

Article

# Evaluation of Total Risk-Weighted Assets in Islamic Banking through Fintech Innovations

Asma S. Alzwi<sup>1</sup>, Jamil J. Jaber<sup>2,3,\*</sup> , Hani Nuri Rohuma<sup>1</sup> and Rania Al Omari<sup>4</sup>

<sup>1</sup> Department of Finance and Banking, Faculty of Economics, University of Benghazi, Benghazi 1308, Libya; alzwiasma@yahoo.com or asma.suliman@uob.edu.ly (A.S.A.); hani.rohuma@uob.edu.ly (H.N.R.)

<sup>2</sup> Department of Finance and Banking, Faculty of Business, Applied Science Private University, Amman 11937, Jordan

<sup>3</sup> Department of Finance, School of Business, The University of Jordan, Aqaba 77110, Jordan

<sup>4</sup> Department of Accounting, School of Business, The University of Jordan, Aqaba 77110, Jordan; r.omari@ju.edu.jo

\* Correspondence: j.jaber@ju.edu.jo or jameljaber2011@hotmail.com

**Abstract:** The assessment of total risk-weighted assets (LTRWAs) in the banking sector is of the utmost importance. It serves as a critical component for regulatory compliance, risk management, and capital adequacy. By accurately assessing LTRWAs, banks can effectively meet regulatory requirements, efficiently allocate capital resources, and proactively manage risks. Moreover, the accurate assessment of LTRWAs supports performance evaluation and fosters investor confidence in the financial stability of banks. This study presents statistical analyses and machine learning methods to identify factors influencing LTRWAs. Data from Bahrain, Jordan, Qatar, the United Arab Emirates, and Yemen, spanning from 2010 to 2021, was utilized. Various statistical tests and models, including ordinary least squares, fixed effect, random effect, correlation, variance inflation factor, tolerance tests, and fintech models, were conducted. The results indicated significant impacts of the unemployment rate, inflation rate, natural logarithm of the loan-to-asset ratio, and natural logarithm of total assets on LTRWAs in regression models. The dataset was divided into a training group (90% of the data) and a testing group (10% of the data) to evaluate the predictive capabilities of various fintech models, including an adaptive network-based fuzzy inference system (ANFIS), a hybrid neural fuzzy inference system (HyFIS), a fuzzy system with the heuristic gradient descent (FS.HGD), and fuzzy inference rules with the descent method (FIR.DM) models. The selection of the optimal model is contingent upon assessing its performance according to specific error criteria. The HyFIS model outperformed others with lower errors in predicting LTRWAs. Independent *t*-tests confirmed statistically significant differences between original and predicted LTRWA for all models, with HyFIS showing closer predictions. This study provides valuable insights into LTRWA prediction using advanced statistical and machine learning techniques, based on a dataset from multiple countries and years.

**Keywords:** Islamic banks; neural network; total risk-weighted assets; financial technology



**Citation:** Alzwi, Asma S., Jamil J. Jaber, Hani Nuri Rohuma, and Rania Al Omari. 2024. Evaluation of Total Risk-Weighted Assets in Islamic Banking through Fintech Innovations. *Journal of Risk and Financial Management* 17: 288. <https://doi.org/10.3390/jrfm17070288>

Academic Editor: M. Veysel Kaya

Received: 31 May 2024

Revised: 2 July 2024

Accepted: 4 July 2024

Published: 8 July 2024



**Copyright:** © 2024 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (<https://creativecommons.org/licenses/by/4.0/>).

## 1. Introduction

The global prominence and acceptance of the Islamic banking sector are experiencing a notable upswing, extending its appeal beyond Muslim nations to non-Muslim regions. According to the International Monetary Fund (IMF), the Islamic finance industry is witnessing substantial growth worldwide and holds significant significance in Asia and the Middle East [Shaheen et al. \(2024\)](#). Islamic banking has attained a global presence, with institutions operating in numerous countries. Its origins can be traced back to the 1970s, marked by significant milestones such as the establishment of the Islamic Development Bank and Dubai Islamic Bank ([Zain and Hassan 2019](#)). The subsequent decades, particularly the 1980s and 1990s, witnessed accelerated growth driven by the escalating demand

for Shariah-compliant services. To cater to this demand, regulations were introduced, and dedicated institutions were established in Muslim-majority countries. In the 2000s, Islamic banking expanded its reach beyond Muslim-majority nations, gaining recognition and acceptance in non-Muslim countries as well (Hussain et al. 2016; Shaheen et al. 2024). During the 2008 financial crisis, Islamic finance gained prominence, and it has established itself as a prominent presence in global financial centers such as Dubai, Kuala Lumpur, and London. These cities have emerged as key hubs for Islamic finance, serving as influential centers for the development, innovation, and promotion of Shariah-compliant financial services.

The Islamic banking sector has undergone rapid growth, prompting increased focus and research on the management of Islamic banking, specifically risk management. At present, Islamic banks hold the majority share of Islamic finance assets, comprising over 76% of the total assets, amounting to more than USD 3.2 trillion. The distinctive nature of the Islamic banking business model, differing from that of traditional banks, highlights the importance of comprehensive risk management practices in the sector (Misman and Bhatti 2020). Islamic banks, as intermediary institutions based on Sharia principles, are required to ensure two types of compliance: Sharia principle compliance and legal compliance. They differ from conventional banks by avoiding interest-based transactions and instead using alternative mechanisms like profit and loss sharing (Mudarabah) and cost-plus financing (Murabaha) (Akkizidis and Khandelwal 2008; Orhan et al. 2023; Thalib et al. 2017). Islamic banks prioritize ethical and responsible banking, abstaining from investments in prohibited sectors and focusing on projects that promote social welfare. Islamic banks offer specialized products such as Islamic mortgages, bonds, and insurance, all structured to comply with Shariah principles (El Mosaïd and Boutti 2014; Jaaffar and Ghazali 2018).

Islamic banks, like conventional banks, are subject to regulatory requirements regarding capital adequacy. One of the internationally recognized frameworks for measuring capital adequacy is the Basel framework, which includes the Basel (I, II, and III) framework. Under the Basel framework, banks are required to maintain a minimum level of capital in relation to their risk-weighted assets. The total risk-weighted assets in banks encompass the risk-weighted assets from credit, market, and operational risks. Credit risk refers to the potential losses arising from borrower defaults, while market risk encompasses losses due to fluctuations in market prices of assets and liabilities. Operating risk captures potential losses arising from non-financial factors such as legal and operational issues. Each category represents a different source of risk that the bank faces in its operations (Hull 2023; Lyons and Rice 2022). The 2008 global financial crisis raised critical questions regarding the efficacy of risk-weighted assets (RWAs) in the banking sector and the target ratios for capital adequacy. It exposed regulatory flaws within the banking industry, prompting a closer examination of the effectiveness of RWAs and banks' capital adequacy objectives (Chang and Hsieh 2015). The RWA plays a crucial role in enhancing the value of the banking system by improving capital adequacy ratios. This can be achieved through increasing regulatory capital or reducing RWAs. Lessons from the financial crisis highlight the importance of having sufficient high-quality capital in the banking system. It became clear that increased capital is necessary to strengthen the financial position and improve preparedness for future crises. Effective capital management and the role of RWAs are emphasized in fortifying the stability and strength of the banking sector (Neisen and Röth 2018).

Capital adequacy ratios remain a fundamental aspect of the regulatory framework for banks, even in the aftermath of the global financial crisis. These ratios serve as a key tool for investors, banks, and policymakers to assess the financial soundness of banks. The post-crisis Basel II reform has focused on raising the minimum capital adequacy ratio and tightening the definition of acceptable capital (BCBS 2017; Hull 2023). In 2011, the European Banking Authority (EBA) temporarily increased risk-based capital requirements as part of its Capital Exercise for European banks. Additionally, a new globally integrated capital buffer has been introduced to address systemic risk (Jobst and Ong 2020).

The use of neural networks in the banking sector has been a topic of interest in recent years. In a Turkish case study on bank failure prediction, various techniques including

neural networks, support vector machines, and multivariate statistical methods were used to categorize banks as healthy or non-healthy. The study evaluated the performance of these techniques and found that the multi-layer perceptron and learning vector quantization models were the most successful in predicting bank financial failure. The study also explored other statistical methods such as discriminant analysis, cluster analysis, and logistic regression (Boyacioglu et al. 2009). A new hybrid model combining the Logit model and a neural network was developed to estimate the probability of the default of corporate customers in a commercial bank. The model was verified using experimental data from companies listed in the Tehran Stock Exchange. The results of the study demonstrate that the proposed hybrid model outperforms both the Logit model and the neural network in credit rating classification. The significant variables identified include gross profit to sale, retained earnings to total asset, fixed asset to total asset, interest to total debt, gross profit to asset, operational profit to sale, and EBIT to sale (Raei et al. 2016). The impact of artificial intelligence on service quality and customer satisfaction in Jordanian banks was examined (Al-Araj et al. 2022). The study revealed that artificial intelligence had a significant influence, leading to the identification of five subscales in the updated service quality model. A novel approach for predicting default risk in bancassurance was proposed, utilizing the group method of data handling (GMDH) technique and a diversified classifier ensemble based on GMDH (dce-GMDH). The dataset comprised 30,000 credit card clients from a large bank in Taiwan, with 23 distinct input variables characterizing each customer. The results demonstrated the superiority of the dce-GMDH model over the conventional GMDH model in predicting default risk, highlighting its usefulness for bancassurance and client segmentation (Jaber et al. 2023). The influence of digital transformation (financial technology) on operational efficiency, customer experience, competitive advantage, organizational performance, and risk management in Jordanian Islamic banks was investigated (Shehadeh et al. 2024). The study emphasized the integration of digital innovation, including financial technology, with robust risk management strategies. Al-shurafat et al. (2024) explored the intention to adopt the Metaverse (financial technology) in Islamic banks, highlighting the importance of perceived usefulness, ease of use, and aligning user experience with religious values.

This study analyzes the influence of macroeconomic variables (such as the inflation rate and unemployment rate) and bank-specific factors (like size and loan-to-total asset ratio) on RWA in Islamic banks. The LTRWAs represent the aggregate value of a bank's assets adjusted for their respective risk levels. Islamic banks rely on LTRWAs to ensure regulatory compliance, manage risks, assess capital adequacy, maintain investor confidence, and adhere to Sharia principles. A higher LTRWA value indicates increased risk and business costs due to higher capital requirements (Hull 2023; Saunders and Schumacher 2000). Inflation rate (IN) refers to the gradual increase in the overall price level of goods and services in an economy over time. It reduces the purchasing power of money as prices increase. Inflation is influenced by factors such as supply and demand dynamics, government policies, and economic conditions (Schiller and Gebhardt 2024). The unemployment rate (UR) indicates the percentage of the labor force that is unemployed and actively seeking employment. It serves as a crucial economic indicator reflecting the health of the job market. A higher unemployment rate signifies a larger share of the workforce without jobs, while a lower rate indicates a higher level of employment. Various factors, including economic conditions, labor market dynamics, government policies, and the business cycle, influence the unemployment rate (Louzis et al. 2012; Schiller and Gebhardt 2024). Log total assets (LNTAs), or bank size, refers to the logarithm of a bank's total assets. It is used to measure the scale of a bank's operations and resources, impacting risk, profitability, and regulatory requirements (Pham et al. 2021). The loan-to-asset (LOTA) ratio is a financial metric that indicates a bank's utilization of its assets for lending activities. A higher ratio signifies a larger portion of the bank's assets being invested in loans, which can imply higher risk and potential profitability. Conversely, a lower ratio suggests a more conservative lending approach (Claeys and Vander Vennet 2008).

