and interacting with all other factors. However, consensus on the relative importance of these determinants remains elusive, both the direction and magnitude of effects differ by model specification and time [1] [15] [24] [35].

For the GCC specifically, prior work richly describes structure, ownership, Islamic finance share, and macro exposure, and documents technology programs and pandemic policy responses, but does not offer bank level, panel evidence that directly links observed AI or data analytics adoption to DEA efficiency scores across crisis and recovery while jointly modeling the standard drivers.

### **Hypotheses development**

This paper addresses that gap by estimating DEA for major GCC banks over 2010 to 2024 under constant return to scale, deriving technical efficiency, and then explaining each score with a decision relevant set of bank level covariates that includes AI adoption alongside capital adequacy, profitability, credit adequacy, branch footprint, and age. By splitting the estimation into a COVID window and a full post pandemic update, it is tested whether the role of AI and data driven decision-making differs under stress versus normalization. The approach aligns with the frontier plus regression tradition while tailoring drivers to the GCC's structural features and the region has accelerated digitization.

Based on the preceding literature review, this study proposes the following hypotheses for examination and testing.

Banks' age has been used as a variable in recent studies examining banks and other financial institutions across different markets [18] [27]. Bank size, i.e., number of branches, is a variable that influences multiple aspects of business performance and shapes how that performance affects bank efficiency [40] [48] [55].

**H1:** The efficiency of a bank is determined by its characteristics, particularly its age and size.

Regarding other economic and financial attributes of the banks, one variable of particular interest is ROA, often measured as net income as a percentage of total assets Conceptual Model [6].

**H2:** The bank's ROA affects efficiency

ROI is another financial attribute of the banks representing the gain or loss generated relative to the invested capital that is used in measuring efficiency [2].

**H3:** The bank's ROI influences efficiency

As per [52], efficiency is affected by bank credit risk. Some efficiency studies have examined credit risk, using non-performing loans (NPLs) as its measure [21] [26].

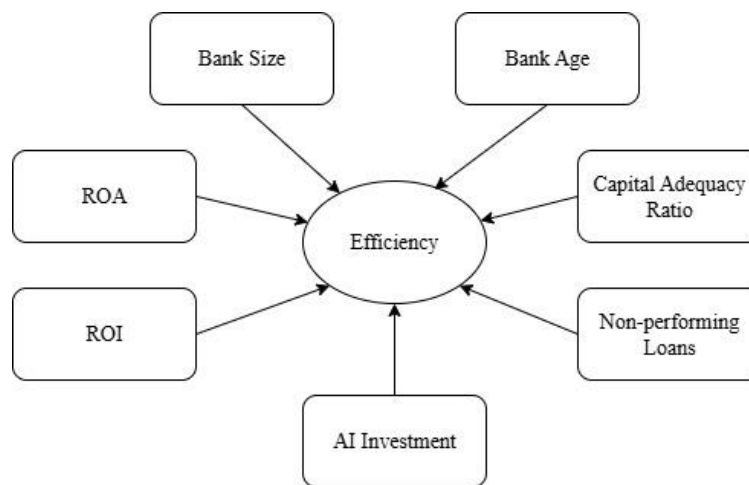
**H4:** Non-performing loans affect a bank's efficiency

The Capital Adequacy Ratio (CAR) is also regarded as an indicator of a bank's efficiency [36], reflecting its ability to meet financial obligations in both the short and long term [49] [57].

**H5:** Capital Adequacy Ratio influences a bank's efficiency

The impact of AI on banking efficiency can be assessed by incorporating it as a variable in DEA models. This approach allows evaluation of how AI technologies influence bank performance and offers insights into the extent to which AI investments enhance operational efficiency and foster innovation [3] [13] [49].

**H6:** AI Investment enhances banks' efficiency



**Figure 1.** Proposed Conceptual Model of efficiency determinants

### 3. Mathematical equations, subsections, tables, and figures

#### A. Decision analytic framing

The relationship between data driven decision-making, particularly AI adoption, and bank efficiency in the Gulf Cooperation Council is examined. Each bank is treated as a decision-making unit, with efficiency first measured and then its determinants analyzed. A dataset covering the period from 2010 to 2024 is extended, enabling comparison across the pre-pandemic, pandemic, and post-pandemic periods to capture the effects of consolidation and technological adoption.

#### B. Setting, sample, and period

The initial sample comprises the top 50 GCC banks as ranked by Gulf Business (2017). After data screening, seven banks were excluded due to missing or inconsistent reporting fields, yielding a final sample of 43 institutions and reducing potential error from data gaps. To examine efficiency in the banking sector, data from the consolidated financial statements over the period 2010–2024 is analyzed. This is an extended period covering various economic cycles, including the recent COVID-19 pandemic. To incorporate this into the model, macroeconomic control variables were included. Monetary values are expressed in USD, with bank level information sourced from audited annual reports and financial statements for relevant banks obtained from their official websites.

### Stage 1: Measuring efficiency with DEA

The concept of efficiency measurement has evolved considerably since [28] foundational work, which assessed efficiency by comparing the inputs required to achieve a given level of output. Early approaches, limited to a single input and a single output, produced only partial productivity measures [37], restricting their practical applicability [17]. Given the complexity of economic relationships, more advanced techniques are required that can incorporate multiple inputs and outputs within a unified framework, recognizing that a single output may result from multiple inputs, and conversely, multiple outputs may be linked to the same input [32] [43].

Data Envelopment Analysis (DEA) is an analytical method that helps organizations identify the best practices in resource use. A nonparametric method builds an effective frontier across the data using a mathematical programming model, and then determines how efficient each data point is in relation to the frontier. Each data point represents a decision-making unit (DMU) whose goal is to efficiently transform inputs into outputs. The DEA efficiency score shows a DMU's transformational capacity to turn multiple inputs into numerous outputs and serves as a proxy for a DMU's distance from the efficient frontier in comparison to its peers [50]. It is a technique that is capable of capturing the complex relationships between several inputs and outputs, where it creates benchmark indices for assessing a firm's or a sub-relative unit's productive efficiency in a specific industry.

The objective of DEA differs fundamentally from that of regression analysis. DEA identifies the best-performing observations, those on the efficiency frontier, and measures how far other observations deviate from this optimal performance. In contrast, regression focuses on estimating the average (central) tendency of a dataset, which does not necessarily represent optimal performance [37].

This type of analysis can reveal areas where companies could enhance their efficiency, allowing them to reach their full potential. One of the nonparametric methods that may be used to evaluate the technical effectiveness (TE) of a manufacturing function is data envelopment analysis (DEA). According to [53], [42] first developed Data envelopment analysis in the year 1978. Their study expands the engineering ratio technique to efficiency evaluation for many input–output combinations, building on the original publication of [28].

Nonparametric Data Envelopment Analysis under CCR for constant returns to scale is used to compute Technical Efficiency, the first DEA model, proposed by [42]. It assumes constant returns to scale, making it valid only when all decision-making units (DMUs) operate at the same optimal scale. When DMUs face differing operating conditions, this assumption can conflate technical efficiency with scale effects [17] [41].

The DEA model is used to create a production frontier and assess productivity and efficiency against a defined formula and is becoming more prevalent in the nonparametric approach [2]. DEA compares the efficiency of a particular business in a certain industry to the efficiency of the best-performing enterprises in that industry [39]. The efficiency measurements ranged from 0 (indicating no efficiency) to 1 (indicating maximum efficiency). DEA measures the ratio of the weighted outputs to weighted inputs; the higher the ratio, the more effective the banks may be [5].

According to [42], the CCR model is input-oriented and presupposes a steady return to scale. The CCR model seeks to optimize relative efficiency, as indicated by the following ratio:

$$\text{relative efficiency} = \frac{\sum_{i=1}^z e_i a_i}{\sum_{i=1}^w g_i b_i}$$

Where:

- 1-  $a$  and  $b$  are semi-positive output and input vectors
- 2-  $z$  represents outputs number.
- 3-  $w$  represents inputs number.
- 4-  $g$  and  $e$  are the weights for the inputs and outputs respectively.

