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DEEP LEARNING APPROACH AS A TOOL FOR SUSTAINABILITY HYPOTHESIS GENERATION

Tamer Sh. Mazen[1*], Ahmed R. Mohamed[2], Sherin M. Omran[3]

[1]Management Information System Dep., Modern Academy of Computer Science and Management, Cairo, Egypt, Email: dr.tamermazen@gmail.com, Tamer. Mazen@cs.modern-academy.edu.eg, Orcid ID: https://orcid.org/0000-0003-2296-4292
[2]Economics Department, Modern Academy for Computer Science and Management Technology, Cairo, Egypt, Email: ahmed.ramzy@ba.modern-academy.edu.eg
[3]Department of Computer Engineering, Modern Academy for Engineering and Technology. Cairo, Egypt, Email: shereen.mohammed@eng.modern-academy.edu.eg

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Corresponding Author: Tamer Sh. Mazen (dr.tamermazen@gmail.com, Tamer)

ABSTRACT

The economy's continued failure to achieve and maintain external sustainability could lead to structural weaknesses, persistent current account imbalances, and poorly thought-out exchange rate mechanisms, all exacerbated by ineffective macroeconomic strategies. These factors will lead to a heavy reliance on external debt and increased exposure to the volatility of global financial markets, ultimately leading to a lack of long-term economic growth. It is essential to recognize this challenge and apply new analytical tools alongside reform-oriented frameworks. In this study, the researchers present a new interdisciplinary approach that attempts to address these shortcomings by integrating deep learning methodologies with economic decision-making analysis. The approach demonstrates that sustainability is not a fixed endpoint, but rather a flexible and adaptive process, unlike traditional economic models. This approach incorporates behavioral variables (policy adaptability and institutional responsiveness) and traditional economic indicators (trade balances and debt ratios). This integration is achieved through a hybrid model architecture that combines the Analytical Hierarchy Process (AHP) with Deep Learning Models (DLM). Three important discoveries were made using this model. First, the dynamic weighting mechanism of the AHP-DLM model allows the identification and quantification of the interaction between economic and behavioral variables that influence sustainability trajectories, thus capturing nonlinear relationships often neglected in conventional models. Second, the path-correcting capability of policymakers provides them with the tools necessary not only to assess the current state of sustainability but also to simulate corrective interventions, thus facilitating proactive policymaking. Finally, the model's inherent contextual adaptability accommodates different economic contexts, thus addressing widespread criticisms of generic approaches in the sustainability literature. This research represents the first application of deep learning to dissect the relationship between structural economic inefficiencies and decision-making processes in the field of sustainability governance. By linking computational capabilities to hierarchical priorities, this study calls for a paradigm shift from reactive responses to proactive economic strategy formulation, providing a scalable framework for diagnosing and guiding economies toward an externally resilient and sustainable future.

KEYWORDS: Analytic Hierarchy Process, Artificial Neural Network, Current Account Deficit, Deep Learning; External Sustainability, Structural Approach.

1. INTRODUCTION

The phenomenon of sustainability has garnered significant attention from researchers and policymakers due to its theoretical and empirical implications. It is a critical issue, as it influences the design, implementation, and effectiveness of macroeconomic policy across different time horizons [1] [2]. Moreover, some view it as a thermometer for measuring an economy's strength and capacity to withstand various economic shocks. In 2002, the International Monetary Fund outlined the fundamental aspects of achieving financial sustainability, categorizing them into three divisions: external sustainability, financial sustainability, and financial sector stability. The International Monetary Fund (IMF) defined external sustainability as the ability of a state to finance its Current Account Deficit (CAD) through official or private foreign capital flows without requiring drastic changes to its economic policies. This ability fosters positive future expectations regarding achieving a balanced current account in the medium term, alongside selecting an optimal exchange rate system to support this balance [2].

A temporary CAD is generally viewed as a healthy phenomenon in both emerging and advanced economies, in stark contrast to a permanent CAD. The first type of deficit reflects the redistribution of capital between countries due to differences in capital productivity, while the second type indicates structural weaknesses within the economy. Although a temporary deficit may not pose significant problems for the domestic economy as it can be financed through net international reserves or external lenders, the risks associated with a permanent deficit are substantial [3]. These risks include high domestic interest rates, a cumulative increase in external debt, rapid depreciation of the exchange rate, and a widening of the financial deficit. Ultimately, this leads to the erosion of future generations' rights, as they will bear the burden of external debt to finance the CAD, resulting in a decline in their standard of living. Recently, many economists have criticized the distinction between types of CADs. The risks associated with deficits have raised concerns about the need to differentiate between an economy's ability and inability to finance such deficits. Regardless of the type of deficit, its size and persistence, even over a relatively short period, raise doubts about the economy's capacity to service and finance it. Consequently, modern applied studies in this field have shifted focus toward testing the status of external sustainability within the economy in question [4], [5] and [6].