This study addresses a significant gap in the literature on the Islamic banking and finance industry and makes a valuable contribution in several ways. Firstly, it addresses the scarcity of studies on RWAs in Islamic banks compared to conventional banking services. To the best of our knowledge, this study is one of the few that directly examines RWAs in the context of Islamic banks. Only one other study has attempted to address this criterion in Islamic banks, conducted by [Mohamad et al. \(2018\)](#). The performance of RWAs in the Malaysian banking system post-global financial crisis was examined. The sample consists of 15 selected Islamic banks and 15 selected conventional banks, covering the period from 2012 to 2016. The findings revealed a significant relationship between risk-taking and RWA performance, with conventional banks demonstrating superior performance compared to Islamic banks. Notably, the impact appears to be more pronounced for Islamic banks. This research emphasizes the importance of considering risk-taking behavior and the type of banking system when evaluating RWA performance post-crisis. Secondly, this pioneering study focuses on the factors influencing the LTRWAs of Islamic banks, filling a significant research gap. It utilizes machine learning methods to assess the impact of variables such as the UR, IN, LOTA, and LNTA variables on LTRWAs. By analyzing data from Bahrain, Jordan, Qatar, the UAE, and Yemen spanning from 2010 to 2021, the study aims to provide valuable insights into regulatory compliance and risk management in the Islamic banking sector. Previous studies (e.g., [Adebola et al. 2011](#); [Čihák and Hesse 2010](#); [Havidz and Setiawan 2015](#); [Jaber et al. 2023](#)) have explored credit risk within the Islamic banking sector. However, none of these studies have specifically examined the impact on LTRWAs. Finally, this paper employs a comprehensive methodology, combining statistical analyses and machine learning methods, to identify factors influencing LTRWAs and make predictions. Unlike previous studies, it incorporates a wide range of statistical tests and Fintech models, including ANFIS, HyFIS, FS.HGD, and FIR.DM.

This study is organized as follows: Section 2 presents a comprehensive of previous studies, while Section 3 provides a detailed explanation of the materials and methods utilized in this study. The study design is discussed in Section 4. The empirical results are thoroughly analyzed in Section 5. Finally, Section 6 draws the conclusions based on the findings.

## 2. Literature Review

Risk management plays a crucial role in the banking industry, particularly during periods of financial instability or uncertain events like the recent global healthcare crisis. [Aysan and Hersi \(2024\)](#) assess the impact of this crisis on the resilience of Islamic and conventional banks in the six GCC countries. They compare financial ratios from the 3q-2020 statements of 51 publicly listed regional banks and find that GCC Islamic banks outperformed conventional banks, with strong capitalization prior to the pandemic. The absence of derivative engagement by Islamic banks also contributed to their robustness. Thus, Islamic banks, along with disruptive FinTech, can help stabilize the post-COVID-19 economic world ([Amalia et al. 2024](#); [Siska 2022](#); [Wan et al. 2023](#)). Meanwhile, the understanding and management of LTRWAs have gained significant attention among researchers and practitioners. However, there is a research gap regarding LTRWAs in the context of Islamic banks and developing countries. Addressing this gap, [Leogrande et al. \(2023\)](#) estimate LTRWAs in 30 European countries over 30 trimesters using data from the European Banking Authority (EBA) and 139 variables. The study period spanned from the first quarter of 2019 to the fourth quarter of 2021. The study employed various econometric models, including Pooled OLS, Panel Data with Fixed Effects, Panel Data with Random Effects, and Weighted Least Squares. The findings revealed a negative association between LTRWA and non-financial corporation (NFC) loans in the mining, public administration, and finance sectors. Conversely, a positive association was observed with NFC loans in health services, education, and net fee and commission income. Furthermore, the study compared the performance of eight different machine learning algorithms in predicting the value of LTRWA. The algorithms tested included Linear Regression, Tree Ensemble

Regression, Random Forest Regression, a Probabilistic Neural Network (PNN), Gradient Boosted Tree Regression, a Simple Regression Tree, an artificial neural network (ANN), and Polynomial Regression. Among these algorithms, Linear Regression emerged as the best predictor. Based on their analysis, the study predicts a 1.5% increase in LTRWAs.

Most risk studies in banking primarily focus on credit risks. Within credit risk management research, systematic and unsystematic variables are identified as the main causes of credit risk. Systematic variables encompass risks that are beyond a bank's control, including macroeconomic factors such as the unemployment rate, interest rate fluctuations, inflation, and shifts in the economic cycle like financial crises and recessions. Additionally, political variables can also influence credit risk (Ashraf and Butt 2019; Ghosh 2017; Messai and Jouini 2013). On the other hand, unsystematic variables refer to factors that are specific to a bank and can be controlled or monitored. These factors may include bank-specific variables designated by the central bank or factors within the bank's control. The literature acknowledges variations in banking industry structures across countries and individuals and suggests that credit risk levels are correlated with unsystematic risk or bank-specific variables (BSV), either positively or negatively (Louzis et al. 2012; Naili and Lahrichi 2022).

In a study by Warue (2013) focusing on commercial banks in Kenya from 1995 to 2009, it was found that bank-specific factors had a greater impact on non-performing loan (NPL) levels compared to macroeconomic factors. Another study by Castro (2013) examined the link between macroeconomic developments and banking credit risk in countries affected by unfavorable economic conditions, emphasizing the significant influence of factors such as GDP growth, housing price indices, unemployment rate, and interest rate. Sitorus (2015) found that LTRWAs played a significant role in determining the credit default in Indonesian banks. Zheng et al. (2018) conducted a study on commercial banks, identifying variables such as profitability, capital, and bank size as inversely associated with credit risk. Kuzucu and Kuzucu (2019) analyzed the determinants of non-performing loans in emerging and advanced countries, highlighting the significant influence of real GDP growth and the persistence of NPLs across different economies. In a study by Al Masud and Hossain (2021) on commercial banks in an emerging economy, it was found that bank-specific variables such as ROA were negatively related to NPL, while macroeconomic variables showed a positive relationship. Jaber et al. (2021) conducted LGD estimation for a credit portfolio using beta regression and found that lower LGD values were associated with higher GDP and lower inflation rates. Naili and Lahrichi (2022) examined NPLs in MENA countries and identified key determinants including GDP growth, unemployment, bank factors, inflation, sovereign debt, and bank size. Antony and Suresh (2023) investigated credit risk in banks and found a negative relationship between return on equity and credit risk, while bank age and ownership type had positive effects. Additionally, GDP showed a positive association with credit risk, while inflation had a negative influence.

However, there has been a predominant focus on credit risk studies in the US and Europe, while the Middle East and Africa have received relatively little attention. European studies account for 30% of the research, followed by 19% in the United States, 15% in Asia, 7% in the Middle East and North Africa (MENA) region, and only 3% in African countries. This highlights the research gap in emerging economies, particularly in the Middle East and Africa (Naili and Lahrichi 2022). This study aims to address this gap by investigating LTRWAs in Islamic banks within developing countries, considering both microeconomic and macroeconomic factors. Understanding these dynamics is crucial for effective risk management in the banking sector (Bonfim 2009; Hull 2023; Incekara and Çetinkaya 2019; Louzis et al. 2012). The LOTA ratio is a key indicator of asset quality in the banking sector (Anbar and Alper 2011). Banks with a higher LOTA ratio are more exposed to default risks and have lower liquidity compared to other asset classes (Ghassan and Guendouz 2019; Imbierowicz and Rauch 2014; Zarei et al. 2019). This can create a conflict between credit and liquidity risk. Research has shown mixed findings regarding the relationship between the LOTA ratio and credit risk. Studies in the Turkish and Nepalese banking sectors have found that a higher proportion of loans to assets ratio is associated with a higher likelihood

of non-performing loans (Bhattacharai 2019). Factors such as the unemployment rate and bank-specific variables like the LOTA ratio have been found to have a statistically significant positive impact on non-performing loans (Kartikasary et al. 2020).

Bank size is a significant factor associated with credit risk. According to Zheng et al. (2018), the logarithm of total assets is used to determine the size of a bank. The bank's size has a significant influence on credit risk. According to the "too-big-to-fail" argument, banks of greater size are more likely to take on more risk and have a higher chance of failing (Ashraf et al. 2016; Ghassan and Guendouz 2019). Nonetheless, there may be a positive correlation between total bank risks and size, suggesting that a bank's size correlates with its well-diversified portfolio and increased efficiency due to economies of scale (Abbas et al. 2021; Imbierowicz and Rauch 2014; Pham et al. 2021). On the other hand, research suggests that credit risk and bank size are negatively correlated (Alhassan et al. 2014; Salas and Saurina 2002; Saunders and Schumacher 2000). Several studies support this notion, indicating that larger banks have better risk management capabilities and diversification (Gulati et al. 2019; Hamzani and Achmad 2018). However, smaller banks may have higher risk tendencies due to limited resources for risk management (Naili and Lahrichi 2022; Tafri et al. 2009). The relationship between credit risk and bank size can vary based on the context and specific factors affecting individual banks.

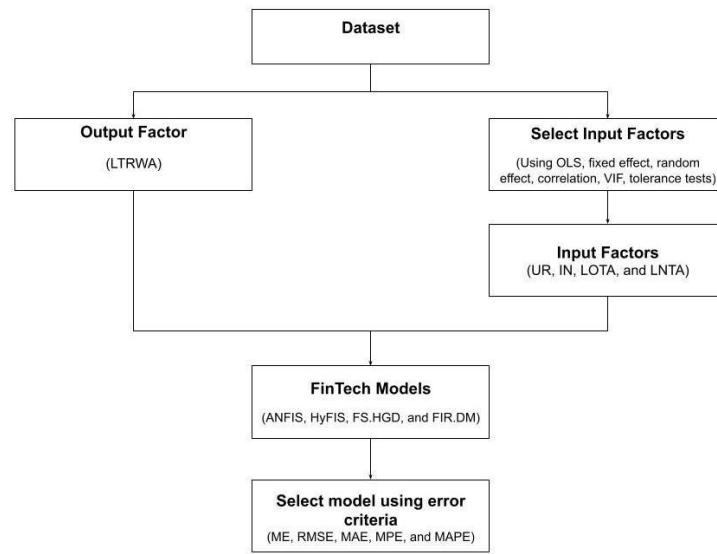
The impact of inflation on credit risk in the banking industry is debated among researchers. Some studies, such as Klein (2013) and Rinaldi and Sanchis-Arellano (2006), suggest that inflation increases credit risk by reducing the value of money and borrowers' income. Others, like Makri et al. (2014) and Nkusu (2011), argue for a negative correlation between inflation and NPLs. Kuzucu and Kuzucu (2019) note that the effects of inflation on NPLs vary depending on the location. Furthermore, Shaheen et al. (2024) found in a study on Islamic banking in Pakistan that inflation had a positive but insignificant impact on credit risk in Islamic banks. The unemployment rate is an important factor in determining credit risk, reflecting the state of the economy. High unemployment reduces borrowers' repayment capacity, leading to an increase in NPL (Ali and Daly 2010). Various studies by Klein (2013) and Louzis et al. (2012) have shown a positive correlation between unemployment and NPLs, indicating that a higher unemployment rate negatively impacts consumers' cash flows and their ability to repay loans. Conversely, Castro (2013), Eldomiatiy et al. (2022), and Kartikasary et al. (2020) found a negative correlation between unemployment, NPLs, and inflation in developed and developing regions. Further research is needed to understand the impact of unemployment on risk-weighted assets in the Islamic financial sector, particularly in the Middle East and North African countries.