The linear programming formulation will be as follows:

Maximized  $e' a_i$

Subject to:  $g' b_i = 1$

$-g' b_i + e' a_i \leq 0$  for  $i = 1, \dots, N$

$$e, g \geq 0$$

Minimize  $\theta$

$$\text{Subject to: } -a_i + A\lambda \geq 0$$

$$\theta b_i + B\lambda \geq 0$$

$$\lambda \geq 0$$

Where:

- 1-  $\theta$  represents the dual variable belonging to  $g'b_i = 1$
- 2- The matrices A and B represent the inputs and outputs respectively
- 3-  $\lambda = (\lambda_1, \dots, \lambda_2)$  represents the dual variables belonging to  $g'^{b_i} + e'a_i \leq 0$

Developing a solution that maximizes the total of input surpluses and output deficits is the aim of this problem's solution while maintaining  $\theta = \theta^*$  (noting that  $\theta^*$ , the CCR model's solution, which is the best one).

In the case of inefficient CCR,  $\theta^*$  is less than 1, the DMU under consideration is considered as inefficient. However, an advantage of this paradigm is the ability to define the value or source of inefficiency in each DMU's input and output. Furthermore, the CCR model defines the reference set (also known as a benchmark member) or peer of the efficient set that was utilized to do these assessments and specifies the inefficiency source.

If  $\theta^* < 1$ , there must be at least one DMU for which the variables ( $e^*$ ,  $g^*$ ) provide equality between the right and left sides; otherwise,  $\theta^*$  can be raised. These DMUs act as the evaluation DMU's reference set. By using the reference set  $\lambda_j^* > 0$  to solve the dual issue, the same outcome may be attained.

In other words, for DMU  $i$ , the referral set, if  $\theta_i^* < 1$ , is provided by:

$$E_i = \{j/\lambda_j^* \text{ for } j = 1, \dots, L\}$$

**Table 1:** Input and output DEA variables

Variables	Type	Definition
IT Expenses	Input	Spending on advanced banking technologies, including artificial intelligence, robotics, automation, data analytics
Staff Expenses	Input	Total costs incurred by a bank for employee compensation, including salaries, wages, bonuses, benefits, training, and related personnel costs.
Customer Deposits	Input	Funds placed by clients with a bank, including savings, current, and term deposits,
Fixed Assets	Input	Long-term tangible resources owned by a bank, such as buildings, equipment, and technology infrastructure, used in operations but not intended for sale.
Net Profit	Output	Remaining income after a bank subtracts all expenses, taxes, and provisions from total revenue
Net Loans	Output	Total value of loans issued by a bank to customers, minus provisions for potential loan losses
Interest income	Output	The revenue a bank earns from charging interest on loans, investments, and other interest-bearing assets

Dimensionality check

[37] claim that there is a rule that must be followed in order to choose the number of outputs and inputs. A straightforward guideline that might be used is as follows:

$$“n \geq \max \{m * s, 3 (m+s)\}”$$

Where n stands for the number of decision-making units, m stands for the input variables number and s stands for the output variables.

Applying the validation formula above on the variables of this study, it is found that

$$n= 43, m= 4, s = 3$$

Thus:

$$43 \geq \max \{12, 21\}$$

Hence, this model satisfies the rule proposed by [37].

Stage 2: Explaining efficiency with panel regressions

In this stage, the hypotheses are aimed to be tested. Fixed-effects and random-effects panel models are estimated and selected between using the Hausman test. The model’s dependent variable is the efficiency score of each bank, while the independent variables represent potential factors influencing that efficiency. The dependent variable is censored at a value of 1, as only banks with an efficiency score equal to 1 are considered fully efficient. As for the candidate drivers, the independent variables include Capital Adequacy Ratio, Return on Assets, Return on Investment, Non-Performing Loans, branch footprint, bank age, and an indicator for AI implementation.

The proposed model is defined as follows:

$$EFF_{it} = \alpha + \beta_1 AGE_t + \beta_2 AI\_IMPLEMENTATION_t + \beta_3 CAR_{it} + \beta_4 BRANCHES_t + \beta_5 NPL_{it} + \beta_6 ROI_{it} + \beta_7 ROA_{it} + \varepsilon$$

The variables are described in detail in Table 2.

**Table 2:** Panel regression variables

Variable	Abbreviation	Type	Definition
CRS Efficiency	Eff	Dependent	Efficiency scores derived from the DEA model
Capital Adequacy Ratio	CAR	Independent	Bank’s capital relative to its risk-weighted assets
Number of Branches	Branches	Independent	The total count of physical banking outlets operated by a bank
Non-Performing Loans	NPL	Independent	Loans on which the borrower has stopped making scheduled payments
Return on Assets	ROA	Independent	Net income as a percentage of total assets
Return on Investment	ROI	Independent	Gain or loss generated relative to the invested capital
AI Investment	AI_INVEST	Independent	Dummy variable taking the value of 1 if the bank invests in AI, and 0 otherwise
Bank Age	AGE	Independent	The number of years since the bank’s establishment

DEA and panel regressions are implemented in R with fixed-effects and random-effects estimators and the Hausman test. Orientation choices follow standard practice and remain unchanged to ensure comparability with the 2010 to 2024 analysis.

Moreover, to deepen the analysis beyond classical regression-based efficiency, the model was extended under the neutrosophic framework, which integrates uncertainty and indeterminacy into the evaluation of each decision-making unit (DMU). Following the approach outlined by [8] and later adapted in efficiency studies, the estimated efficiency score from the panel regression ( $\theta_{it}$ ) was reinterpreted as a neutrosophic triplet:

$$\widetilde{EFF}_{it} = \langle T_{it}^{(E)}, I_{it}^{(E)}, F_{it}^{(E)} \rangle$$

where  $T_{it}^{(E)}$  denotes the degree of truth (confirmed efficiency),  $I_{it}^{(E)}$  represents indeterminacy (uncertainty in the efficiency estimate), and  $F_{it}^{(E)}$  measures falsity (inefficiency adjusted for uncertainty).

The neutrosophic efficiency was derived using the fitted values from the random-effects panel regression model:

$$CRS_{it} = \beta_0 + \beta_1 LAGE_{it} + \beta_2 AI\_INVEST_{it} + \beta_3 CAR_{it} + \beta_4 Branches_{it} + \beta_5 NPL_{it} + \beta_6 ROA_{it} + \beta_7 ROI_{it} + \varepsilon_{it}$$

The predicted scores ( $\theta_{it}$ ) were then adjusted by a measurement uncertainty index ( $\rho_{it}$ ), defined as:

$$\rho_{it} = w_M M_{it} + w_S S_{it} + w_T V_{i,rolling}^\theta$$

where ( $M_{it}$ ) captures data completeness, ( $S_{it}$ ) reflects model sensitivity, and ( $V_{i,rolling}^\theta$ ) measures temporal volatility of efficiency scores.

Weights were assigned as ( $w_M = 0.3$ ), ( $w_S = 0.4$ ), and ( $w_T = 0.3$ ), reflecting balanced contributions of data quality, model robustness, and time-based stability.

Subsequently, the three-neutrosophic components were calculated as:

$$\begin{aligned} T_{it}^{(E)} &= \theta_{it}(1 - \rho_{it}) \\ I_{it}^{(E)} &= \rho_{it} \\ F_{it}^{(E)} &= (1 - \theta_{it})(1 - \rho_{it}) \end{aligned}$$

## 4. Findings

### A. Sample selection

To evaluate efficiency scores for GCC banks, consolidated financial statement data for a sample of 43 banks from the 6 GCC countries over the period 2010–2024 is examined. This extended timeframe spans multiple business fluctuations, including the recent COVID-19 crisis. The data are obtained from the financial statements and integrated annual reports published on banks' websites, including full data records for the input and output variables. This refinement ensured that the analysis was based solely on complete and reliable data, thereby improving the accuracy and robustness of the results.