Adedeji et al. [7] define External sustainability as referring to a situation where an economy finances its current (CA) imbalances under existing economic policies. This means maintaining the government's intertemporal budget constraint across different periods without disruption, avoiding the need for drastic policy changes or the risk of triggering economic crises.

Dülger, et al. [7] Proponents of the broad concept of sustainability argue that defining external sustainability begins with clarifying the term "sustainability" itself. Sustainability refers to maintaining a certain level indefinitely. Within this framework, external sustainability means "the ability to sustain current economic policies and private behavior without requiring drastic changes or abrupt halts to existing policies (e.g., sudden adoption of stricter monetary or fiscal policies that could trigger a major depression) or without causing a crisis (e.g., sharp interest rate hikes, sudden depletion of net international reserves, or a collapse in the foreign exchange rate, all of which weaken the economy's ability to meet external obligations)."

Brissimis et al. [8] define external sustainability in terms of the current account balance as a percentage of GDP, which ensures the stability of the net foreign asset ratio relative to GDP.

They advocate for the narrow concept of external sustainability, which can be expressed through the following functional form:

$$CA_t / GDP_t = g\,k \;;\; k = \sum_{i=0}^{\infty} NFA_{t-i} \Big/ \sum_{i=0}^{\infty} GDP_{t-i} \quad ;\; i = 0,1,\dots,\infty\,; \qquad (1)$$

Here CA_t / GDP_t is the current account balance to GDP ratio, which stabilizes at a level reflecting the economy's net external debt k. This has been expressed as the sum of the net foreign assets to GDP ratio across different periods NFA_{t-i} / GDP_{t-i}.

Lane et al. [9] External adjustments in advanced economies and developing markets revealed that nations with external balances that exceeded basic economic fundamentals experienced the greatest contractions. In deficit countries, adjustment was generally accomplished through demand compression rather than expenditure switching, with variations noted across exchange rate regimes. Changes in other investment flows were the key conduit for financial account adjustment, with the European Central Bank (ECB) providing external assistance and liquidity provisions. The significant compression in current account balances between the pre-crisis period and 2010 presents a significant opportunity to analyze the mechanics of external adjustment, as cross-country trends corresponded with the rectification of pre-crisis "excesses." Countries that made the most remarkable and significant improvements in their external balances employed measures such as currency devaluation and increased savings.

In summary, Scholars' understanding of external sustainability differs, with disputes often focusing on methodology rather than its underlying meaning. Proponents of the broad concept emphasize overall economic conditions, whereas supporters of the narrow concept concentrate on specific metrics such as net foreign assets and external debt-to-GDP ratios. A comprehensive definition incorporates both approaches, defining external sustainability as a state's ability to fund current account deficits without significant policy adjustments, thus protecting future generations from debt loads. According to applied research, deficits exceeding 5% of GDP present significant sustainability issues, mainly when supported by short-term capital flows. The intertemporal balance of payments constraint is frequently used to analyze long-term equilibrium between exports and imports, but model-based conclusions differ by country. While debates about deficit categorization and financing techniques have subsided, research on defining external sustainability remains divided, reflecting arguments over whether the concept's scope is narrow or broad [10], [11], [12]. This ongoing discussion highlights the complexities of designing macroeconomic policies that foster sustainable account balances.

In this paper, the researcher presents a new model based on the Analytical Hierarchy Process (AHP) and Deep Learning (DL) to evaluate and correct the sustainability path, particularly in terms of external sustainability. The proposed model tested two hypotheses. The integration of AHP and DL can enhance decision-making by allowing for a systematic evaluation of sustainability criteria while leveraging the predictive capabilities of deep learning. The proposed algorithm may facilitate the generation of new hypotheses through data-driven insights, enabling a more robust framework for assessing and refining sustainability strategies, particularly regarding external factors.

The next sections of the paper will be as follows. In Section 2, a background is provided for the Egyptian Recent Experience's Framework for Sustainability, including the AHP and DL models. Section 3 explains the proposed model, which is further detailed in Section 4, followed by the experimental section in Section 5. The experimental results are then presented in Section 6. Finally, the conclusion and limitations are presented in sections 7 and 8.