### 3. Methodology and Mathematical Models

In our study, we focus on four key models: ANFIS, HyFIS, FS.HGD, and FIR.DM. These models play a crucial role in our study and require specific input and output factors. To fulfill these requirements, we gathered yearly data from Islamic banks located in Bahrain, Jordan, Qatar, the United Arab Emirates, and Yemen. The data cover the period from 2010 to 2021, allowing us to conduct a comprehensive analysis. The flowchart illustrates the process of selecting a FinTech model, starting with the collection of data from official sources such as the World Bank (Bankscope (Orbis Bank Focus)). This step is crucial to ensure the reliability of the data. The collected data are then divided into two categories: output factors, represented by TRWAs, and input factors, which include the UR, IN, LOTA, and LNTA variables.

To select the appropriate input factors, several tests are conducted, such as OLS, fixed effect, random effect, correlation, VIF, and tolerance tests. These tests help determine the most relevant and influential input factors for the analysis. The selected input and output factors are then utilized in various FinTech models, namely, ANFIS, HyFIS, FS.HGD, and FIR.DM. These models are designed to analyze the relationship between the input and output factors, providing insights into the FinTech domain. Finally, the models are evaluated and compared using error criteria such as ME, RMSE, MAE, MPE, and MAPE.

This evaluation process helps in selecting the most suitable model for the given analysis (see Figure 1).



**Figure 1.** Flowchart based on FinTech models (ANFIS, HyFIS, FS.HGD, and FIR.DM).

### 3.1. ANFIS Model

ANFIS, proposed by Jang in 1993, is a fuzzy logic system that utilizes artificial neural networks for fuzzy inference. It is commonly used to model complex nonlinear systems that are challenging to represent using traditional regression techniques. ANFIS combines the strengths of neural networks and fuzzy logic systems. The neural network component determines the membership functions, while the fuzzy inference component employs rules. The ANFIS algorithm consists of five stages. First, the input variables are fuzzified using membership functions. Second, fuzzy IF–THEN rules are created based on the fuzzy sets. Third, the degree of membership for each rule is assessed using the input values. Fourth, the outputs of each rule are aggregated based on their respective degree of membership. Finally, the aggregated output is defuzzified to obtain a crisp result. The learning algorithm of ANFIS involves two processes: the forward and backward steps. The forward process proceeds through five layers, each with its own specific function (Lei 2016; Saleh et al. 2023).

In Figure 2, ANFIS consists of five layers, each with its own set of equations that perform specific functions. These layers are as follows: 1. The Fuzzification Layer is responsible for transforming the crisp inputs into fuzzy values using the membership function  $\mu$ . The equation for this layer can be expressed as  $\mu_{A_i} = \frac{x_i - c_i}{b_i}$ , where  $i = (1, 2, \dots, n)$ ,  $x_i$  is the scaler input,  $c_i$  represents the center value of the  $i$ th membership function, and  $b_i$  is the width of the  $i$ th input. 2. The Rule Layer calculates the firing strength of each rule by multiplying the fuzzified values of the inputs.  $w_i = \mu_{A_{i1}} * \mu_{A_{i2}} * \dots * \mu_{A_{in}}$ , where  $i = (1, 2, \dots, m)$ .  $m$  is the number of rules. 3. The Normalization Layer is responsible for normalizing the weights ( $w_i$ ) of the fuzzy rules. This ensures that the sum of all the rule firing strengths is equal to 1.  $w_i' = \frac{w_i}{(w_1 + w_2 + \dots + w_n)}$ . 4. The Consequent Layer in ANFIS involves a first-order polynomial equation that determines the system’s output.  $y_i = p_i * x_i + q_i$ , where  $p_i$  and  $q_i$  are the adjustable coefficients that represent the output function of the  $i$ th rule. 5. The Defuzzification Layer in ANFIS is responsible for converting the fuzzy output into a crisp output. The commonly used method in this layer is the weighted average method. The equation used for this process is given by the following equation:

$$y = \frac{(w_1' * y_1 + w_2' * y_1 + \dots + w_m' * y_m)}{(w_1' + w_2' + \dots + w_m y_m)} \tag{1}$$

where  $y$  is the crisp output (Saleh et al. 2023).

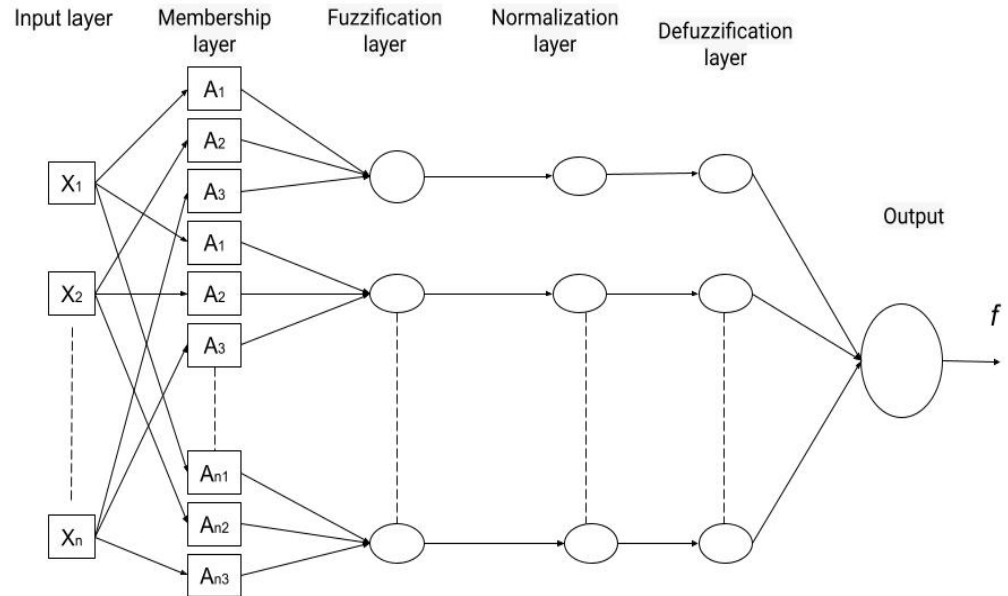


Figure 2. ANFIS flowchart of  $n$  inputs and one output with five rules.

### 3.2. FS.HGD Model

The FS.HGD function is a fuzzy rule-based system (FRBS) function that combines heuristics and the gradient descent approach to implement a simplified TSK (Takagi–Sugeno–Kang) fuzzy-rule-generating method proposed by Ishibuchi et al. (1993). The steps involved in using the FS.HGD method are as follows: 1. Data collection: Gather input and output data required for training the FS.HGD method. The input data represent the features that the FS.HGD method will utilize, while the output data represent the desired or target values that the method should aim to predict. 2. Space Partitioning: the input space is divided into regions using space partitioning techniques, generating the antecedent components of the fuzzy rules. 3. Weighted Mean Initialization: The initial consequent part of each rule is determined by calculating the weighted mean value of the training data associated with that rule. This step initializes the output values of the rules. 4. Gradient Descent: The gradient descent method is applied to update the consequent part of each rule iteratively. The process adjusts the output values based on the error between the actual and desired outputs, optimizing the fuzzy rule outputs. 5. Output Optimization: The output values of the fuzzy rules are optimized through gradient descent updates, improving the accuracy of the system’s output. For more details see Alenezy et al. (2023).

#### 3.2.1. Fuzzy System

The simplified fuzzy inference model assumes  $n$ -dimensional input and output spaces, denoted as  $[0, 1]^n$  and  $[0, 1]$ , respectively. To partition the input space, a simple fuzzy grid is employed, utilizing triangular fuzzy sets. The input variable is denoted as  $x_p = (x_{p1}, \dots, x_{pm})$ , belonging to the set of real numbers  $x \in R$ . Similarly, the output variable is denoted as  $y$ , also belonging to the set of real numbers  $y \in R$ . This formulation establishes the rule for the simplified fuzzy inference model.

$$\text{Rule } i : \text{ IF } x_1 \text{ is } A_{i1} \text{ and } x_j \text{ is } A_{ij} \text{ and } x_m, \text{ THEN } y \text{ is } \omega_i, \tag{2}$$

where  $(j = 1, \dots, m)$  represents the rule number,  $(i = 1, \dots, n)$  represents the factor number,  $A_{ij}$  denotes the membership function of the antecedent part  $(x_{p1}, \dots, x_{pm})$ , and  $w_i$  repre-



sents a real number associated with the consequent part ( $y$ ). The membership value  $\mu_i$  of the antecedent part for a specific input  $x$  can be expressed as

$$\mu_i = \prod_{j=1}^m A_{ij}(x_j). \tag{3}$$

The output of fuzzy reasoning  $y$  can be expressed as

$$y = \frac{\sum_{i=1}^n \mu_i * \omega_i}{\sum_{i=1}^n \mu_i}. \tag{4}$$

If the Gaussian membership function is used, then  $A_{ij}$  is expressed as

$$A_{ij}(x_j) = \exp\left(\frac{-1}{2} \left(\frac{x_j - c_{ij}}{b_{ij}}\right)^2\right) \tag{5}$$

where  $c_{ij}$  and  $b_{ij}$  denote the center and the width value of  $A_{ij}$ , respectively.

### 3.2.2. Heuristic Method

In the training data, we have  $m$  input–output pairs, denoted as  $(x_p, y_p)$ ,  $p = 1, 2, \dots, m$ , respectively, along with the corresponding value of  $\omega_i$  for each fuzzy IF–THEN rule specified in Equation (2). The heuristic method is expressed as a mechanism or approach used to determine the weight or importance assigned to each input–output pair during the training process.

$$\omega_j^{HM} = \frac{\sum_{p=1}^m \mu_{jp} * y_p}{\sum_{p=1}^m \mu_{jp}}, \quad j = 1, 2, \dots, N. \tag{6}$$

That is,  $\omega_j^{HM}$  is the average of  $y_p$  weighted by  $\mu_{jp}$ .

The heuristic method offers a notable advantage in its simplicity. It proves to be particularly valuable in scenarios where there is limited computational time available for learning a specific task. This is because the value of  $\omega_i$  can be determined using Equation (6) directly, eliminating the need for iterative learning procedures. As a result, the heuristic method provides a time-efficient approach to achieving satisfactory results without the computational overhead associated with iterative learning.