The detailed distribution of observations is presented in Table 3. The following section presents the results for the two phases described earlier.

**Table 3:** Detailed distribution of observations

	Number of Observations
Full observation of the variables	9000
Observations with missing/misleading values	1260
Final number of observations	7740

**Table 4:** Descriptive statistics for DEA Inputs/Outputs (Millions\$)

Variable	Type	Mean	Median	Standard Deviation	Min	Max	Skewness
IT Expenses	Input	1,343.882	74.757	7,044.731	1,380.261	84,103.270	7.86
Staff Expenses	Input	279.071	194.007	268.437	2.289	2,255.188	2.18
Customer Deposits	Input	31,678.913	18,203.232	37,909.080	5.120	243,484.138	2.62
Fixed Assets	Input	770.059	283.838	2,414.104	8.387	29,096.724	8.55
Net Profit	Output	806.619	381.500	1,062.144	0	6,116.402	2.33
Net Loans	Output	29,990.088	16,452	36,920.866	1.061	250,003.002	2.69
Interest Income	Output	1,615.161	677.413	2,806.418	10.974	34,401.084	5.44

After the application of technical efficiency (CRS), the efficiency scores for each bank-year observation are obtained. The table shows the average relative efficiency CRS of the banking system in each analyzed country by year, with bold highlighting the average efficiency greater than 0.9000 (90.00%).

**Table 5:** Average efficiency CRS by year

Country	Average efficiency CRS of the whole banking system															Average for the whole period
	Year															
	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023	2024	
KSA	0.5831	0.4840	0.5008	0.5246	0.5361	0.5006	0.4852	0.5021	0.5380	0.4637	0.4824	0.4321	0.5566	0.5515	0.5545	0.5130
UAE	0.5884	0.5408	0.5396	0.5205	0.5391	0.5547	0.5262	0.62668	0.6271	0.5827	0.5796	0.5762	0.6946	0.8126	0.8331	0.6094
<b>Qatar</b>	<b>0.9416</b>	<b>0.9567</b>	<b>0.9092</b>	0.8996	0.8729	0.8954	<b>0.9353</b>	<b>0.8832</b>	<b>0.9084</b>	0.8880	0.8885	0.8517	<b>0.9147</b>	<b>0.9473</b>	<b>0.9309</b>	<b>0.9082</b>
Bahrain	0.6878	0.6267	0.6384	0.7142	0.6611	0.6894	0.6568	0.6788	0.6840	0.6601	0.5949	0.5882	0.5889	0.6089	0.659	0.6487
Kuwait	0.5939	0.5126	0.5492	0.5456	0.5214	0.4865	0.4912	0.4729	0.4744	0.4648	0.4649	0.4675	0.4736	0.5133	0.5398	0.5047
Oman	0.7713	0.6947	0.7109	0.7241	0.7226	0.6885	0.6909	0.6731	0.6865	0.7827	0.7989	0.7751	0.8112	0.7791	0.7177	0.7351

The CRS efficiency values range between 43% and 95%, meaning there are notable variations in how efficiently banks in these countries operate over time. Qatar consistently leads with the highest efficiency scores across all years, rarely dropping below 85%. KSA, UAE, Kuwait, and Bahrain maintain moderate efficiency levels (generally 45%–65%), with fluctuations but no sustained long-term upward trend. Oman shows relatively high efficiency compared to most GCC peers, second only to Qatar in most years.

Qatar and Oman have been the most consistent high performers over the entire period, while UAE shows the most significant late-period improvement, especially post-2020. KSA and Kuwait exhibit long-term stagnation with low-to-moderate efficiency. Finally, Bahrain has a mid-range but slightly declining efficiency trend, with a small recent recovery.

Bank efficiency scores across three reference years, 2019 (pre-COVID period), 2021 (during COVID), and 2024 (post-COVID recovery), were analyzed using the Constant Returns to Scale (CRS) framework. This approach allowed us to track performance changes in the banking systems of six GCC countries over time, highlighting how the pandemic affected operational efficiency and whether banks have recovered or improved in the post-crisis period.

Before the pandemic in 2019, Qatar exhibited the highest efficiency score of 0.8880, confirming its strong and stable banking sector. Oman followed with 0.7827, showing robust operational performance, while Bahrain scored 0.6601, indicating moderate efficiency. The UAE and KSA recorded lower scores of 0.5827 and 0.4637, respectively, suggesting greater room for optimization. Kuwait had the lowest pre-COVID score at 0.4648, pointing to efficiency challenges even before the crisis.

During the pandemic year of 2021, efficiency levels shifted noticeably. The UAE was the only country to record a significant improvement, rising to 0.5762 from its 2019 level, reflecting rapid digital transformation and operational adjustments in response to lockdowns. Qatar experienced a slight decline to 0.8517, though it remained the most efficient banking system in the region. Oman maintained relatively high efficiency at 0.7751, while Bahrain dropped to 0.5882. Both KSA and Kuwait recorded marginal improvements compared to 2019, with KSA rising to 0.4321 and Kuwait to 0.4675, though these remained among the lowest in the GCC.

By the post-COVID year of 2024, several countries demonstrated signs of recovery. The UAE achieved substantial gains, reaching 0.8331, marking one of the most significant improvements in the region and potentially reflecting structural reforms and digital banking adoption. Qatar continued to lead with 0.9309, nearly regaining its pre-pandemic peak. Oman’s efficiency declined slightly to 0.7177, indicating some post-recovery challenges. Bahrain improved to 0.6525, reversing part of its pandemic decline. KSA recovered to 0.5545, surpassing its pre-COVID level, while Kuwait also improved to 0.5398, showing gradual efficiency restoration.

Overall, the analysis reveals three key patterns: Qatar maintained its position as the most efficient banking system throughout the period; the UAE demonstrated the strongest post-pandemic recovery; and Kuwait and KSA, while improving, still lag behind the regional leaders. These results suggest that resilience strategies, technological adoption, and structural reforms played a significant role in determining how well banking systems adapted to and recovered from the COVID-19 crisis.

To further examine the impact of digitalization, particularly the adoption of artificial intelligence on banking efficiency; the approach established in the literature was followed, where DEA efficiency indicators have been employed as dependent variables in second-stage analysis in numerous studies. In line with this methodology, we first measured the DEA efficiency scores in the initial stage for each country and year under review. The DEA measures were then used as a dependent variable in a second-stage regression analysis, with both the fixed-effect model and the random-effect model applied to evaluate the determinants of efficiency. This two-step approach enabled us to quantify the role of AI adoption in shaping banking efficiency across uncertain periods.

**Table 6:** Descriptive statistics for Panel Regression Model variables

	Mean	Min	Max	St dev
CRS	0.868	0.104	1	0.212
AGE	43	15	70	14.725
ROA	2.4	-4.43	30.79	3.049
ROI	1.8	-2.11	175	14.16
Branches	113	4	855	142.4
CAR	18.695	11.5	37.7	3.7
NPL	3.128	0.05	13.9	2.338

**Table 7:** Correlation matrix

	CRS	AGE	ROA	ROI	Branchs	AI_Invest	CAR	NPL
CRS	1							
AGE	.023	1						
ROA	.245**	-.225**	1					
ROI	.097*	-.210**	.365**	1				
Branchs	-.232**	.193**	-.202**	-.099*	1			
AI_Invest	-.096*	.090*	-.055	-.044	.101*	1		
CAR	.120**	-.015	-.039	.014	-.055	.018	1	
NPL	-.372**	-.028	-.189**	-.131**	-.099*	.029	-.023	1

The effects between efficiency indicators (considered as dependent variables) and these models (independent variables) demonstrate their drivers clearly. A Hausman test is conducted using the null hypothesis that the best model is random effects and the alternative model is fixed effects, in order to select between fixed and random effects (Greene 2002). It simply evaluates whether the unique errors are connected to the regressors, with the null hypothesis being that they are not.