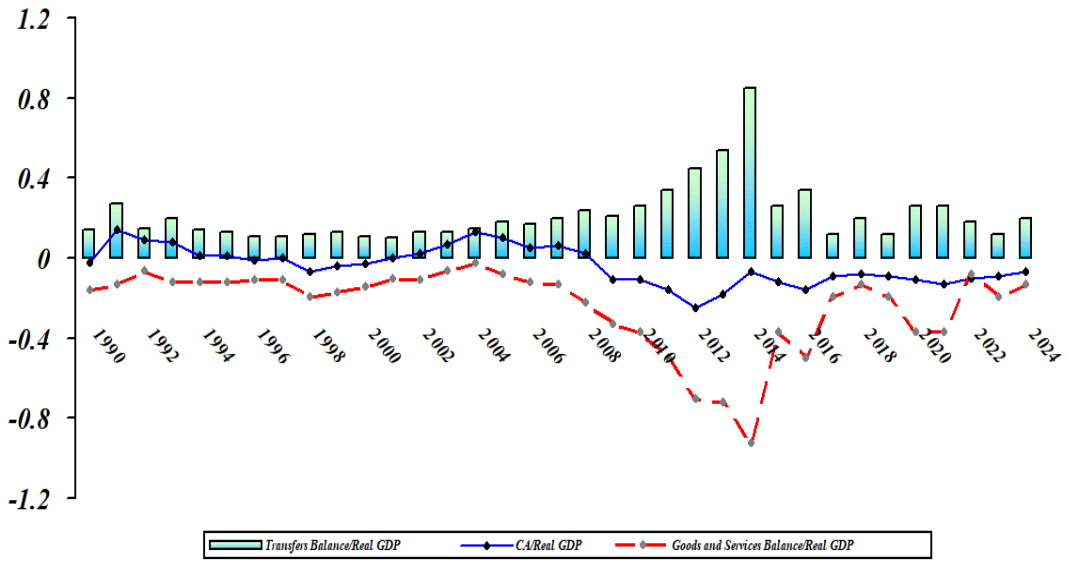


Figure 1: Historical Development of The Egyptian Cab Comonents.

1.1. State Of the Art

A. Context And Framework: Egypt's Recent Experience

An observer of Egypt's external economic balance situation would note that the trade balance experienced a continuous deficit, growing at increasing annual rates before the economic reform program was implemented in the early 1990s, as seen in Figure 1. With the Egyptian economic authorities' adoption of the financial reform program and the economy's adherence to traditional peg regimes, the trade balance deficit decreased from –5470.3 million USD in 1990 to –3811.7 million USD in 1995 as seen in Figure 1, This reduction helped transform the current account balance from a deficit of $634 million USD to a surplus of $385.9 million USD during the same period. However, the bilateral trade balance surplus declined from 4836.3 million USD to 4197.6 million USD over the same period. However, at the beginning of 1998, the Egyptian economy faced three external shocks that significantly negatively affected its economic balance. First, the contagion of the 1997 Southeast Asian financial crisis spread to Egypt. Second, the Luxor terrorist incident at the end of the same year negatively impacted the tourism sector. Third, global oil prices experienced a sharp decline in 1998. These shocks depleted foreign exchange resources and caused the current account deficit to rise again, reaching $2,478.6 million, its highest level during the initial period of traditional exchange rate pegging regimes. This deficit amounted to 7% of real GDP. Although the bilateral transfer balance surplus reached 12% of real GDP in the same year, it was insufficient to offset the trade balance deficit, which stood at 19%. As a result, the current account deficit surpassed the 5% threshold, indicating that it had reached an unsustainable level when the Egyptian economy adhered to traditional pegged exchange rate regimes [13].

The Egyptian economy has taken the necessary steps toward achieving external sustainability, with monetary authorities allowing some flexibility in the exchange rate and adopting a creeping peg regime. As a result, the current account deficit decreased to 1163.1 million USD (–3% of real GDP) in 2000 [14]. This decline was primarily driven by a reduction in the trade balance deficit, which fell to 14% of real GDP, while the surplus in the unilateral transfers balance remained stable.

As seen in Figure 1, from 2003 to 2014, monetary authorities granted greater flexibility to the Egyptian pound's exchange rate against foreign currencies, and the economy adopted a managed float system. During this period, economic conditions shifted toward external sustainability, with the current account balance achieving a surplus of $1,751.9 million (5% of real GDP) in 2006. This improvement resulted from a decline in the trade balance deficit to 12% of real GDP. Commodity exports increased to approximately $ 18.4 billion, driven by a 92.9% rise in natural gas and petroleum exports. Additionally, the services balance surplus reached 8.2 billion USD that same year [15].