### 3.2.3. Learning Method

In a sufficient computation time, learning methods have the potential to surpass the heuristic method in generating fuzzy IF–THEN rules, resulting in improved performance. Within this subsection, we provide a concise overview of a simple learning method that relies on the gradient descent approach. The total error for the  $p$ -th input–output pair  $(x_p, y_p)$  is defined as

$$E = \sum_{p=1}^m E_p = \frac{1}{2} \sum_{p=1}^m \{\hat{y}_p - y_p\}^2. \tag{7}$$

The learning rule for  $\omega_i$  is derived from Equations (4) and (7) with intersect 0.5, and the denominator in Equation (4) equals 1 for any  $x_p$ , such that

$$\begin{aligned} \omega_j^{new} &= \omega_j^{old} + \beta \left( \frac{-\partial E_p}{-\partial \omega_j} \right) \\ &= \omega_j^{old} - \beta * \mu_j * \hat{y}_p - y_p, \quad j = 1, 2, \dots, N. \end{aligned} \tag{8}$$

where  $\beta$  is the learning rate. The learning procedure is as follows. Step 1: Specify the initial value  $\omega_j^{init}$  of  $\omega_j$ , the value of  $\beta$ , and the maximum iteration number  $t_j$ . Let  $t := 0$ . Step 2: For  $p = 1, 2, \dots, m$ , adjust each  $\omega_j$  by (4). Let  $t := t + 1$ . Step 3: If  $t \geq t_{max}$ , then stop this procedure; otherwise, go to Step 2. In computer simulations, the initial value  $\omega_j^{init}$  of  $\omega_j$  is specified in the following two ways:

1.  $\omega_j^{init} = 0, j = 1, 2, \dots, N,$
2.  $\omega_j^{init} = \omega_j^{HM}, J = 1, 2, \dots, N.$

### 3.3. HyFIS Model

HyFIS is a unique approach that combines fuzzy logic concepts with artificial neural networks (ANNs) to optimize learning. Proposed by [Kim and Kasabov \(1999\)](#), it improves upon the traditional fuzzy inference system (FIS) by incorporating heuristic fuzzy logic rules and input–output fuzzy membership functions. The HyFIS optimizes learning through a hybrid approach involving two steps: rule generation and rule tuning. During rule generation, heuristic fuzzy logic rules are developed based on input data. In the rule-tuning phase, error backpropagation learning is employed to fine-tune these rules and modify the input–output fuzzy membership functions. This enables the neural network to learn more efficiently and accurately. The steps involved in using the HyFIS are as follows: 1. Data collection: gather input and output data for training the HyFIS. 2. Fuzzy rule generation: utilize heuristic fuzzy logic rules to generate a set of rules that establish the relationship between input and output data. 3. Neural network initialization: initialize the neural network with input–output fuzzy membership functions derived from the fuzzy rule generation phase. 4. Neural network training: Train the neural network by employing an error backpropagation learning process. This process adjusts the input–output fuzzy membership functions to minimize the error between predicted output and actual output. 5. Rule base refinement: enhance the fuzzy rule base by making adjustments to the fuzzy logic rules based on the results obtained from the neural network training. 6. Testing: evaluate the performance of the trained HyFIS by testing it with new data.

### 3.4. FIR.DM Model

The FIR.DM, proposed by [Saleh et al. \(2023\)](#), is a specific case within the TSK (Takagi–Sugeno–Kang) model. It employs a simplified fuzzy reasoning approach, where the membership functions in the antecedent part and the real numbers in the consequent part of inference rules are tuned using the descent method. Compared to conventional backpropagation-type neural networks, the FIR.DM exhibits higher learning speed and better generalization capability. The following steps explain the FIR.DM: 1. Input-Output Data: gather a dataset consisting of input–output pairs for training the FIR.DM. 2. Fuzzy Rule Generation: Use the input data to generate a set of fuzzy rules. Each fuzzy rule consists of an antecedent part (membership functions) and a consequent part (real numbers). 3. Initialization: initialize the membership functions and consequent values of the fuzzy rules. 4. Forward Pass: perform a forward pass for each input by evaluating the membership values of the input variables using the respective membership functions. 5. Weighted Sum: calculate the weighted sum of the consequent values based on the membership values obtained in the previous step. 6. Output Calculation: compute the overall output by aggregating the weighted sums from all the fuzzy rules. 7. Error Calculation: calculate the error between the desired output and the computed output for each input–output pair. 8. Gradient Descent: Utilize the gradient descent method to update the membership functions and consequent values of the fuzzy rules, aiming to minimize the error. Adjustments are made in the direction that reduces the error. 9. Repeat Steps 4–8: iterate the forward pass, weighted sum calculation, output calculation, error calculation, and gradient descent steps until the desired convergence or stopping criteria are met. 10. Output Generation: once the training process is completed, the tuned membership functions and consequent values of the fuzzy rules are used to generate the output for new inputs.

### 3.5. Evaluation Measures

To evaluate the accuracy of our forecasting method, we utilize several types of criteria. These criteria include the Mean Absolute Percentage Error (MAPE), Mean Percentage Error (MPE), Mean Error (ME), Mean Absolute Error (MAE), and Root Mean Squared Error (RMSE). The MAPE criterion, also known as Mean Absolute Percentage Deviation

(MAPD), is a statistical measure that assesses the prediction accuracy of a forecasting method. Typically expressed as a percentage, it calculates the average absolute percentage difference between the predicted and actual values.

$$MAPE = \frac{1}{n} \sum_{t=1}^n \left| \frac{X_t - F_t}{X_t} \right|, \quad (9)$$

$$MPE = \frac{1}{n} \sum_{t=1}^n \frac{X_t - F_t}{X_t}, \quad (10)$$

$$MAE = \frac{1}{n} \sum_{t=1}^n |X_t - F_t|, \quad (11)$$

$$ME = \frac{1}{n} \sum_{t=1}^n (X_t - F_t), \quad (12)$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{t=1}^n (X_t - F_t)^2} \quad (13)$$

where  $X_t$  and  $F_t$  represent the actual value and the forecasted value, respectively, while  $n$  denotes the sample size.

#### 4. Dataset Selection

A comprehensive study was conducted to gather data on the factors influencing the total risk-weighted assets (TRWA) in Bahrain, Jordan, Qatar, the United Arab Emirates, and Yemen. The study relied on official sources such as the World Bank (Bankscope (Orbis Bank Focus)) to ensure the reliability of the data. The research focused on examining the TRWA as the dependent variable, while considering various factors that potentially affect it. The factors analyzed in the study included the UR, IN, loan-to-asset ratio, and total assets. These factors were selected based on their perceived impact on the TRWA. The data collection process was carried out systematically, gathering information on a yearly basis from 2010 to 2021. This approach allowed for a comprehensive understanding of the relationships between the TRWA and its influencing factors.

Table 1 presents descriptive statistics for various factors across Bahrain, Jordan, Qatar, the United Arab Emirates, and Yemen. The sample sizes vary across countries, with Bahrain and Jordan having three banks each, Qatar having two banks, the United Arab Emirates having four banks, and Yemen having one bank. For the LTRWA variable (the natural logarithm of total risk-weighted assets), the mean values indicate that the average values of LTRWAs in Bahrain and Jordan are 7.1000, while in the United Arab Emirates and Yemen, they are 9.5000 and 7.0000, respectively. Qatar has the highest average LTRWA value of 9.6000. The standard deviation values show the variability around the mean, with Bahrain having a standard deviation of 0.3000, Jordan and Qatar both with 0.6000, Yemen with 0.1000, and the United Arab Emirates with the highest standard deviation of 1.1000. The minimum and maximum values for LTRWAs indicate that the lowest and highest observations in each country range from 6.6000 to 7.7000 in Bahrain, 5.8000 to 8.2000 in Jordan, 8.4000 to 10.5000 in Qatar, 4.5000 to 11.0000 in the United Arab Emirates, and 6.8000 to 7.2000 in Yemen.

Moving on to the UR, the mean values reveal that Bahrain has an average UR of 0.0121, Jordan with 0.1582, Qatar with 0.0025, the United Arab Emirates with 0.0239, and Yemen with 0.1234. The standard deviation values reflect the variability around the mean, with Bahrain having a standard deviation of 0.0015, Jordan with 0.0267, Qatar with 0.0016, the United Arab Emirates with 0.0069, and Yemen with the highest standard deviation of 0.0348. The minimum and maximum values for the UR range from 0.0105 to 0.0167 in Bahrain, 0.1190 to 0.1921 in Jordan, 0.0010 to 0.0056 in Qatar, 0.0164 to 0.0429 in the United Arab Emirates, and 0.0133 to 0.1389 in Yemen. For the IN rate, the mean values indicate that Bahrain has an average IN rate of 0.0128, Jordan with 0.0316, Qatar with 0.0099, the United Arab Emirates with 0.0106, and Yemen with 0.1858. The standard deviation values

show the variability around the mean, with Bahrain having a standard deviation of 0.0149, Jordan with 0.0249, Qatar with 0.0199, the United Arab Emirates with 0.0176, and Yemen with the highest standard deviation of 0.0838. The minimum and maximum values for the IN rate range from  $-0.0232$  to  $0.0330$  in Bahrain,  $-0.0088$  to  $0.0851$  in Jordan,  $-0.0254$  to  $0.7594$  in Qatar,  $0.0410$  to  $0.6816$  in the United Arab Emirates, and  $0.3365$  to  $0.5188$  in Yemen.

**Table 1.** Descriptive statistics of dependent and independent factors.

Variables	Stat.	Bahrain	Jordan	Qatar	UAE	Yemen
No. of Banks		3	3	2	4	1
LTRWA	Mean	7.1000	7.1000	9.6000	9.5000	7.0000
	Standard Deviation	0.3000	0.6000	0.6000	1.1000	0.1000
	Minimum	6.6000	5.8000	8.4000	4.5000	6.8000
	Maximum	7.7000	8.2000	10.5000	11.0000	7.2000
UR	Mean	0.0121	0.1582	0.0025	0.0239	0.1234
	Standard Deviation	0.0015	0.0267	0.0016	0.0069	0.0348
	Minimum	0.0105	0.1190	0.0010	0.0164	0.0133
	Maximum	0.0167	0.1921	0.0056	0.0429	0.1389
IN	Mean	0.0128	0.0316	0.0099	0.0106	0.1858
	Standard Deviation	0.0149	0.0249	0.0199	0.0176	0.0838
	Minimum	$-0.0232$	$-0.0088$	$-0.0254$	$-0.0210$	0.0810
	Maximum	0.0330	0.0851	0.0335	0.0410	0.3365
LOTA	Mean	0.6211	0.6950	0.7594	0.6816	0.5188
	Standard Deviation	0.0831	0.1445	0.0791	0.1049	0.0775
	Minimum	0.4578	0.4593	0.5140	0.4738	0.3978
	Maximum	0.7540	0.9175	0.8686	0.9498	0.6971
LNTA	Mean	7.6000	7.8000	9.8000	9.9000	7.7000
	Standard Deviation	0.3000	0.8000	0.7000	0.7000	0.2000
	Minimum	7.1000	5.9000	8.5000	8.4000	7.3000
	Maximum	8.2000	8.9000	10.9000	11.3000	7.8000

Next, the loan-to-asset ratio mean values indicate that Bahrain has an average ratio of 0.6211, Jordan with 0.6950, Qatar with 0.7594, the United Arab Emirates with 0.6816, and Yemen with 0.5188. The standard deviation values reflect the variability around the mean, with Bahrain having a standard deviation of 0.0831, Jordan with 0.1445, Qatar with 0.0791, the United Arab Emirates with 0.1049, and Yemen with 0.0775. The minimum and maximum values for the loan-to-asset ratio range from 0.4578 to 0.7540 in Bahrain, 0.4593 to 0.9175 in Jordan, 0.5140 to 0.8686 in Qatar, 0.4738 to 0.9498 in the United Arab Emirates, and 0.3978 to 0.6971 in Yemen. Lastly, for the LNTAs, the mean values indicate that Bahrain and Jordan have average LNTA values of 7.6000 and 7.8000, respectively, while Qatar and Yemen have average values of 9.8000 and 7.7000, respectively. The United Arab Emirates has the highest average LNTA value of 9.9000. The standard deviation values show the variability around the mean, with Bahrain having a standard deviation of 0.3000, Jordan with 0.8000, Qatar with 0.7000, the United Arab Emirates with 0.7000, and Yemen with the lowest standard deviation of 0.2000. The minimum and maximum values for LNTAs range from 7.1000 to 8.2000 in Bahrain, 5.9000 to 8.9000 in Jordan, 8.5000 to 10.9000 in Qatar, 8.4000 to 11.3000 in the United Arab Emirates, and 7.3000 to 7.8000 in Yemen.