**Table 8:** Results from Panel Regression Random Effect Model efficiency

	Estimate	Std. Error	z-value	Pr(> z )
(Intercept)	3.14E-01	6.79E-02	4.6288	3.68E-06 ***
LAGE	2.08E-03	1.12E-03	1.8558	0.06348 .
AI_INVEST	4.66E-02	1.13E-02	4.1112	3.94E-05 ***
CAR	5.28E-03	1.34E-03	3.9468	7.92E-05 ***
Branches	1.65E-04	9.08E-05	1.8206	0.06866 .
NPL	-1.07E-03	2.80E-03	-0.381	0.70317
ROA	2.56E-02	2.29E-03	11.2037	< 2.2E-16 ***
ROI	-4.76E-04	4.64E-04	-1.0269	0.30447

Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

Based on the table, the significant variables affecting the model are: AI\_INVEST ( $p < 0.001$ ): A highly significant positive effect, indicating that investment in AI substantially improves the dependent variable. CAR (Capital Adequacy Ratio) ( $p < 0.001$ ): Also highly significant with a positive impact, suggesting that better capital adequacy is associated with higher efficiency. ROA (Return on Assets) ( $p < 0.001$ ): The most statistically significant variable with a positive coefficient, indicating that banks that are more profitable tend to be more efficient. Intercept is significant as well ( $p < 0.001$ ).

Variables LAGE (age) and Branches have marginal significance at around the 10% level ( $p \sim 0.06-0.07$ ), implying a weak positive effect.

The variables NPL (Non-Performing Loans) and ROI (Return on Investment) are not statistically significant ( $p > 0.3$ ), suggesting no clear effect on efficiency in this model.

Main test:

$$EFF_{it} = \alpha + \beta_1 AGE_t + \beta_2 AI\_IMPLEMENTATION_t + \beta_3 CAR_{it} + \beta_4 BRANCHES_t + \beta_5 NPL_{it} + \beta_6 ROI_{it} + \beta_7 ROA_{it} + \varepsilon$$

$$i = 1 \dots n; t = 1 \dots m$$

After both the fixed-effect model and the random-effect model were estimated in R, the suitability of each approach was evaluated using the Hausman test. Based on the Hausman test results, we identified that the best fit for CRS efficiency determinants is the Random Effect Model and subsequently derived the following equation, which represents the relationship between the selected determinants and the efficiency scores:

### B. Determining the Equation:

$$EFF_{it} = 0.31 + 0.002AGE_t + 0.0466AI\_IMPLEMENTATION_t + 0.0053CAR_{it} + 0.0001BRANCHES_t - 0.00107NPL_{it} - 0.000476ROI_{it} + 0.02564ROA_{it} + \varepsilon$$

The estimated equation for efficiency under constant returns to scale CRS shows the combined impact of various bank-level and time-specific factors on efficiency scores. The constant term (0.31) represents the baseline efficiency

when all explanatory variables are equal to zero. The coefficient for bank age (0.002) suggests that, on average, each additional year in operation slightly increases efficiency, though the effect is relatively small. AI implementation has a positive and comparatively large coefficient (0.0466), indicating that adopting AI technologies substantially improves efficiency, consistent with the expectation that digital transformation enhances operational performance.

The capital adequacy ratio (CAR) coefficient (0.0052) implies that higher capital adequacy ratios are associated with better efficiency, reflecting stronger financial stability. The number of branches (0.0001) shows a negligible positive relationship with efficiency, suggesting minimal scale-related operational benefits. NPL carries a negative coefficient (-0.001), indicating that higher non-performing loans reduce efficiency, highlighting the detrimental effect of poor credit quality. ROI has a small negative effect (-0.0004), possibly reflecting inefficiencies in investment returns. In contrast, ROA (0.0256) has a positive impact, suggesting that banks that are more profitable tend to operate more efficiently. The term  $\varepsilon$  captures all other unobserved factors affecting efficiency.

Overall, the model highlights that among the factors considered, AI implementation and ROA appear to have the most substantial positive influence on efficiency, while NPL exerts a negative effect.

Building on these results, the next stage of analysis incorporates the neutrosophic regression framework to account for the uncertainty and indeterminacy inherent in efficiency measurement. By extending the classical model into a neutrosophic context, the analysis provides a more nuanced view of how each determinant influences efficiency across varying conditions, allowing for a richer interpretation of banks' performance stability and adaptability.

The resulting neutrosophic representation provides a multidimensional view of efficiency performance. The majority of DMUs displayed moderate to high truth-values ( $T^E$ ), indicating that most efficiency estimates remain stable even when adjusted for uncertainty. However, variations in indeterminacy ( $I^E$ ) were evident, signaling differences in data reliability and model sensitivity across banks and periods.

A subset of DMUs exhibited higher  $F^E$  values, reflecting inefficiency compounded by uncertainty typically associated with volatile or incomplete data. The average indeterminacy hovered around medium levels, implying that, while efficiency estimates were generally robust, they were not free from model and data ambiguity.

The neutrosophic panel regression for bank efficiency ( $EFF_{it}$ ) is expressed as an interval model:

$$\begin{aligned} CRS_{it}^N = & [0.1812, 0.3143, 0.4474] + [-0.00012, 0.00208, 0.00427]LAGE_{it} \\ & + [0.02439, 0.04662, 0.06884]AI\_INVEST_{it} + [0.00266, 0.00528, 0.00791]CAR_{it} \\ & + [-0.00001, 0.00017, 0.00034]Branches_{it} + [-0.00655, -0.00107, 0.00442]NPL_{it} \\ & + [0.02116, 0.02564, 0.03013]ROA_{it} + [-0.00139, -0.00048, 0.00043]ROI_{it} + \varepsilon_{it} \end{aligned}$$

Each coefficient here is represented as a triplet  $[\beta_L, \beta_M, \beta_U]$  capturing truth ( $\beta^M$ ), indeterminacy ( $\beta^U - \beta^L$ ), and falsity (the possibility of deviation from  $\beta^M$ ).

The neutrosophic regression model integrates uncertainty into the traditional panel regression framework, generating an efficiency function defined through interval coefficients  $[\beta_L, \beta_M, \beta_U]$ .

The central ( $\beta^M$ ) values indicate the expected deterministic impact of each determinant on banking efficiency, whereas the interval width ( $\beta_U - \beta_L$ ) quantifies the indeterminacy which is the possible variation due to data quality, model sensitivity, or temporal volatility.

Results reveal that AI implementation and profitability (ROA) exhibit the most stable and positive neutrosophic intervals, signifying robust contributors to efficiency across all uncertainty bounds. Capital adequacy (CAR) also maintains a consistent positive impact, confirming its stabilizing role in the sector's resilience.

In contrast, NPL and ROI demonstrate wide and overlapping intervals that span both positive and negative zones, highlighting considerable uncertainty and potential inconsistency in their influence. Bank age and branch density display relatively small effects, suggesting that structural maturity and physical expansion contribute marginally to overall efficiency once digital and capital factors are accounted for.

The intercept's interval  $[0.181, 0.314, 0.447]$  reflects the baseline neutrosophic efficiency of the GCC banking system, with moderate uncertainty yet a clearly positive central tendency.