However, this period of stability under the managed float system was short-lived. By the second half of 2007, the global economic crisis spread uncertainty across financial and credit markets, affecting all economic activities. The crisis shadowed the Egyptian economy, disrupting its path toward external sustainability. No sooner had the Egyptian economy begun implementing the initial stages of plans to develop the banking sector and improve economic performance than tensions escalated. Security, political, financial, and social crises intensified from January 25, 2011, through June 30, 2013, and beyond [15].

These external and internal shocks directly contributed to the Egyptian current account deficit reaching its peak during the study period, with a deficit of $ –10,146.3 million USD in 2012, its highest level, equivalent to 25% of real GDP. Despite a surplus in the unilateral transfer balance, which reached 111368.4 million USD in the same year, it was insufficient to offset the trade balance deficit, which stood at 11% of nominal GDP. This deficit indirectly pushed the Egyptian current account deficit into the late stages of unsustainability. The Egyptian economy continued on an unsustainable path, with the current account deficit surpassing the 5% threshold and reaching 7% of real GDP by the end of 2014 [16]. This occurred despite the unilateral transfer balance achieving its highest surplus during the study period, amounting to 221685.7 million USD in the same year. By 2016, it became apparent that there was an inconsistency between the application of macroeconomic policies in the Egyptian economy and the method used to manage the exchange rate. This resulted in an unstable economic environment characterized by increased real exchange rate fluctuations due to the different exchange rate regimes in place, decreased monetary policy effectiveness, and rising financial deficit levels [17] .

This matter led to an increase in transaction costs, reflected in the low competitiveness of national industries and the depletion of the net international reserves level held by monetary authorities, as well as decreased economic growth rates, investment, employment, and output. High inflation rates and the accumulation of gross domestic debt levels have made it difficult for the Egyptian economy to continue bearing. Therefore, it was logical that the executive board of the international monetary fund agreed in November 2016 to provide financial assistance to Egypt through an agreement to benefit from the Extended Fund Facility (EFF) with a value of 8.59

billion Special Drawing Rights (SDR), about 12 billion USD. The Egyptian economy has begun a new journey with an economic reform program. It finds itself facing a scenario that has not been achieved in 16 years: achieving a primary surplus in the state's general budget of 4.66 billion L.E. at a rate of 0.1%. In addition, it reached an inflation rate of 9.37% in 2019, after recording its highest rate during the study period of 29.76% in 2017, following the exchange rate liberalization [18].

The monetary authorities also contributed to achieving the targeted economic growth rate, which reached 5.56% in 2019 after falling to 2.92% in 2015. Not even the most optimistic economists anticipated a day when the international economic arena would witness the outbreak of a global health crisis (COVID–19) that would swiftly escalate into a worldwide economic crisis within a matter of days. This crisis devastated entire economies, upending established economic theories and literature on the patterns, nature, and transmission channels of economic crises and blurring the analytical ability to distinguish between supply and demand shocks. The memories and repercussions of the great depression resurfaced, casting a shadow over global economic scenarios and trajectories. The global economy faced a crisis comparable in scale to the 1930s, aptly named the Great Lockdown Crisis [19].

The COVID-19 pandemic-triggered lockdown crisis imposed an exceptional trajectory on the Egyptian economy. The focus was not only on mitigating its adverse effects but also on preserving the gains of Egypt's economic reform program, both financial and real. The monetary authorities implemented measures to strengthen the economy's key components and mitigate the pandemic's impact. These swift actions boosted the economic growth rate to nearly 2% in 2021, a relatively high figure compared to some advanced economies, which recorded negative growth rates in the same year [19].

However, this rate remained the second lowest growth rate achieved by the Egyptian economy during the study period. This scenario reinforced arguments supporting the Egyptian economy's success in containing the pandemic's repercussions while maintaining favorable growth rates. This resilience was attributed to the economy's flexibility, diversity, and adoption of proactive and effective economic policies, supported by the gains of the economic reform program. These factors contributed to the stability of economic and financial indicators, mitigated the severity of the pandemic's economic and social impacts across sectors, and bolstered investor confidence in the Egyptian economy's performance. As a result, the outlook for its future performance in the coming years remains optimistic.