## 5. Empirical Results and Discussion

### 5.1. Multicollinearity Tests

In this section, we explore the challenge of multicollinearity. Multicollinearity occurs when the input factors in a regression model exhibit significant correlations with each other. This phenomenon complicates model interpretation and leads to overfitting issues. Assessing the presence of multicollinearity is a fundamental step in deciding which factors to include in the regression model. Common methods used to detect multicollinearity in

ordinary least squares (OLS) regression analysis include examining correlations, calculating the variance inflation factor (VIF), and performing tolerance tests. These techniques help determine the severity of multicollinearity and guide the decision-making process when constructing the regression model.

Table 2 presents correlation coefficients that provide insights into the relationships between different factors. Correlation values less than 0.5 are considered weak correlations, while values greater than 0.5 are considered strong correlations. Examining each pair of variables, the logarithm of total risk-weighted assets (LTRWA) exhibits specific correlations. It shows a weak negative correlation of  $-0.469$  with the UR, suggesting that higher UR values are associated with lower LTRWAs. The LTRWA value also has a weak negative correlation of  $-0.273$  with the IN value, indicating that higher IN rates are associated with lower LTRWAs, although to a lesser extent. Furthermore, the LTRWA value displays a weak positive correlation of  $0.417$  with the LOTA value, suggesting that higher loan percentages are associated with higher LTRWAs. In contrast, the LTRWA value exhibits a strong positive correlation of  $0.933$  with the logarithm of total assets (LNTAs), indicating a strong relationship where higher total assets correspond to higher LTRWAs. Examining the correlations involving the IN, we find that it exhibits a weak negative correlation of  $-0.244$  with the LOTA value, indicating that higher IN rates are associated with a slight decrease in the percentage of loans to assets. Furthermore, the IN shows a weak negative correlation of  $-0.309$  with the logarithm of total assets (LNTAs), suggesting that higher IN rates are associated with slightly lower total assets.

**Table 2.** Correlation between factors in our study.

Factors	LTRWA	UR	IN	LOTA	LNTA
LTRWA	1	$-0.469$	$-0.273$	$-0.417$	$0.933$
UR		1	$0.387$	$-0.038$	$-0.420$
IN			1	$-0.244$	$-0.309$
LOTA				1	$0.334$
LNTA					1

Examining the correlation between the UN and IN, we find that they exhibit a weak positive correlation of  $0.387$ . This correlation suggests that there is a modest association between higher UR and higher IN rates. Examining the correlations involving unemployment, we find that it exhibits a weak negative correlation of  $-0.038$  with the LOTA value, indicating a minimal association, where higher UR values are slightly associated with lower percentages of loans to assets. Moreover, unemployment shows a strong negative correlation of  $-0.420$  with the logarithm of total assets (LNTAs), suggesting a significant relationship, where higher UR values are associated with lower total assets. Lastly, the loan-to-asset ratio exhibits a weak positive correlation of  $0.334$  with LNTAs, indicating that higher percentages of loans to assets are associated with higher values of LNTAs. However, it is important to note that correlation does not imply causation and additional analysis is needed to understand the underlying dynamics between input and output factors.

In Table 3, the collinearity statistics are presented for the following factors in the study: the unemployment rate, IN, LOTA, and LNTA values. The tolerance values for each factor indicate the proportion of variance not explained by the other factors, with values ranging from  $0.718$  to  $0.839$ . These tolerance values are calculated using the formula  $Tolerance = 1/VIF$ , where VIF represents the variance IN factor. The VIF is a statistical measure that quantifies the increase in variance of a regression coefficient due to collinearity. A higher VIF value indicates a stronger connection between the variable and the other factors. In general, a VIF greater than 4 or a tolerance less than  $0.25$  suggests the possibility of multicollinearity, which can complicate the interpretation of regression model estimates. However, in this case, the VIF values ranging from  $1.192$  to  $1.392$ , and the tolerance values above  $0.718$  indicate no significant multicollinearity issue among the factors in the study, providing confidence in the stability of the regression model estimates.

**Table 3.** Collinearity statistics between factors in our study.

Factors	Collinearity Statistics	
	Tolerance	VIF
UR	0.727	1.375
IN	0.789	1.268
LOTA	0.839	1.192
LNTA	0.718	1.392

5.2. Multiple Regression Models

The results in Table 4 illustrate the findings of an analysis that utilizes OLS, fixed effect, and random effect models to explore the influence of input factors (UR, IN, LOT A, and LNTA values) on the output factor (the LTRWA value). In OLS, the results show that the intercept term of  $-1.324$  indicates the estimated value of LTRWAs when all input factors are zero. The coefficient for UR ( $\beta = -3.020$ ) exhibits a significant negative effect on LTRWAs at a level of significance less than 1%, indicating that, for a one-unit increase in the UR, the estimated decrease in the LTRWA value is  $-3.020$  units. This finding rejects the null hypothesis ( $H_{01}$ ) and suggests that the UR has a substantial impact on LTRWAs. The coefficient for the IN ( $\beta = 2.153$ ) reveals a significant positive effect on LTRWAs at a level of significance less than 5%. This indicates that, for a one-unit increase in the IN, the estimated impact on the LTRWAs is an increase of 2.153 units. This finding rejects the null hypothesis ( $H_{02}$ ) and suggests that the IN has a substantial and statistically significant influence on the LTRWAs.

**Table 4.** The OLS, fixed effect, and random effect.

Dep. Var.	Indep. Var.	OLS			Fixed Effect			Random Effect		
		B	S.E	t-stat	B	S.E	Z	B	S.E	Z
LTRWA	Intercept	-1.324	0.335	-3.948 ***				-0.973	0.406	-2.399 **
	UR	-3.020	0.673	-4.489 ***	-3.111	1.054	-2.953 ***	-3.120	0.789	-3.956 ***
	IN	2.153	0.798	2.699 **	1.220	1.155	1.057	2.028	0.904	2.243 **
	LOTA	1.733	0.336	5.157 ***	2.112	0.371	5.700 ***	1.869	0.349	5.351 ***
	LNTA	0.974	0.035	27.606 ***	0.701	0.068	10.264 ***	0.925	0.043	21.342 ***
	<b>R-square</b>		0.8975			0.60236			0.8377	
<b>F-stat.</b>		328.5 ***			52.6416 ***			783.411 ***		

Signif. codes: '\*\*\*' 0.01 '\*\*' 0.05.

Likewise, the coefficient for LOT A ( $\beta = 1.733$ ) demonstrates a significant positive effect on the LTRWAs at a level of significance less than 1%. This implies that for a one-unit increase in LOT A, the estimated increase in the LTRWA value is 1.733 units. This finding rejects the null hypothesis ( $H_{03}$ ) and suggests that LOT A has a substantial impact on the LTRWAs. The coefficient for the LNTAs ( $\beta = 0.974$ ) exhibits a significant positive effect on the LTRWAs at a level of significance less than 1%. This implies that for a one-unit increase in the LNTAs, the estimated increase in the LTRWA value is 0.974 units. This finding rejects the null hypothesis ( $H_{04}$ ) and suggests that the LNTAs have a substantial impact on the LTRWAs. R-square is a statistical measure that represents the proportion of the total variation in the dependent variable (LTRWA) that can be explained by the independent variables (UR, IN, LOT A, and LNTA) included in the regression model. In this case, the R-square value of 0.8975 indicates that approximately 89.75% of the variation in the LTRWAs can be explained by the variation in the independent variables. The F-statistic tests the overall significance of the regression model. In this case, the F-statistic value of 328.5 \*\*\* indicates a highly significant model at level 1%, demonstrating that at least one

independent variable has a significant impact on the LTRWAs. This provides evidence that the regression model is meaningful for understanding the relationship between the input factors and the LTRWAs.

In fixed effect, the results show that the intercept term does not have a specific coefficient value mentioned in the table. For the UR factor, the coefficient of  $\beta = -3.111$  is statistically significant at the level of 1%, suggesting that a one-unit increase in the UR is associated with a significant estimated decrease in the LTRWAs. So, we reject  $H_{01}$ . The coefficient for the IN factor  $\beta = 1.220$  is not statistically significant based on the reported Z-value of 1.057, indicating that its effect on the LTRWAs is not statistically distinguishable from zero. Therefore, we accept  $H_{02}$ . Regarding the LOTA variable, the coefficient of  $\beta = 2.112$  is statistically significant at the level of 1%, indicating that a one-unit increase in LOTA is associated with a significant estimated increase in the LTRWAs. So, we reject  $H_{03}$ . Similarly, the LNTA variable has a coefficient of  $\beta = 0.701$ , which is also statistically significant at the level 1%, suggesting that a one-unit increase in the LNTA value is associated with a significant estimated increase in the LTRWAs. Therefore, we reject  $H_{04}$ . The R-square value of 0.60236 indicates that approximately 60.24% of the variation in the LTRWA value can be explained by the included input factors. The F-statistic of 52.6416 \*\*\* indicates that the regression model, as a whole, is statistically significant at the 1% level, providing evidence that at least one of the input factors has a significant impact on the LTRWAs.

In random effects, the results show that the intercept term has a coefficient of  $-0.973$ , indicating that, when all independent variables are zero, the estimated value of the LTRWA value is  $-0.973$ . The coefficient is statistically significant at the 5% level based on the Z-value of  $-2.399$ . For the UR variable, the coefficient is  $\beta = -3.120$ , suggesting that a one-unit increase in the UR is associated with an estimated decrease in the LTRWA value by 3.12 units. The coefficient is statistically significant at the 1% level, as indicated by the Z-value of  $-3.956$ . So, we reject  $H_{01}$ . The coefficient for the IN variable is  $\beta = 2.028$ , indicating that a one-unit increase in the IN corresponds to an estimated increase in the LTRWA value by 2.028 units. The coefficient is statistically significant at the 5% level based on the Z-value of 2.243. Therefore, we reject  $H_{02}$ . Regarding the LOTA variable, the coefficient is 1.869, suggesting that a one-unit increase in LOTA is associated with an estimated increase in the LTRWA value by 1.869 units. This coefficient is statistically significant at the 1% level, as indicated by the Z-value of 5.351. So, we reject  $H_{03}$ . Similarly, the LNTA variable has a coefficient of 0.925, indicating that a one-unit increase in the LNTA value corresponds to an estimated increase in the LTRWA value by 0.925 units. The coefficient is statistically significant at the 1% level, as indicated by the Z-value of 21.342. Therefore, we reject  $H_{04}$ . The R-square value of 0.8377 suggests that approximately 83.77% of the variation in the LTRWA value can be explained by the included independent variables. The F-statistic of 783.411 \*\*\* indicates that the regression model, as a whole, is statistically significant at the 1% level, providing evidence that at least one of the input factors has a significant impact on the LTRWA value when considering the random effects.

In summary, the findings of the study reveal important relationships between various variables and the LTRWAs. The UR demonstrates a significant negative relationship with the LTRWAs, consistent with previous studies (Castro 2013; Eldomyaty et al. 2022; Kartikasary et al. 2020) that found a negative correlation between unemployment and non-performing loans as part of the LTRWAs. On the other hand, the IN shows a significant positive relationship with the LTRWAs, in line with studies (Klein 2013; Rinaldi and Sanchis-Arellano 2006) that suggest the IN increases credit risk by reducing the value of money and borrowers' income. However, Shaheen et al. (2024) found, in a study on Islamic banking in Pakistan, that inflation had a positive but insignificant impact on credit risk in Islamic banks. Furthermore, the LOTA value exhibits a significant positive relationship with the LTRWAs, consistent with studies in the Turkish and Nepalese banking sectors, such as Bhattarai (2019), which found that a higher proportion of loans to assets is associated with a higher likelihood of non-performing loans. Additionally, the bank size (LNTA) demonstrates a significant positive relationship with the LTRWAs, consistent with studies

by Abbas et al. (2021), Imbierowicz and Rauch (2014), and Pham et al. (2021), indicating a positive correlation between total bank risks and size, reflecting a well-diversified portfolio and increased efficiency due to economies of scale.