To better illustrate the uncertainty embedded within the regression estimates, Figure 1 presents the neutrosophic interval coefficients for each explanatory variable. The plot depicts the central (truth) coefficient  $\beta^M$  as a point, with vertical bars indicating the lower  $\beta_L$  and upper  $\beta_U$  bounds of indeterminacy. This visual representation highlights both

the direction and magnitude of each variable’s influence, while simultaneously reflecting the degree of uncertainty surrounding its effect on efficiency. Wider intervals correspond to higher indeterminacy, signaling parameters that are more sensitive to contextual or data-driven variations.

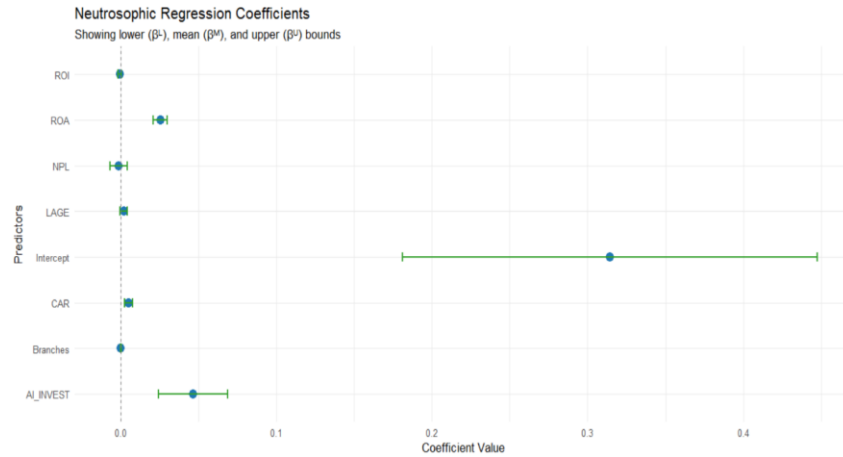


Figure 2. Neurosophic Regression Coefficients

Overall, the neurosophic formulation reveals a nuanced efficiency landscape where truth (central tendency) aligns with strong profitability and digitalization effects, while indeterminacy (interval width) captures the instability of credit risk and investment performance under evolving market conditions. The neurosophic efficiency mapping (Figure X) plots DMUs in the ( $T^E$ – $I^E$ – $F^E$ ) space.

Banks located in the lower-right region (high  $T^E$ , low  $I^E$ , small  $F^E$  bubbles) demonstrate stable and consistent efficiency. Banks near the center of the map exhibit intermediate truth and indeterminacy, indicating sensitivity to input-output perturbations. Banks with large bubbles and higher  $I^E$  values face significant uncertainty and potential structural instability, suggesting that their efficiency levels may not be fully reliable under changing conditions.

In practical terms, the neurosophic approach reveals that traditional regression-based efficiency measures ( $\theta_{it}$ ) tend to overstate performance when uncertainty is ignored. The decomposition into  $T^E$ ,  $I^E$ , and  $F^E$  enables distinguishing between genuinely efficient banks and those whose performance is uncertain or data-dependent.

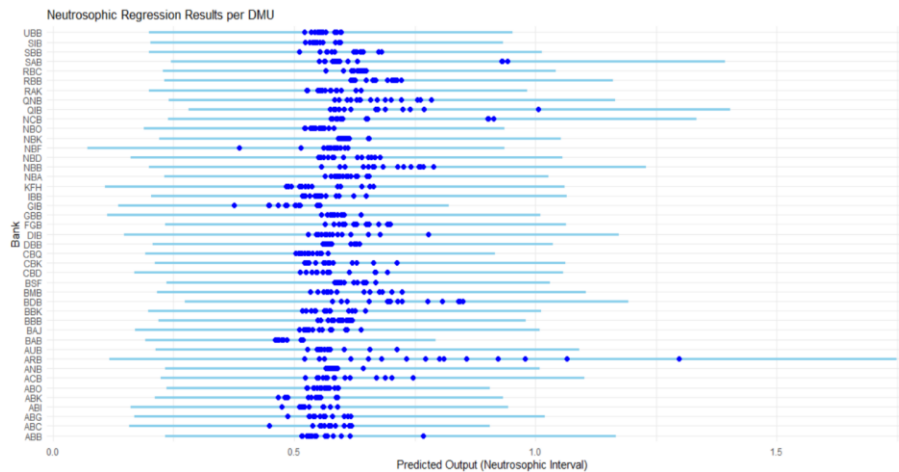


Figure 3. Neurosophic Regression Results per DMU

This framework enhances decision support by quantifying the degree of reliability associated with each efficiency score. Policymakers and bank managers can use:

$T^E$  as an indicator of reliable operational efficiency,  $I^E$  as a diagnostic measure for data or structural issues, and  $F^E$  as a risk-adjusted inefficiency indicator.

The neutrosophic efficiency concept thus enriches traditional DEA and panel-based assessments, promoting more transparent and uncertainty-aware evaluations of banking sector performance.

### C. Hypotheses Testing

The empirical analysis yields mixed support for the proposed hypotheses. H1, which posited that bank efficiency is influenced by institutional characteristics such as age and size, receives only marginal support. Bank age (LAGE) exhibits a small positive effect on efficiency that approaches conventional significance levels ( $p \approx 0.063$ ), suggesting that more established banks may benefit from accumulated market knowledge, mature client relationships, and refined internal processes. However, the effect is not robust, likely reflecting the fact that legacy institutions may also face structural rigidities, slower digital adoption, and higher overhead costs. Similarly, branch network size shows a weak positive association ( $p \approx 0.069$ ), indicating that larger geographic footprints can enhance accessibility and deposit mobilization, but their efficiency impact is diluted in an era of growing digital channel adoption.

H2 is strongly supported. Return on Assets (ROA) demonstrates a highly significant and positive relationship with efficiency ( $p < 0.001$ ), consistent with the notion that more profitable banks allocate resources more effectively, maintain cost discipline, and exploit economies of scale in revenue generation. In practice, high-ROA institutions in the GCC often leverage strong fee-based income, optimized loan portfolios, and efficient cost structures to sustain operational efficiency.

In contrast, H3 is not supported. Return on Investment (ROI) carries a negative but statistically insignificant coefficient ( $p \approx 0.304$ ). This may be due to ROI capturing specific project-based returns or investment portfolio performance, which can fluctuate with market volatility and may not directly translate into core banking efficiency. For instance, GCC banks with high ROI from non-core activities (e.g., real estate holdings) may still face operational inefficiencies in lending or service delivery.

Similarly, H4 is rejected. Non-performing loans (NPL) show a negative but non-significant effect on efficiency ( $p \approx 0.703$ ), suggesting that in the GCC context, strong government support, high provisioning levels, and robust collateralization practices may buffer the operational impact of impaired assets. Moreover, relatively low systemic NPL ratios in the region reduce the variation needed to detect a strong statistical effect.

H5 is confirmed. Capital Adequacy Ratio (CAR) displays a positive and highly significant effect ( $p < 0.001$ ), aligning with the idea that well-capitalized banks are better equipped to absorb shocks, sustain lending during downturns, and invest in process improvements.

#### Efficiency Patterns Before, During, and After COVID

The CRS efficiency scores for 43 banks were then tracked across three reference years—2019 (pre-COVID), 2021 (during COVID), and 2024 (post-COVID)—along with their identified peer banks in each period.

According to Appendix 1, the consistency of top performers such as ARB, ABO, DBB, DIB, FGB, IBB, NBF, NCB, QIB, and QNB is observed, with a CRS score of 1.000 maintained in all three years, indicating that they operated on the efficiency frontier consistently. This demonstrates that robust operational models are maintained, resilient to both economic disruptions (COVID) and the post-crisis competitive landscape.

On the other hand, we observe performance fluctuations for several banks that experienced notable efficiency volatility. For example, BAB improved sharply from 0.4233 in 2019 to 1.000 in 2021 and 2024, suggesting significant operational restructuring or resource optimization during and after COVID. In contrast, ABG saw a decline from 0.7662 in 2019 to 0.4895 in 2021 and 2024, indicating possible persistent structural challenges.