As shown in Figure 1, the CA deficit followed this positive trend, declining sharply to $–2,957.8 million USD during the second quarter of 2022. However, the Egyptian current account balance was destined to face successive crises, and the glimmer of hope did not last long. Just as early signs of recovery emerged after nearly two years of the COVID–19 pandemic, global geopolitical risks escalated due to the Russian-Ukrainian war. This led to increased uncertainty, a sharp rise in global inflation rates driven by soaring commodity, food, and energy prices, as well as a surge in capital outflows. Additionally, severe bottlenecks and ongoing disruptions in global value chains further disrupted global trade and deteriorated international exchange rates. [20]

The Egyptian economy was not immune to these successive economic shocks. As a result, the current account deficit rose again, reaching –7463.1 million USD by the end of the first quarter of 2024. As evident from the previous figure 1, the deficit in the Egyptian current account during the study period is primarily driven by the trade balance deficit, reflecting the magnitude of this deficit in relation to the surplus in the unilateral transfer balance. This deficit highlights structural issues related to the competitiveness of the Egyptian economy, posing significant challenges to achieving external sustainability [21].

B. Analytical Hierarchy Process Calculation

An organized method for classifying and evaluating complicated decisions, the analytic hierarchy process (AHP) is founded on psychology and mathematics. It is a multi-criteria decision-making method. There are four steps to calculate AHP. First, the relevant data is estimated, but this is done in matrix A. Its parameters have been based on the Intensity of Importance. The second step is copying matrix A to matrix B. The third step involves squaring the matrix by multiplying matrix A by B, and the fourth step consists of computing the eigenvector [23]. Table 1 illustrates the Intensity of Importance Scale, as proposed by Saaty.

Table 1: Intensity of the Importance Scale.

Intensity of Importance	Definition
1	Objectives □ and □ are of equal importance.
3	Objective □ is weakly more important than□.

5	Objective □ is strongly more critical than □.
7	Objective □ is significantly more critical than □.
9	Objective □ is more critical than □.
2, 4, 6, 8	Intermediate values.

The degree of inconsistency in the square matrix is measured using a Consistency Index (CI). The Random Consistency Index (RCI), obtained from a randomly generated square matrix and displayed in Table 2, was compared with the predicted Consistency Index (CI) by A. Saaty (1980). For n fewer than three, the RCI value is 0, and the table does not display them [22] , [23]

Table 2: The Random Consistency Index (Rci).

n	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**
RCI	0.58	0.90	1.12	1.24	1.32	1.41	1.45	1.49	1.51	1.48	1.56	1.57	1.59

C. Deep Learning Models

Deep learning models (DLM) are a subset of machine learning algorithms that use multiple layers of neural networks to extract high-level features from raw data. These models are capable of learning complex patterns and representations, making them highly effective for tasks such as image recognition, natural language processing, speech recognition, and other related applications. Below is an overview of key deep learning models and their applications. By following the simulated effect of the biological neural network model, it is possible to deduce the artificial neural network models, which function as interconnected groups of neurons organized into layers that exchange information with one another. This process involves understanding how neurons interact and transmit information within the network. Neural networks receive information and signals through several cells called the input layer [24]. Thus, each neuron in the input layer represents an independent variable that affects the network's outputs, with different weights reflecting the relative importance of each variable in determining the behavior of the outputs. The weights assigned to each neuron in the input layer are crucial in determining the overall performance of the neural network, as they influence the strength of the connections between neurons [25].

The input layer connects to the hidden layers through communication channels. This layer corresponds to the biological axon, the nucleus represents the mechanism of action, and the communication channels are analogous to neurotransmitters. The hidden layer is connected to another layer, known as the output layer, which contains one or more cells depending on the model being explained. The connection between the hidden and output layers is crucial, as it enables the neural network to process and transform input data into meaningful information. This connection is established through the activation functions of the cells, which are determined by the weighted inputs and their corresponding relative weights at the meeting points.

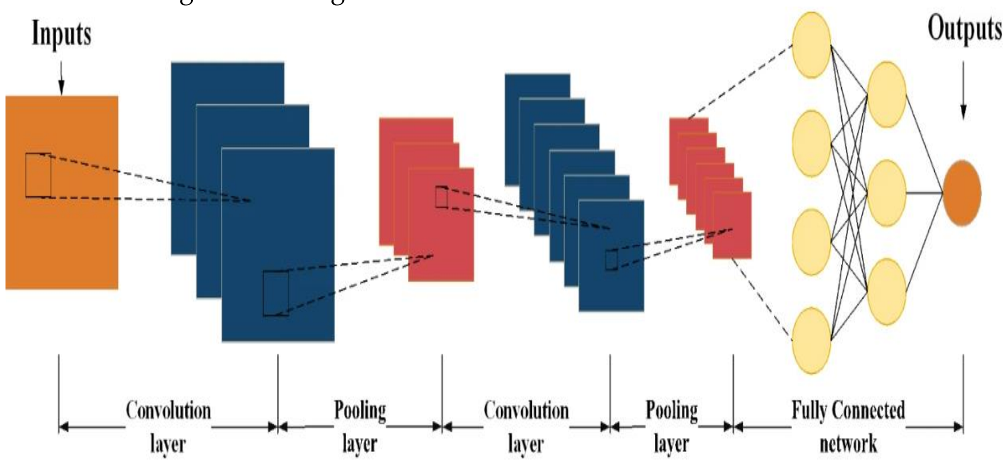


Figure 2: Operational Diagram of Deep Learning Model.