Figure 3 represents a residuals vs fitted diagram, also known as a residual plot, which is a graphical representation of the residuals on the vertical axis against the fitted values on the horizontal axis from a regression analysis. Residuals are the differences between the observed values of the dependent variable and the values predicted by the regression model. In a diagram, the random scatter of points is around the horizontal line at zero. This suggests that the model has a good fit, as the residuals (the differences between the actual values and the predicted values from the model) are randomly distributed around zero. This randomness indicates that the model is capturing the underlying relationships between the variables and that there are no systematic patterns or biases in the residuals. Therefore, a random scatter of points around the zero line is typically indicative of a well-fitting multiple regression model. A Q-Q Residual diagram is a statistical tool used to assess whether the residuals in a regression model follow a normal distribution. In this diagram, the residuals are plotted against quantiles from a theoretical normal distribution. If the residuals fall along a straight line, it suggests that the residuals are normally distributed.

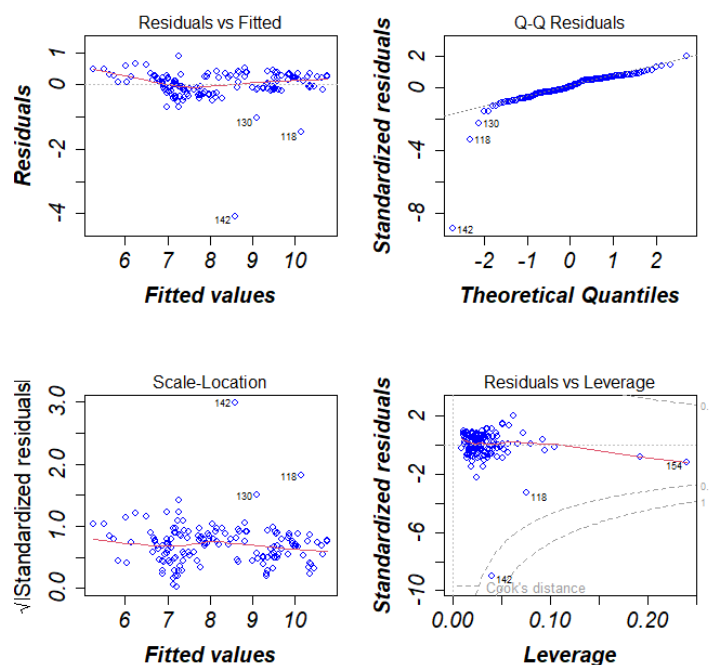


Figure 3. Scatter plot of residuals and fitted values for multiple regression.

A Scale–Location diagram, also known as a Spread–Location plot, is a type of residual plot used in regression analysis to check the assumption of homoscedasticity. In this plot, the square root of the standardized residuals (or studentized residuals) is plotted against the standardized predicted values (fitted values) or a transformation of the fitted values. The purpose of this plot is to detect any patterns in the spread of residuals across the range of fitted values. In this diagram, if the points show a random scatter around a horizontal line, then the assumption of homoscedasticity (constant variance of residuals) is met. A Residual vs Leverage diagram is a graphical representation used in regression analysis to identify influential data points that may have a large effect on the estimated regression coefficients.

### 5.3. Results of Neural Network Models

In this study, a dataset was partitioned into two distinct groups. The first group comprised 90% (140 observations) of the data and was utilized for training purposes. The second group, consisting of 10% (16 observations) of the data, was specifically designated for assessing the predictive capabilities of adaptive ANFIS, HyFIS, FS.HGD, and FIR.DM



models. To forecast the output factor of the LTRWAs, the models employed four distinct input factors: UR, IN, LOTA, and LNTA. To enhance accuracy, the models ran five iterations while utilizing a step size of 0.01. Table 5 compares the error criteria of the ANFIS, HyFIS, FS.HGD, and FIR.DM models with the original LTRWA value, using various performance metrics such as ME, RMSE, MAE, MPE, and MAPE.

**Table 5.** Comparison of ANFIS, HyFIS, FS.HGD, and FIR.DM neural network models.

Tests	ME	RMSE	MAE	MPE	MAPE
ANFIS	3.836743	3.941246	3.836743	56.87908	56.87908
HyFIS	0.8832772	1.643153	1.25163	15.29947	20.06073
FS.HGD	1.387002	1.731094	1.551293	17.51105	21.14192
FIR.DM	1.387002	1.731094	1.551293	17.51105	21.14192

For the ME, the ANFIS model has a value of 3.836743, indicating an average deviation of approximately 3.84 between predicted and target values. The HyFIS model has an ME of 0.8832772, indicating a smaller average deviation of around 0.88. Both the FS.HGD and FIR.DM models have an ME of 1.387002, suggesting a similar average deviation of approximately 1.39. Moving on to the RMSE, the ANFIS model has a value of 3.941246, reflecting the overall prediction accuracy with a deviation of approximately 3.94. The HyFIS, FS.HGD, and FIR.DM models have RMSE values of 1.643153, 1.731094, and 1.731094, respectively. The HyFIS model demonstrates a lower overall prediction error when compared to the other models.

For the MAE, the ANFIS model has an MAE of 3.836743, while the HyFIS, FS.HGD, and FIR.DM models have MAE values of 1.25163, 1.551293, and 1.551293, respectively. These values represent the average absolute deviations between predicted and target values. The HyFIS model demonstrates a lower value when compared to the other models. Moving on to the MPE, the ANFIS, HyFIS, FS.HGD, and FIR.DM models have MPE values of 56.87908, 15.29947, 17.51105, and 17.51105, respectively. These values indicate the average percentage deviation between predicted and target values, with lower values indicating better accuracy. Also, the HyFIS model demonstrates a lower value. Finally, the MAPE measures the average absolute percentage deviation between predicted and target values. The ANFIS, HyFIS, FS.HGD, and FIR.DM models have MAPE values of 56.87908, 20.06073, 21.14192, and 21.14192, respectively. Therefore, the HyFIS model exhibits commendable performance based on its lower overall prediction error when compared to the other models.

Table 6 displays the outcomes of an independent *t*-test conducted on two distinct groups: the original LTRWAs and the predicting LTRWAs. The independent *t*-test is a statistical test employed to compare the means of these two groups. The null hypothesis ( $H_0$ ) suggests that there is no significant difference between the means of the two groups, while the alternative hypothesis ( $H_1$ ) suggests that a significant difference exists. The independent *t*-test assesses the means of the two groups, denoted as  $\mu_1$  for the original EH and  $\mu_2$  for the predicting LTRWAs. The table provides the outcomes of an independent *t*-test that compares the original LTRWAs with the predicting LTRWAs for the ANFIS, HyFIS, FS.HGD, and FIR.DM models. The table includes the mean values, *t*-test values, degrees of freedom (DF), and significance level for each model. This *t*-test analysis allows for the assessment of the statistical significance and potential differences between the predicted and original LTRWA values across the different models. Based on the results presented in Table 5, the significance level is found to be lower than 5%. This implies that the null hypothesis, which states that there is no significant difference between the means of the original LTRWAs and the predicting LTRWAs for both models, is rejected. The findings strongly suggest that there exists a statistically significant difference between the means of the original LTRWAs and the predicting LTRWAs for the ANFIS, HyFIS, FS.HGD, and FIR.DM models.

**Table 6.** Independent *t*-test with original output factor.

Tests	Independent <i>t</i> -Test with Original Dependent Variable			
	Mean	<i>t</i> -Test	DF	Sign.
ANFIS	10.980752	−13.556	15.266	$6.40 \times 10^{-10}$
HyFIS	8.027287	−2.3103	27.934	0.02847
FS.HGD	5.757007	5.0102	14	0.0001909
FIR.DM	5.757007	5.0102	14	0.0001909
Original (EH)	7.144009			

The mean value of 10.980752 for the ANFIS model represents the average prediction for the original output factor. The *t*-test value of −13.556 indicates a significant difference between the means of the original output factor and the ANFIS predictions. The DF is 15.266, and the small significance level of  $6.40 \times 10^{-10}$  suggests a highly significant difference. Furthermore, the mean value of 8.027287 for the HyFIS model represents the average prediction for the original output factor. The *t*-test value of −2.3103 indicates a significant difference between the means of the original output factor and the HyFIS predictions. The DF is 27.934, and the significance level of 0.02847 suggests a statistically significant difference. In addition, both the FS.HGD and FIR.DM models have the same mean value of 5.757007, representing the average predictions for the original output factor. The *t*-test value of 5.0102 indicates significant differences between the means of the original output factor and the predictions made by these models. The degrees of freedom (DF) for both models are 14, and the small significance level of 0.0001909 suggests a highly significant difference. Lastly, the value 7.144009 represents the mean of the original output factor used for comparison with the predicted values. In summary, it can be observed that the mean value of the HyFIS model is closer to the mean of the original output factor when compared to the other models. This suggests that the HyFIS model provides predictions that are more similar to the original output factor compared to the other models in the analysis.

#### 5.4. Managerial Applications

The capital adequacy is a key measure used to evaluate the relationship between capital and risk-weighted assets. It is calculated by dividing the bank's capital by its risk-weighted assets. The CAR acts as a buffer that protects depositors and other stakeholders from potential losses. Regulators set minimum CAR requirements to ensure the stability of the banking system and protect depositors' funds. Predicting the CAR in Islamic banks is essential for ensuring regulatory compliance and maintaining the stability and integrity of the banking system. Islamic banks, like their conventional counterparts, must adhere to regulatory requirements imposed by regulatory bodies. Compliance with these standards, such as the capital adequacy ratio (CAR) or the Islamic Financial Services Board (IFSB) guidelines, is crucial for safeguarding the soundness of the bank's operations and instilling stakeholders' confidence. Accurate prediction of capital adequacy enables Islamic banks to effectively manage risks associated with their operations. By maintaining sufficient capital levels, these banks can absorb potential losses, thereby protecting depositors' funds and fortifying themselves against financial distress. Proactive risk management practices and vulnerability identification become possible through precise capital adequacy prediction, promoting a proactive approach to risk mitigation. Furthermore, predicting capital adequacy plays a pivotal role in enhancing investor confidence in Islamic banks. Investors, including equity shareholders and debt holders, rely on capital adequacy ratios as indicators of a bank's financial health and stability. Demonstrating robust capital adequacy positions Islamic banks as reliable and secure institutions, attracting both domestic and international investors. Heightened investor confidence can result in improved access to capital markets and reduced borrowing costs for the bank.

The key findings of the study have significant managerial implications for risk managers and policymakers in Bahrain, Jordan, Qatar, the United Arab Emirates, and Yemen. The study demonstrates that HyFIS outperforms other methods (ANFIS, FS.HGD, and FIR.DM) in predicting the LTRWAs. Moreover, the study identifies several variables that have a significant influence on the LTRWAs, including IN, UR, LNTA, and LOTA. Risk managers and policymakers can utilize the identified variables, such as IN, UR, LNTA, and LOTA, to develop effective plans and strategies for managing future LTRWAs. Islamic banks can align their risk management practices and capital allocation strategies to ensure Sharia compliance while effectively managing LTRWAs. Banks can enhance regulatory compliance by recognizing the variables that significantly influence LTRWAs and aligning their capital levels with regulatory requirements. Strengthening risk absorption capabilities through the assessment and adjustment of capital adequacy levels enables banks to protect depositors' funds and avoid financial distress. Understanding the relationship between the LTRWA value and its determinants enhances investor confidence, attracting domestic and international investors and facilitating access to capital markets.