During COVID-era, some banks saw efficiency peaks during the pandemic such as CBD rose from 0.5214 in 2019 to 0.891 in 2021, but did not improve further in 2024, possibly due to post-crisis normalization. Others, like NBA, reached full efficiency in 2021 after a moderate pre-COVID score, suggesting they adapted quickly to digitalization or operational shifts during the pandemic.

It was also observed that banks like Samba (SAB), with an efficiency score of 0.4607 in 2019, had to undergo a merger with the National Commercial Bank (NCB), a fully efficient bank with a CRS value of 1, to form the Saudi National Bank and continue to perform at full efficiency in 2024.

On the other hand, it is found that Al Khaliji Commercial Bank (ACB), which had a high efficiency score of 0.8997, also underwent a merger with the fully efficient Masraf Al Rayan (ARB) in 2021 and maintained full efficiency in 2024.

A peer network stability is observed, where highly efficient banks such as FGB, NCB, and QNB appear repeatedly as peers for multiple others, reinforcing their role as best-practice leaders in the region. The stability of these reference banks across years indicates that they set enduring efficiency standards. In the post-COVID period, some banks experienced recovery while others experienced stagnation. Banks like ABC improved from 0.8395 in 2019 to 0.971 in 2021, sustained it in 2024, while others like NBB declined from 0.7001 in 2019 to 0.3528 in 2021, and stayed low, suggesting challenges in adapting to the post-COVID competitive environment.

Overall, the data shows that while a core group of banks consistently operates at the efficiency frontier, a substantial portion of the sector experiences fluctuations tied to external shocks (like COVID-19) and internal adaptation capacity. The recurring presence of certain banks as peers indicates that best-practice benchmarks are well established, but the ability to reach and maintain that frontier varies widely.

#### **D. Discussion**

The observed patterns across GCC banks indicate that efficiency is shaped by a consistent set of structural and managerial factors, which remain influential despite changing conditions. Banks entering the COVID-19 period with stronger capitalization and profitability maintained positions closer to the efficiency frontier. These relationships persist through 2024, suggesting that they reflect fundamental operational and strategic dynamics rather than transitory crisis effects. From a Neutrosophic perspective, these factors exhibit a high degree of truth in promoting efficiency, while residual indeterminacy arises from differences in governance, regulatory environments, and country-specific shocks [8] [9].

The evolution of AI adoption illustrates how technological interventions interact with lagged outcomes and uncertainty. Initially, the association between AI adoption and efficiency is weak to neutral, reflecting transitional frictions, learning costs, and the delay between investment and operational impact. By 2024, AI adoption demonstrates a clear and economically meaningful positive effect. Interpreted through Neutrosophic theory, AI's contribution moves from partially indeterminate to a higher truth membership as data pipelines are stabilized, models are embedded in core processes, and staff adapt decision routines. This also explains why branch footprint contributes little to efficiency: in an increasingly digital environment, the marginal effect of physical expansion is largely indeterminate, whereas scalable digital capabilities and analytics provide verifiable gains.

Capital adequacy and profitability consistently emerge as essential drivers of efficiency. Adequate capital allows banks to maintain lending and fee-based operations during periods of stress, while strong operating profits fund technological investments and absorb transitional costs. These factors demonstrate high truth membership in their contribution to efficiency, though partial indeterminacy remains due to macroeconomic and regulatory variability. Non-performing loans, by contrast, exert a negative effect on efficiency. Their magnitude may vary, reflecting falsity membership with some indeterminacy depending on credit cycles and government interventions.

Cross-country differences further reflect Neutrosophic dynamics. Banks in countries with earlier or more comprehensive digital initiatives and more competitive markets recovered more rapidly from the COVID shock, whereas slower-recovering countries faced delays in analytics adoption, weaker asset quality, and reliance on physical branches. The concentration of the efficiency frontier, with a few banks serving as benchmarks, represents high-truth examples of effective operations, while other banks display varying degrees of indeterminacy due to structural, technological, and managerial differences.

Managerial implications are clear. The extended model provides a framework for executives to assess how capital strength, asset quality, profitability, and AI adoption jointly affect distance from the efficiency frontier, while explicitly acknowledging uncertainty. Prioritizing credit risk management and data capabilities before expanding operational footprints can reduce indeterminacy, and treating AI as an ongoing strategic initiative enhances its truth membership in promoting efficiency.

The positive impact observed by 2024 underscores the importance of governance, data quality, model validation, and staff training. In Neutrosophic terms, these factors reduce indeterminacy and increase the reliability of AI's effect.

Regulators can facilitate efficiency improvements by promoting common data standards, privacy-preserving data sharing, and robust model validation practices, lowering fixed costs associated with AI implementation. Targeted incentives and cross-country knowledge sharing further allow smaller or late-adopting banks to reduce indeterminacy, narrow the gap to the frontier, and accelerate the adoption of best practices without increasing risk.

Caution is warranted. The AI measure used in this study reflects adoption rather than intensity of use, and reverse causality cannot be fully ruled out, as well-managed banks are more likely to adopt AI and achieve higher efficiency. Neutrosophic theory provides a conceptual framework to interpret these uncertainties, enabling decision-makers to assign degrees of truth, falsity, and indeterminacy rather than treating relationships as fully deterministic.

Overall, the evidence supports a Neutrosophic conclusion: in GCC banking, efficiency improves when balance sheets are strong, credit risk is effectively managed, and AI moves from pilot adoption to full operational integration. The key value lies not in identifying a single “best” model but in providing a transparent, interpretable framework that enables leaders to navigate uncertainty, assess potential outcomes, and make informed decisions under conditions of partial knowledge and indeterminacy [8] [9].

### **5. Future research, research limitations and conclusion**

Macro conditions and regulatory reforms differ across countries and years. Although year effects capture much of this variation, some unobserved policy details may still have an impact. Additionally, Data Envelopment Analysis measures relative performance, not absolute technology, so changes across the entire industry can affect all banks without altering their efficiency scores.

These limitations point to areas for future research. Using more detailed measures of digital adoption, preferably validated by independent audits, would improve accuracy. Additionally, quasi-experimental studies focused on specific technology implementations or regulatory changes could strengthen causal conclusions.

Behavioral studies on how decision-makers adopt and trust AI in areas like credit, treasury, and operations would link the statistical findings to how people accept and use new technologies. Combining these insights with the coefficient map would provide a clearer picture of how judgment, uncertainty, and analytics interact in real-world decision-making.

### **6. Conclusion and implications**

This study assessed the efficiency of the Gulf Cooperation Council (GCC) banking sector using Data Envelopment Analysis (DEA) and panel regression to identify key determinants, with particular emphasis on artificial intelligence (AI) adoption and data-driven decision-making (DDDM) during both crisis and recovery periods. The findings reveal consistent patterns across the COVID-19 and post-pandemic periods, underscoring the robustness of the approach. Strong capital adequacy, higher profitability, and fully integrated AI capabilities emerge as significant drivers of efficiency, while elevated non-performing loans (NPLs) reduce efficiency, and branch footprint exerts minimal impact in an increasingly digitalized environment. Interpreted through a Neutrosophic lens, these results reflect high-truth relationships for core financial and technological factors, alongside varying degrees of indeterminacy due to differences in governance, regulatory regimes, and country-specific market conditions [8] [9].

The study highlights the temporal evolution of AI’s impact on efficiency. Early adoption shows weak or neutral effects, consistent with implementation lags, learning costs, and the transitional nature of technology integration. By 2024, AI demonstrates a clear positive effect, illustrating a transition from partial indeterminacy to stronger truth membership as data pipelines, risk models, and decision workflows mature. This dynamic underscores the importance of treating AI adoption as a continuous, strategic process rather than a one off investment, emphasizing governance, staff training, and integration into managerial routines. Prioritizing capital adequacy and credit risk management before expanding physical networks further strengthens efficiency outcomes, consistent with the triadic view of Neutrosophic theory, where truth, falsity, and indeterminacy coexist in operational decision-making.