As shown in Figure 2. Each set of inputs is processed to produce a corresponding set of outputs. This is achieved by weighting the inputs through multiplication with their relative weights at the meeting points, after which they are grouped to determine the activation functions of the cells. By referring to Figure 2, and before illustrating the activation functions within artificial neural network models, the following functional form of artificial neural network models can be clarified [26].

$$\begin{bmatrix} H_1 \\ H_2 \\ \vdots \\ \vdots \\ H_N \end{bmatrix} = \begin{bmatrix} \alpha_{01} \\ \alpha_{02} \\ \vdots \\ \vdots \\ \alpha_{0N} \end{bmatrix} + \begin{bmatrix} \beta_{11} \\ \beta_{12} \\ \vdots \\ \vdots \\ \beta_{1N} \end{bmatrix} X_1 + \cdots + \begin{bmatrix} \beta_{K1} \\ \beta_{K2} \\ \vdots \\ \vdots \\ \beta_{KN} \end{bmatrix} X_K \quad ;^{n=1,2,\ldots,N}_{k=0,1,2,\ldots,K} \qquad (2)$$

This previous model illustrates the receiving process of the hidden layer [H1,…., HN], information and signals from the input layer [X0, X1,....., XK], where $[\alpha_{01}, \alpha_{02}, \ldots, \alpha_{0N}]$ are the constant–Bias Terms–, $[\beta_{1N}, \beta_{2N}, \ldots, \beta_{KN}]$ are the relative weights that represent the channels of transmission and communication between inputs K and the hidden layer after processing and operation, leading to the output layer [Y1, Y2, ..., YK].

$$\begin{bmatrix} Y_1 \\ Y_2 \\ \vdots \\ \vdots \\ Y_K \end{bmatrix} = \begin{bmatrix} \gamma_{01} \\ \gamma_{02} \\ \vdots \\ \vdots \\ \gamma_{0K} \end{bmatrix} + \begin{bmatrix} \omega_{11} \\ \omega_{12} \\ \vdots \\ \vdots \\ \omega_{1K} \end{bmatrix} H_1 + \cdots + \begin{bmatrix} \omega_{N1} \\ \omega_{N2} \\ \vdots \\ \vdots \\ \omega_{NK} \end{bmatrix} H_N \quad ;^{n=1,2,\ldots,N}_{k=1,2,\ldots,K} \qquad (3)$$

Here, $[\gamma_{01}, \gamma_{02}, \ldots, \gamma_{0N}]$ are bias terms, $[\gamma_{01}, \gamma_{02}, \ldots, \gamma_{0N}]$is the relative weight representing the transmission and communication between hidden layer, and outputs. As discussed earlier in the context of biological neurons, the production of these cells is a function of the impulse intensity contained in them and the activation, learning functions in the cell itself to match the same output layer of artificial neural network models, which depend primarily on the fundamental function of activation functions in stimulating explanatory variables of the input layer, and the hidden layer to reach the best estimation for the artificial neural network models [27].

Many activation functions are used to train neural networks; however, nonlinear activation functions provide an opportunity to leverage the capabilities of artificial neural network models, enabling them to achieve the optimal weighted relative weights and the most accurate estimation results, even when dealing with complex data.

The Sigmoid Function is one of the most essential types of nonlinear logistical activation functions and is mainly used to activate explanatory variables within the input layer or units of the hidden layer in the network, as shown in Figure 2 This function is used to train multi-layer networks that are trained by backpropagation processes1; this function also considered a continuous function. It can take the form of a hyperbolic function, which is a continuous function over the period [− 1, 1], i.e., the function is a differential function with the following functional form:

$$F(x) = \frac{e^{x} - e^{-x}}{e^{x} + e^{-x}} \; ; \qquad (4)$$

The sigmoid function may take the form of a sigmoid binary function, which is a continuous function over the period [0, 1], i.e., it is a differential function, and if the period of this function closes to one, this means that the signals, information, and impulses that have reached the neuron have led to the maximum level of activation. In addition, if this period is close to zero, the neurons do not react or respond to the information they receive. The sigmoid binary function takes the following form [28]