In summary, this study's managerial application section highlights the significance of its findings for risk managers and policymakers. The identified variables and the superiority of HyFIS in predicting the LTRWAs provide valuable insights for planning future LTRWAs, ensuring Sharia and regulatory compliance, managing risk absorption, enhancing investor confidence, and facilitating business expansion. Incorporating these findings into managerial decision-making can contribute to more robust risk management practices and sustainable growth in the banking industry.

#### 5.5. Limitations and Future Work

One limitation of this study is the limited number of input variables used to predict the LTRWAs. The study only considered IN, UR, LNTA, and LOTA as input variables. While these variables are important in the Bahrain, Jordan, Qatar, the United Arab Emirates, and Yemen context, incorporating additional variables could enhance the accuracy of LTRWA prediction. Another limitation is the focus on a specific dataset from five Arab countries. While these countries provide significant insights, expanding the analysis to include data from other countries, such as Saudi Arabia, Egypt, Iraq, Syria, and others, would offer a broader understanding of LTRWA prediction. Furthermore, this study only utilized yearly data from 2010 to 2021. In future work, it is important to extend the analysis to include data up to 2024, considering significant events such as the Russian–Ukrainian war, the Gaza conflict, and the global COVID-19 pandemic. Incorporating more recent data allows for the examination of potential shifts in LTRWA patterns and the assessment of the impact of these crucial events on the predictive model.

Additionally, it is worth noting that, in this study, we focused on utilizing four specific fintech models: ANFIS, HyFIS, FS.HGD, and FIR.DM. While these models have demonstrated their effectiveness in predicting LTRWAs, future research should consider exploring other fintech models as well. There is a wide range of neural network architectures and algorithms available, each with its unique strengths and capabilities. By incorporating alternative neural network models in future studies, we can further investigate their suitability for LTRWA prediction and compare their performance against the models used in this study. This will contribute to a more comprehensive understanding of the applicability of different neural network approaches in predicting LTRWAs and offer insights into potential improvements in modeling accuracy and robustness.

#### 6. Conclusions

This study effectively presents a comprehensive methodology for identifying the factors influencing LTRWAs and making predictions using a combination of statistical analyses and machine learning methods. The data collected from Bahrain, Jordan, Qatar, the United Arab Emirates, and Yemen, spanning from 2010 to 2021, were utilized for conducting various statistical tests and models. These included OLS, fixed effects, random effects, cor-

relations, the VIF, tolerance tests, the ANFIS, HyFIS, FS.HGD, and FIR.DM. The correlation, tolerance, and VIF statistics demonstrate that there is no notable multicollinearity among the input factors, confirming the reliability and validity of the regression model. Based on the findings, the variables UR, IN, LOTA, and LNTA were selected as input factors, taking into account multicollinearity tests (correlation, tolerance, and VIF) as well as multiple regression analyses (OLS, fixed effect, and random effect). The results of OLS and random effect models indicated that the IN, LOTA, and LNTA values had a statistically significant positive impact on LTRWAs at a significance level of 0.05. Conversely, the UR showed a statistically significant negative impact on LTRWAs at the same significance level. However, according to the fixed effect model, both LOTA and LNTA values exhibited a statistically significant positive influence on LTRWAs at a significance level of 0.01. On the other hand, the IN did not demonstrate a significant effect on LTRWAs in this model, and the UR had a statistically significant negative impact on LTRWA at the 0.01 significance level.

Furthermore, the dataset was divided into two groups: a training group (90% of the data) and a testing group (10% of the data) for evaluating ANFIS, HyFIS, FS.HGD, and FIR.DM models' predictive capabilities. These models utilized the UR, IN, LOTA, and LNTA variables as input factors to forecast the LTRWAs. The performance metrics, including ME, RMSE, MAE, MPE, and MAPE, were compared. The HyFIS model demonstrated superior performance with lower errors compared to the other models, indicating its effectiveness in predicting LTRWAs. The results of an independent *t*-test conducted on the original LTRWA and the predicted LTRWA groups were used to compare their means. The *t*-test analysis reveals a statistically significant difference between the means of the original LTRWAs and the predicted LTRWAs for all models (ANFIS, HyFIS, FS.HGD, and FIR.DM). The mean values and *t*-test statistics indicate that the HyFIS model demonstrates predictions that are closer to the original LTRWAs compared to the other models in the analysis.

**Author Contributions:** Conceptualization, A.S.A. and J.J.J.; methodology, A.S.A. and J.J.J.; software, J.J.J.; validation, H.N.R.; formal analysis, A.S.A. and J.J.J.; investigation, A.S.A., R.A.O. and H.N.R.; resources, R.A.O. and H.N.R.; data curation, R.A.O.; writing—original draft preparation, J.J.J.; writing—review and editing, A.S.A., R.A.O. and H.N.R.; visualization, H.N.R.; supervision, J.J.J.; project administration, A.S.A. and J.J.J.; funding acquisition, A.S.A., J.J.J., R.A.O., and H.N.R. All authors have read and agreed to the published version of the manuscript.

**Funding:** This research received no external funding.

**Data Availability Statement:** The collection of data The data was collected from official sources such as the World Bank. Specifically, data was sourced from the Bankscope and Orbis Bank Focus databases, which are available on the World Bank's DataBank website (<https://databank.worldbank.org/>, accessed on 3 July 2024) and (<https://login.bvdfinfo.com/R0/BankFocus>, accessed on 3 July 2024).

**Conflicts of Interest:** The authors declare no conflict of interest.

## References

- Abbas, Faisal, Omar Masood, and Shoaib Ali. 2021. Financial development and bank risk-taking: Empirical evidence from the USA. *Intelektinė Ekonomika* 15: 64–87.
- Adebola, Solarin Sakiru, Wan Sulaiman B. Wan Yusoff, and Jauhari Dahalan. 2011. An Ardl Approach to the Determinants of Nonperforming Loans in Islamic Banking System in Malaysia. *Kuwait Chapter of Arabian Journal of Business and Management Review* 1: 20–30.
- Akkizidis, Ioannis, and Sunil Kumar Khandelwal. 2008. *Financial Risk Management for Islamic Banking and Finance*. Berlin/Heidelberg: Springer.
- Al-Araj, Reem, Hossam Haddad, Maha Shehadeh, Elina Hasan, and Mohammad Yousef Nawaiseh. 2022. The effect of artificial intelligence on service quality and customer satisfaction in Jordanian banking sector. *WSEAS Transactions on Business and Economics* 19: 1929–47. [CrossRef]
- Alenezzy, Abdullah H, Mohd Tahir Ismail, Sadam Al Wadi, and Jamil J. Jaber. 2023. Predicting Stock Market Volatility Using MODWT with HyFIS and FS. HGD Models. *Risks* 11: 121. [CrossRef]
- Alhassan, Abdul Latif, Charles Andoh, and Anthony Kyereboah-Coleman. 2014. Asset quality in a crisis period: An empirical examination of Ghanaian banks. *Review of Development Finance* 4: 50–62. [CrossRef]

- Ali, Asghar, and Kevin Daly. 2010. Macroeconomic determinants of credit risk: Recent evidence from a cross country study. *International Review of Financial Analysis* 19: 165–71. [CrossRef]
- Al Masud, Abdullah, and Mohammad Azhar Hossain. 2021. Determinants of Non Performing Loan (NPL): A Case of an Emerging Economy. *Southeast Business Review* 10: 46–60.
- Alshurafat, Hashem, Omar Arabiat, and Maha Shehadeh. 2024. The intention to adopt metaverse in Islamic banks: An integrated theoretical framework of TAM and religiosity intention model. *Journal of Islamic Marketing*. ahead of print. [CrossRef]
- Amalia, Shendy, Suskim Riantani, and John Henry Wijaya. 2024. Future-Proofing Islamic Finance: A Bibliometric Review of the Fintech Era. *Economics and Business Quarterly Reviews* 7: 1–15. [CrossRef]
- Anbar, Adem, and Deger Alper. 2011. Bank specific and macroeconomic determinants of commercial bank profitability: Empirical evidence from Turkey. *Business, and Economics Research Journal* 2: 139–52.
- Antony, Tisa Maria, and G. Suresh. 2023. Determinants of Credit Risk: Empirical Evidence from Indian Commercial Banks. *Banks Bank Systems* 18: 88–100. [CrossRef]
- Ashraf, Dawood, Muhammad Suhail Rizwan, and Barbara L’Huillier. 2016. A net stable funding ratio for Islamic banks and its impact on financial stability: An international investigation. *Journal of Financial Stability* 25: 47–57. [CrossRef]
- Ashraf, Naseem, and Qurrat Ul Ain Butt. 2019. Macroeconomic and idiosyncratic factors of non-performing loans: Evidence from Pakistan’s banking sector. *Journal of Finance and Accounting Research* 1: 44–71. [CrossRef]
- Aysan, Ahmet Faruk, and Farah Ahmed Hersi. 2024. The Impact of the Pandemic on the Financial Markets: The Resilience of GCC Islamic Banks During the COVID-19 Crisis. In *BANKING RESILIENCE: New Insights on Corporate Governance, Sustainability and Digital Innovation*. Singapore: World Scientific, pp. 265–99.
- BCBS. 2017. *Basel Committee for Banking Supervision. Finalizing Post-Crisis Reforms*. Basel: BCBS, p. 424.
- Bhattarai, Bishnu Prasad. 2019. Determinants of commercial banks’ lending behavior in Nepal. *International Journal of Accounting Finance Review* 4: 51–60. [CrossRef]
- Bonfim, Diana. 2009. Credit risk drivers: Evaluating the contribution of firm level information and of macroeconomic dynamics. *Journal of Banking, and Finance* 33: 281–99. [CrossRef]
- Boyacioglu, Melek Acar, Yakup Kara, and Ömer Kaan Baykan. 2009. Predicting bank financial failures using neural networks, support vector machines and multivariate statistical methods: A comparative analysis in the sample of savings deposit insurance fund (SDIF) transferred banks in Turkey. *Expert Systems with Applications* 36: 3355–66. [CrossRef]
- Castro, Vítor. 2013. Macroeconomic determinants of the credit risk in the banking system: The case of the GIPSI. *Economic Modelling* 31: 672–83. [CrossRef]
- Chang, Ming-Chung, and Hsin-Jung Hsieh. 2015. Risk-weighted assets efficiency and the target capital adequacy ratio: A case study of financial holding company banks in Taiwan. *Soochow Journal of Economics and Business* 90: 1–24.
- Claeys, Sophie, and Rudi Vander Vennet. 2008. Determinants of bank interest margins in Central and Eastern Europe: A comparison with the West. *Economic Systems* 32: 197–216. [CrossRef]
- Čihák, Martin, and Heiko Hesse. 2010. Islamic banks and financial stability: An empirical analysis. *Journal of Financial Services Research* 38: 95–113. [CrossRef]
- El Mosaid, Fadma, and Rachid Boutti. 2014. Sukuk and bond performance in Malaysia. *International Journal of Economics and Finance* 6: 226–34. [CrossRef]
- Eldomyaty, Tarek, Amr Youssef, and Heba Mahrous. 2022. The Robustness of the Determinants of Overall Bank Risks in the MENA Region. *Journal of Risk Financial Management* 15: 445. [CrossRef]
- Ghassan, Hassan Belkacem, and Abdelkrim Ahmed Guendouz. 2019. Panel modeling of z-score: Evidence from Islamic and conventional Saudi banks. *International Journal of Islamic Middle Eastern Finance, and Management* 12: 448–68. [CrossRef]
- Ghosh, Amit. 2017. Sector-specific analysis of non-performing loans in the US banking system and their macroeconomic impact. *Journal of Economics, and Business* 93: 29–45. [CrossRef]
- Gulati, Rachita, Anju Goswami, and Sunil Kumar. 2019. What drives credit risk in the Indian banking industry? An empirical investigation. *Economic Systems* 43: 42–62. [CrossRef]
- Hamzani, Umiaty, and Dinarjad Achmad. 2018. Bankruptcy prediction: SMEs case study in Pontianak, Indonesia. *Accounting and Finance Review* 3: 9–15. [CrossRef] [PubMed]
- Havidz, Shinta Amalina Hazrati, and Chandra Setiawan. 2015. Bank efficiency and non-performing financing (NPF) in the Indonesian Islamic banks. *Asian Journal of Economic Modelling* 3: 61–79. [CrossRef]
- Hull, John. 2023. *Risk Management and Financial Institutions*, 6th ed. Hoboken: John Wiley & Sons, vol. 832.
- Hussain, Mumtaz, Asghar Shahmoradi, and Rima Turk. 2016. An overview of Islamic finance. *Journal of International Commerce Economics, and Policy* 7: 1650003. [CrossRef]
- Imbierowicz, Björn, and Christian Rauch. 2014. The relationship between liquidity risk and credit risk in banks. *Journal of Banking and Finance* 40: 242–56. [CrossRef]
- Incekara, Ahmet, and Harun Çetinkaya. 2019. Credit risk management: A panel data analysis on the Islamic banks in Turkey. *Procedia Computer Science* 158: 947–54. [CrossRef]
- Ishibuchi, Hisao, Ken Nozaki, Hideo Tanaka, Yukio Hosaka, and Masanori Matsuda. 1993. Empirical study on learning in fuzzy systems. Paper presented at the [Proceedings 1993] Second IEEE International Conference on Fuzzy Systems, San Francisco, CA, USA, March 28–April 1.