From a policy perspective, the findings indicate that well designed AI enabled risk management and process automation can enhance efficiency without compromising financial stability. Promoting common data standards and privacy preserving data sharing frameworks reduces the fixed costs of technology adoption, allowing smaller or late adopting banks to benefit from advances while mitigating uncertainty. Cross-country benchmarking of leading banks’ practices can further reduce indeterminacy and guide less experienced institutions, minimizing costly trial-and-error approaches during digital transformation.

The stability of the GCC banking sector also depends on maintaining robust capital and asset quality standards. Regulators can enhance resilience by embedding AI related governance into supervisory frameworks, ensuring that technology adoption aligns with careful identification, assessment, and control of risks. In Neutrosophic terms, this approach reduces indeterminacy and falsity in the relationship between technological investments and operational outcomes, thereby increasing the truth membership of efficiency improvements.

Country-specific institutional and competitive factors remain relevant in explaining efficiency differences. Nations with earlier and broader digital programs, such as Qatar and the UAE, demonstrate faster recovery and higher efficiency, while others face constraints related to asset quality and delayed analytics adoption. Future research could examine how variations in regulatory frameworks, competition intensity, and national digital strategies influence the pace and depth of efficiency gains, and how these factors interact with uncertainty, indeterminacy, and partial truth in performance outcomes.

Overall, this study provides a structured, evidence driven framework for understanding how financial strength, effective risk management, and AI integration jointly influence efficiency in the GCC banking sector. By linking technology adoption to operational performance under both crisis and recovery conditions, and explicitly acknowledging uncertainty through a Neutrosophic perspective, the study offers actionable guidance for decision-makers seeking to sustain competitiveness while safeguarding stability.

## References

- [1] Řepková, I., “Banking efficiency determinants in the Czech banking sector,” *Procedia Economics and Finance*, vol. 23, pp. 191–196, 2015, doi: 10.1016/s2212-5671(15)00367-6.
- [2] Y. Zhu, Y. Li, and L. Liang, “A variation of two-stage SBM with leader–follower structure: An application to Chinese commercial banks,” *Journal of the Operational Research Society*, vol. 69, no. 10, pp. 1601–1610, 2017, doi: 10.1057/s41274-017-0262-z.
- [3] K. Zhong, C. Li, and Q. Wang, “Evaluation of bank innovation efficiency with data envelopment analysis: From the perspective of uncovering the black box between input and output,” *Mathematics*, vol. 9, no. 24, p. 3318, 2021, doi: 10.3390/math9243318.
- [4] G. Whalen, “A proportional hazards model of bank failure: An examination of its usefulness as an early warning tool,” *Economic Review*, vol. 27, no. 1, pp. 21–31, 1991.
- [5] Sufian, “The efficiency of Islamic banking industry: A non-parametric analysis with non-discretionary input variable,” *Islamic Economic Studies*, vol. 15, no. 1, pp. 1–30, 2007.
- [6] R. B. Staub, G. da Silva e Souza, and B. M. Tabak, “Evolution of bank efficiency in Brazil: A DEA approach,” *European Journal of Operational Research*, vol. 202, no. 1, pp. 204–213, 2010, doi: 10.1016/j.ejor.2009.04.018.
- [7] S. Smith, “Digital transformation in the GCC,” 2021.
- [8] Smarandache, *Neutrosophy: Neutrosophic Probability, Set, and Logic*. American Research Press, 1998.
- [9] Smarandache and S. Pramanik, Eds., *New Trends in Neutrosophic Theory and Applications*. Pons Editions, 2016.
- [10] Z. Selman and K. Faiq, “Technology in the GCC: Leading the way and driving value,” *Deloitte Middle East*, 2018.
- [11] L. M. Seiford and J. Zhu, “Modelling the influence of certain environmental variables on technical efficiency: A comparison of DEA and SFA,” *European Journal of Operational Research*, vol. 116, no. 3, pp. 520–530, 1999, doi: 10.1016/S0377-2217(98)00154-1.
- [12] J. Presley and R. Wilson, *Banking in the Arab Gulf*. Routledge, 1991.
- [13] O. Perals, S. Rambaud, and J. Sánchez García, “Does AI private investment really matter for financial institutions’ efficiency? Evidence from a country panel,” *Finance Research Open*, vol. 1, p. 100009, 2025, doi: 10.1016/j.finr.2025.100009.

- [14] S. Papazian, M. Rizk, S. Bohsali, and A. Matar, “Empowering the GCC digital workforce,” *Ideation Center Insight*, 2017.
- [15] Mirzaei and A. Samet, “Effectiveness of macroprudential policies: Do stringent bank regulation and supervision matter?” *International Review of Economics and Finance*, vol. 80, pp. 342–360, 2022, doi: 10.1016/j.iref.2022.02.037.
- [16] O. Mahmood, V. Krishnaswamy, A. Al-Shabibi, and N. Hneini, “COVID-19: Implications for the GCC banking sector,” *KPMG in Qatar*, 2020.
- [17] Lita and T. Stamule, “Using non-parametric technical data envelopment analysis (DEA) for measuring productive technical efficiency,” in *Proceedings of the International Conference on Business Excellence*, vol. 12, no. 1, pp. 533–543, 2018, doi: 10.2478/picbe-2018-0048.
- [18] Licerán-Gutiérrez, M. P. Horno-Bueno, A. Gómez-Ortega, and N. Mirza, “Key factors of European banking efficiency: An application of DEA methodology,” *Journal of Financial Reporting and Accounting*, 2025, doi: 10.1108/JFRA-09-2024-0668.
- [19] S. B. Kelly, Ed., *Desert Dispute: The Diplomacy of Boundary-Making in South-Eastern Arabia*, vols. 1–2. Gerlach Press, 2018, doi: 10.2307/j.ctvvn7d.
- [20] K. Kelley, “Technology trends in GCC countries: A bird’s eye overview,” 2021.
- [21] G. Karagiannis and S. Kourtzidis, “On modelling non-performing loans in bank efficiency analysis,” *International Journal of Finance and Economics*, vol. 30, no. 2, pp. 1742–1757, 2025, doi: 10.1002/ijfe.2986.
- [22] F. Kane, “Gulf banks are weathering the pandemic storm — for now,” Arab News, 2020.
- [23] Y.-B. Ji and C. Lee, “Data envelopment analysis,” *The Stata Journal*, vol. 10, no. 2, pp. 267–280, 2010, doi: 10.1177/1536867X1001000207.
- [24] Z. He, G. Qiao, L. Zhang, and W. Zhang, “Regulator supervisory power and bank loan contracting,” *Journal of Banking and Finance*, vol. 126, p. 106062, 2021, doi: 10.1016/j.jbankfin.2021.106062.
- [25] Gulf Business, “Top 50 GCC banks 2017,” Gulf Business, 2017. [Online]. Available: <https://gulfbusiness.com/lists/top-50-gcc-banks-2017/>
- [26] Fukuyama, R. Matousek, and N. G. Tzeremes, “A unified framework for nonperforming loan modeling in bank production: An application of data envelopment analysis,” *Omega*, vol. 126, p. 102778, 2024, doi: 10.1016/j.omega.2021.102778.
- [27] S. Flores-Ureba, V. Gelashvili, A. Gómez-Ortega, and M. L. D. Jalón, “R&D companies based on their age, size and type of field, are they solvent companies?” *International Entrepreneurship and Management Journal*, vol. 20, no. 2, 2023, doi: 10.1007/s11365-023-00895-w.
- [28] M. J. Farrell, “The measurement of productive efficiency,” *Journal of the Royal Statistical Society: Series A (General)*, vol. 120, no. 3, pp. 253–290, 1957, doi: 10.2307/2343100.
- [29] R. Fare, S. Grosskopf, and C. A. K. Lovell, *The Measurement of Efficiency of Production*. Kluwer Academic Publishers, 1985.
- [30] Emrouznejad and G. L. Yang, “A survey and analysis of the first 40 years of scholarly literature in DEA: 1978–2016,” *Socio-Economic Planning Sciences*, vol. 61, pp. 4–8, 2018, doi: 10.1016/j.seps.2017.01.008.
- [31] M. Duro and G. Ormazabal, “Does regulating banks’ corporate governance help?” in *CSR, Sustainability, Ethics and Governance*, S. Arjoon and J. B. McIntosh, Eds. Springer, 2018, doi: 10.1007/978-3-319-70007-6\_1.
- [32] Deville, “Branch banking network assessment using DEA: A benchmarking analysis – A note,” *Management Accounting Research*, vol. 20, no. 4, pp. 252–261, 2009, doi: 10.1016/j.mar.2009.08.001.
- [33] M. Delis, M. Iosifidi, and M. G. Tsionas, “Endogenous bank risk and efficiency,” *European Journal of Operational Research*, vol. 260, no. 1, pp. 376–387, 2017, doi: 10.1016/j.ejor.2016.12.024.