$$\begin{bmatrix} H_1 \\ H_2 \\ \vdots \\ \vdots \\ H_N \end{bmatrix} = \begin{bmatrix} \dfrac{1}{1 + e^{-(\alpha_{01} + \beta_{11}X_1 + \beta_{21}X_2 + \cdots + \beta_{K1}X_K)}} \\ \dfrac{1}{1 + e^{-(\alpha_{02} + \beta_{12}X_1 + \beta_{22}X_2 + \cdots + \beta_{K2}X_K)}} \\ \vdots \\ \vdots \\ \dfrac{1}{1 + e^{-(\alpha_{0N} + \beta_{1N}X_1 + \beta_{2N}X_2 + \cdots + \beta_{KN}X_K)}} \end{bmatrix} \qquad (5)$$

By replacing Eq. 5 in Eq. 3, the essential functions of feedforward neural network models are as follows:

$$\begin{bmatrix} Y_1 \\ Y_2 \\ \vdots \\ \vdots \\ Y_K \end{bmatrix} = \begin{bmatrix} \gamma_{01} \\ \gamma_{02} \\ \vdots \\ \vdots \\ \gamma_{0K} \end{bmatrix} + \begin{bmatrix} \frac{\omega_{11}}{1+e^{-(\alpha_{01}+\beta_{11}X_1+\beta_{21}X_2+\cdots+\beta_{K1}X_K)}} \\ \frac{\omega_{12}}{1+e^{-(\alpha_{01}+\beta_{11}X_1+\beta_{21}X_2+\cdots+\beta_{K1}X_K)}} \\ \vdots \\ \vdots \\ \frac{\omega_{1K}}{1+e^{-(\alpha_{01}+\beta_{11}X_1+\beta_{21}X_2+\cdots+\beta_{K1}X_K)}} \end{bmatrix} + \cdots$$

$$\cdot + \begin{bmatrix} \frac{\omega_{N1}}{1+e^{-(\alpha_{0N}+\beta_{1N}X_1+\beta_{2N}X_2+\cdots+\beta_{KN}X_K)}} \\ \frac{\omega_{N2}}{1+e^{-(\alpha_{0N}+\beta_{1N}X_1+\beta_{2N}X_2+\cdots+\beta_{KN}X_K)}} \\ \vdots \\ \vdots \\ \frac{\omega_{NK}}{1+e^{-(\alpha_{0N}+\beta_{1N}X_1+\beta_{2N}X_2+\cdots+\beta_{KN}X_K)}} \end{bmatrix} \quad (6)$$

2. THE PROPOSED MODEL

There are significant differences in how external sustainability is conceptualized, as the previous discussion illustrates. Additionally, a review of how external sustainability status is interpreted reveals a considerable variation among the numerous studies on the topic. It is quite challenging to establish a unified economic framework for evaluating external sustainability. In this regard, the three most critical economic frameworks are the structural approach to external sustainability, the portfolio balance model, and the intertemporal balance of payments method. These approaches capture the main patterns in how external sustainability is interpreted.

The debate among previous approaches regarding the methodology for interpreting and measuring the status of external sustainability in an economy has been addressed by several studies presented by the IMF since 2006. IMF has acknowledged that these approaches do not differ in the fact that the intertemporal constraint serves as the foundation from which the standard models explaining external sustainability are derived [29], [30]. This study adopts the same perspective; however, it diverges from previous studies in the explanatory model derived from the intertemporal constraint.

This study differs from previous literature not only in terms of methodology but also in the determinants and structural variables of the approach itself. After completing the first stage, which involves estimating the long-run parameters of the current account determinants, the second stage consists of calculating the optimal current account balance. This is achieved by weighting the values of the parameters estimated in the first stage with the values of the current account determinants in the medium term. After obtaining the standard values of the economic variables in the medium term, these values are weighted by the long–term elasticities, which reflect the extent of their impact on the current account balance. This step completes the stage and leads into the final stage of this approach.

The Research aims to introduce a new concept and vision for the structural approach, proposing a novel hypothesis through which the path and status of sustainability, both in general and external sustainability in particular, can be assessed. The proposed structural approach, designed to explain the sustainability situation in an economy, relies on three fundamental stages to achieve its goal. The following stages will be described in detail.