- Jaaffar, Sharifah Arni Syed, and Puspa Liza Ghazali. 2018. The structure in existing Shariah principle of Islamic home financing: A review. *International Journal of Academic Research in Business and Social Sciences* 8: 1337–44. [\[CrossRef\]](#) [\[PubMed\]](#)
- Jaber, Jamil, Rami S. Alkhalwaldeh, and Ibrahim N. Khatatbeh. 2023. Predicting default risk bancassurance using GMDH and dce-GMDH neural network models. *Competitiveness Review: An International Business Journal*. ahead of print.
- Jaber, Jamil J., Noriszura Ismail, Siti Norafidah Mohd Ramli, Baker Albadareen, and Nawaf N. Hamadne. 2021. Estimating Loss Given Default Based on Beta Regression. *Computers, Materials Continua* 66: 3329. [\[CrossRef\]](#)
- Jobst, Andreas A., and Li Lian Ong. 2020. *Stress Testing: Principles, Concepts, and Frameworks*. Washington, DC: International Monetary Fund.
- Kartikasary, Metya, Frihardina Marsintauli, Erla Serlawati, and Sebastianus Laurens. 2020. Factors affecting the non-performing loans in Indonesia. *Accounting* 6: 97–106. [\[CrossRef\]](#)
- Kim, Jaesoo, and Nikola Kasabov. 1999. HyFIS: Adaptive neuro-fuzzy inference systems and their application to nonlinear dynamical systems. *Neural Networks* 12: 1301–19. [\[CrossRef\]](#) [\[PubMed\]](#)
- Klein, Nir. 2013. *Non-Performing Loans in CESEE: Determinants and Impact on Macroeconomic Performance*. Washington, DC: International Monetary Fund.
- Kuzucu, Narman, and Serpil Kuzucu. 2019. What drives non-performing loans? Evidence from emerging and advanced economies during pre-and post-global financial crisis. *Emerging Markets Finance Trade* 55: 1694–708. [\[CrossRef\]](#)
- Lei, Yaguo. 2016. *Intelligent Fault Diagnosis and Remaining Useful Life Prediction of Rotating Machinery*. Oxford: Butterworth-Heinemann.
- Leogrande, Angelo, Alberto Costantiello, Lucio Laureti, and Marco Maria Matarrese. 2023. The Determinants of Risk Weighted Assets in Europe. *Academy of Entrepreneurship Journal* 29: 1–23. [\[CrossRef\]](#)
- Louzis, Dimitrios P., Angelos T. Vouldis, and Vasilios L. Metaxas. 2012. Macroeconomic and bank-specific determinants of non-performing loans in Greece: A comparative study of mortgage, business and consumer loan portfolios. *Journal of Banking and Finance* 36: 1012–27. [\[CrossRef\]](#)
- Lyons, Paul, and Jonathan Rice. 2022. *Risk Weights on Non-Financial Corporate Lending by Irish Retail Banks*. Dublin: Central Bank of Ireland.
- Makri, Vasiliki, Athanasios Tsagkanos, and Athanasios Bellas. 2014. Determinants of non-performing loans: The case of Eurozone. *Panoeconomicus* 61: 193–206. [\[CrossRef\]](#)
- Messai, Ahlem Selma, and Fathi Jouini. 2013. Micro and macro determinants of non-performing loans. *International Journal of Economics and Financial Issues* 3: 852–60.
- Misman, Faridah Najuna, and M. Ishaq Bhatti. 2020. The determinants of credit risk: An evidence from ASEAN and GCC Islamic banks. *Journal of Risk and Financial Management* 13: 89. [\[CrossRef\]](#)
- Mohamad, Siti Nor Amira, Mohamad Yazis Ali Basah, and Muhammad Ridhwan Ab Aziz. 2018. Examining Risk-Weighted Assets (RWA) Performance after Recent Financial Crisis in Malaysian Banking System. *International Journal of Economics Finance* 10: 129. [\[CrossRef\]](#)
- Naili, Maryem, and Younès Lahrichi. 2022. Banks' credit risk, systematic determinants and specific factors: Recent evidence from emerging markets. *Heliyon* 8: e08960. [\[CrossRef\]](#) [\[PubMed\]](#)
- Neisen, Martin, and Stefan Röth. 2018. *Basel IV: The Next Generation of Risk Weighted Assets*. Hoboken: John Wiley & Sons.
- Nkusu, Mwanza. 2011. *Nonperforming Loans and Macrofinancial Vulnerabilities in Advanced Economies*. Washington, DC: International Monetary Fund.
- Orhan, Zeyneb Hafsa, Sajjad Zaheer, and Fatih Kazanci. 2023. Evaluating the current interest-free monetary policy tools and suggesting a new one: Case of Turkey via examples of Malaysia, Pakistan, and Bahrain. *Qualitative Research in Financial Markets* 16: 108–34. [\[CrossRef\]](#)
- Pham, Thuy Tu, Le Kieu Oanh Dao, and Van Chien Nguyen. 2021. The determinants of bank's stability: A system GMM panel analysis. *Cogent Business and Management* 8: 1963390. [\[CrossRef\]](#)
- Raei, Reza, Mahdi Saeidi Kousha, Saeid Fallahpour, and Mohammad Fadaeinejad. 2016. A hybrid model for estimating the probability of default of corporate customers. *Interdisciplinary Journal of Management Studies* 9: 651–73.
- Rinaldi, Laura, and Alicia Sanchis-Arellano. 2006. *Household Debt Sustainability: What Explains Household Non-Performing Loans? An Empirical Analysis*. Frankfurt: European Central Bank.
- Salas, Vicente, and Jesus Saurina. 2002. Credit risk in two institutional regimes: Spanish commercial and savings banks. *Journal of Financial Services Research* 22: 203–24. [\[CrossRef\]](#)
- Saleh, Mohammad H., Rami S. Alkhalwaldeh, and Jamil J. Jaber. 2023. A predictive modeling for health expenditure using neural networks strategies. *Journal of Open Innovation: Technology Market, and Complexity* 9: 100132. [\[CrossRef\]](#)
- Saunders, Anthony, and Liliana Schumacher. 2000. The determinants of bank interest rate margins: An international study. *Journal of international Money and Finance* 19: 813–32. [\[CrossRef\]](#)
- Schiller, Bradley R, and Karen Gebhardt. 2024. *The Economy Today*, 17th ed. New York: McGraw-Hill Education.
- Shaheen, Fazeelat Iqra, Nadia Ameer Uddin Khan, Mirza Adnan Baig, and Mohammad Muzammil. 2024. Determinant of credit risk of Islamic banks in Pakistan. *Future Business Journal* 10: 4. [\[CrossRef\]](#)
- Shehadeh, Maha, Anas Bani Atta, Thamir Al Barrak, Abdalwali Lutfi, and Mahmood Alrawad. 2024. Digital transformation: An empirical analysis of operational efficiency, customer experience, and competitive advantage in Jordanian Islamic banks. *Uncertain Supply Chain Management* 12: 695–708. [\[CrossRef\]](#)

- Siska, Elmira. 2022. Financial Technology (FinTech) and its impact on financial performance of Islamic banking. *Journal of Economics Accounting* 2: 80–92.
- Sitorus, Tigor. 2015. The Study of Risk-Weighted Assets on the Effects of Loan Exposure Valuation towards Credit Default (an empirical study on middle and top local banks listed in Indonesia stock exchange period 2008–2012). *Copernican Journal of Finance Accounting* 4: 159–76. [[CrossRef](#)]
- Tafri, Fauziah Hanim, Zarinah Hamid, Ahamed Kameel Mydin Meera, and Mohd Azmi Omar. 2009. The impact of financial risks on profitability of Malaysian commercial banks: 1996–2005. *International Journal of Economics and Management Engineering* 3: 1320–34.
- Thalib, Prawitra, Hilda Sabrie, Faizal Kurniawan, and Erni Agustin. 2017. Hisbah (Supervision) Application in Determining of Standarize Standard Akad Modes on Islamic Financial Institution in Indonesia. Paper presented at the International Conference on Law, Governance and Globalization 2017 (ICLGG 2017), Surabaya, Indonesia, November 16–17.
- Wan, Qilong, Xiaodong Miao, Chenguang Wang, Hasan Dinçer, and Serhat Yüksel. 2023. A hybrid decision support system with golden cut and bipolar q-ROFSs for evaluating the risk-based strategic priorities of fintech lending for clean energy projects. *Financial Innovation* 9: 10. [[CrossRef](#)] [[PubMed](#)]
- Warue, Beatrice Njeru. 2013. The effects of bank specific and macroeconomic factors on nonperforming loans in commercial banks in Kenya: A comparative panel data analysis. *Advances in Management Applied Economics* 3: 135.
- Zain, Nor Razinah Binti Mohd, and Rusni Hassan. 2019. Settlement of Islamic finance disputes in the United Arab Emirates. In *Dispute Resolution in Islamic Finance*. London: Routledge, pp. 136–57.
- Zarei, Alireza, Mohamed Ariff, and M. Ishaq Bhatti. 2019. The impact of exchange rates on stock market returns: New evidence from seven free-floating currencies. *The European Journal of Finance* 25: 1277–88. [[CrossRef](#)]
- Zheng, Changjun, Niluthpaul Sarker, and Shamsun Nahar. 2018. Factors affecting bank credit risk: An empirical insight. *Journal of Applied Finance Banking* 8: 45–67.

**Disclaimer/Publisher's Note:** The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.