- [34] Delcea, I. A. Bradea, and M. I. Bolos, "Modeling the covariance of financial assets using neutrosophic fuzzy numbers," *Symmetry*, vol. 15, no. 2, p. 320, 2023.
- [35] M. Degl'Innocenti, S. A. Kourtzidis, Z. Sevic, and N. G. Tzeremes, "Bank productivity growth and convergence in the European Union during the financial crisis," *Journal of Banking and Finance*, vol. 75, pp. 184–199, 2017, doi: 10.1016/j.jbankfin.2016.11.016.
- [36] T. Cronjé and J. de Beer, "Combining efficiency with ROA: Indicator of future relative performance – South African banking groups," *Corporate Ownership and Control*, vol. 7, no. 4-2, pp. 287–296, 2010, doi: 10.22495/cocv7i4c2p4.
- [37] W. W. Cooper, L. M. Seiford, and K. Tone, *Introduction to Data Envelopment Analysis and Its Uses: With DEA-Solver Software and References*. Springer Science and Business Media, 2006, doi: 10.1007/0-387-29122-9.
- [38] Conde and A. Pataud, "COVID-19 crisis response in MENA countries," OECD Policy Responses to Coronavirus (COVID-19), 2020.
- [39] T. J. Coelli, D. S. P. Rao, C. J. O'Donnell, and G. E. Battese, *An Introduction to Efficiency and Productivity Analysis*, 2nd ed. Springer Science and Business Media, 2005, doi: 10.1007/978-0-387-24265-1.
- [40] W. W. Choi, J. Kim, and M. Kim, "Derivatives holdings and market values of US bank holding companies," *Applied Economics*, vol. 48, no. 49, pp. 4747–4757, 2016, doi: 10.1080/00036846.2016.1167826.
- [41] C. F. Chen and K. T. Soo, "Some university students are more equal than others: Efficiency evidence from England," *Economics Bulletin*, vol. 30, no. 4, pp. 1–12, 2010.
- [42] Charnes, W. W. Cooper, and E. Rhodes, "Measuring efficiency of decision making units," *European Journal of Operational Research*, vol. 2, no. 6, pp. 429–444, 1978, doi: 10.1016/0377-2217(78)90138-8.
- [43] W. F. Bowlin, "Measuring performance: An introduction to data envelopment analysis (DEA)," *The Journal of Cost Analysis*, vol. 15, no. 2, pp. 3–27, 1998, doi: 10.1080/08823871.1998.10462318.
- [44] M. I. Bolos, I. A. Bradea, and C. Delcea, "Modeling the performance indicators of financial assets with neutrosophic fuzzy numbers," *Symmetry*, vol. 11, no. 8, p. 1021, 2019.
- [45] Bisetti, "The value of regulators as monitors: Evidence from banking," *Management Science*, vol. 70, no. 12, pp. 8464–8483, 2024, doi: 10.1287/mnsc.2023.4848.
- [46] Bischof, U. Brüggemann, and H. Daske, "Asset reclassifications and bank recapitalization during the financial crisis," *Management Science*, vol. 69, no. 1, pp. 75–100, 2023, doi: 10.1287/mnsc.2021.4245.
- [47] N. Berger and D. B. Humphrey, "Efficiency of financial institutions: International survey and directions for future research," *European Journal of Operational Research*, vol. 98, no. 2, pp. 175–212, 1997, doi: 10.1016/S0377-2217(96)00342-6.
- [48] H. Bazih and D. Vanwalleghem, "Deriving value or risk? Determinants and the impact of emerging market banks' derivative usage," *Research in International Business and Finance*, vol. 56, p. 101379, 2021, doi: 10.1016/j.ribaf.2021.101379.
- [49] R. Barrell, E. P. Davis, D. Karim, and I. Liadze, "Bank regulation, property prices and early warning systems for banking crises in OECD countries," *Journal of Banking & Finance*, vol. 34, no. 9, pp. 2255–2264, 2010, doi: 10.1016/j.jbankfin.2010.02.015.
- [50] Bardhan and E. Zheng, "A data envelopment analysis approach to estimate IT-enabled production capability," *MIS Quarterly*, vol. 41, no. 1, pp. 189–205, 2017, doi: 10.25300/MISQ/2017/41.1.09.
- [51] R. D. Banker, A. Charnes, and W. W. Cooper, "Some models for estimating technical and scale inefficiencies in data envelopment analysis," *Management Science*, vol. 30, no. 9, pp. 1078–1092, 1984, doi: 10.1287/mnsc.30.9.1078.

- [52] P. P. Athanasoglou, S. N. Brissimis, and M. D. Delis, “Bank-specific, industry-specific and macroeconomic determinants of bank profitability,” *Journal of International Financial Markets, Institutions and Money*, vol. 18, no. 2, pp. 121–136, 2008, doi: 10.1016/j.intfin.2006.07.001.
- [53] Asmild, J. C. Paradi, D. N. Reese, and F. Tam, “Measuring overall efficiency and effectiveness using DEA,” *European Journal of Operational Research*, vol. 178, no. 1, pp. 305–321, 2007, doi: 10.1016/j.ejor.2006.01.015.
- [54] Arrigoni and M. Rivolti, “Fit and proper requirements in the EU banking sector: A step further,” *European Business Organization Law Review*, vol. 23, no. 4, pp. 977–996, 2022, doi: 10.1007/s40804-022-00244-4.
- [55] Antunes, A. Hadi-Vencheh, A. Jamshidi, Y. Tan, and P. Wanke, “Bank efficiency estimation in China: DEA-RENNNA approach,” *Annals of Operations Research*, vol. 315, no. 2, pp. 1373–1398, 2022, doi: 10.1007/s10479-021-04111-2.
- [56] Al-Hassan, M. Khamis, and N. Oulidi, “The GCC banking sector: Topography and analysis,” International Monetary Fund, 2010.
- [57] E. Aksoy, C. Dirik, and İ. E. Kandil Göker, “Opening the black-box of bank efficiency in Turkey with two-stage data envelopment analysis: A study on capital adequacy ratio,” *Ege Academic Review*, vol. 22, no. 1, pp. 75–91, 2022, doi: 10.21121/eab.1064816.
- [58] D. J. Aigner, C. A. K. Lovell, and P. Schmidt, “Formulation and estimation of stochastic frontier production functions,” *Journal of Econometrics*, vol. 6, no. 1, pp. 21–37, 1977, doi: 10.1016/0304-4076(77)90052-5.