Our structural approach begins with the first stage of identifying the economic determinants that influence the current account balance. that is achieved by constructing a standard model that examines the form, strength, and direction of the relationship between the current account balance as an endogenous (dependent) variable in the model and a set of explanatory or independent variables, which includes external economic determinants such as exchange rates, economic openness degree, and global real interest rate. Additionally, the vector incorporates internal economic determinants, including the current account, fiscal deficit-to-GDP ratio, economic growth rate, real effective exchange rate, net foreign assets, and external debt-to-GDP ratio. These variables are expected to contribute to explaining the behavior of the current account balance by establishing economic theory and drawing on the most widely recognized literature addressing this topic. The approach uses one of the dynamic models to estimate the long- and short-term elasticities of the explanatory variables vector for the behavior of the current account balance. This approach aims to test the significance of short-term parameters and estimate long-term parameters, which are considered essential and standard values for determining the optimal current account deficit. This ensures that the country's economy remains on the correct path toward external sustainability.

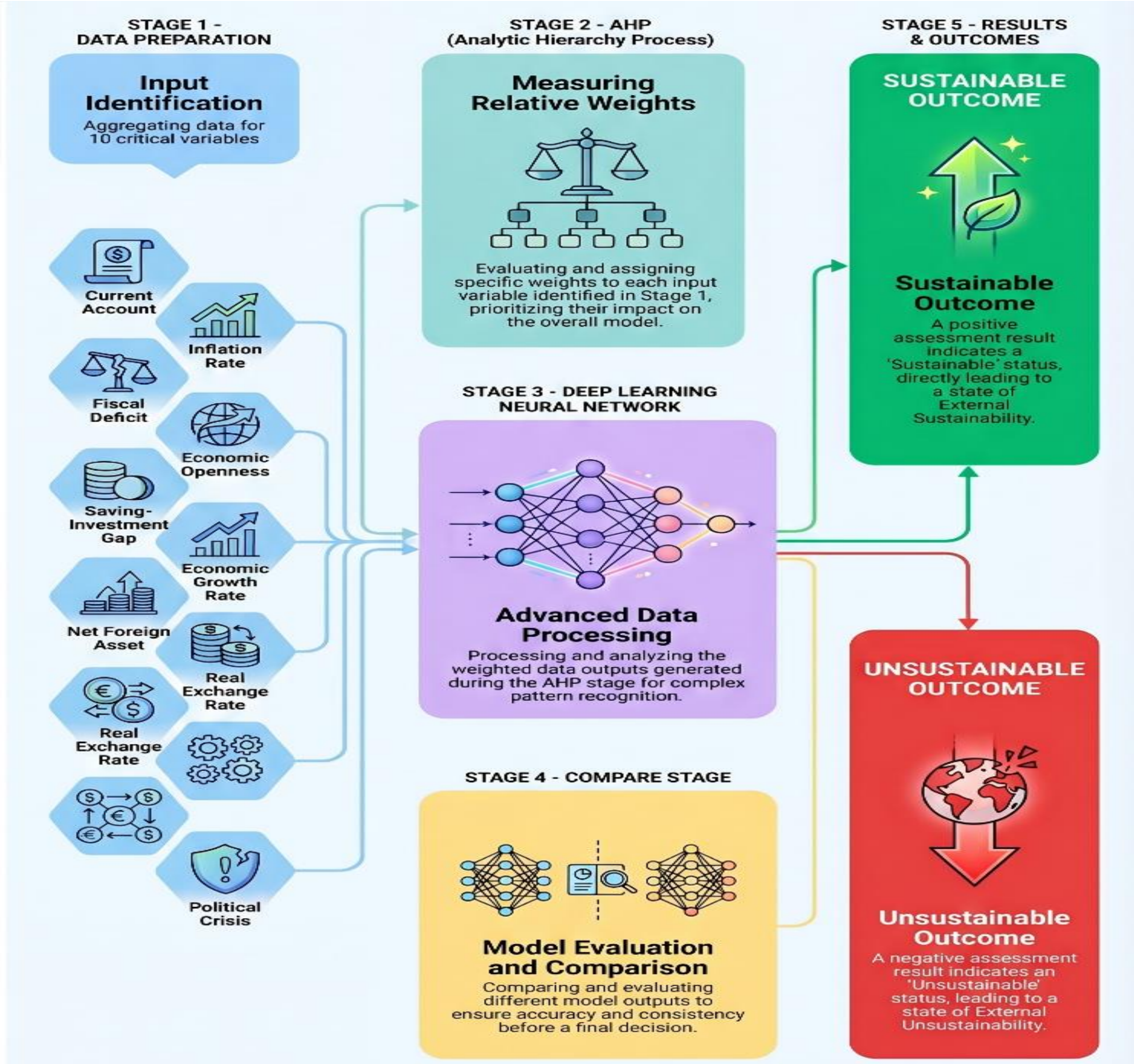


Figure 3: The Proposed Model Diagram

The proposed structural model diagram in Figure 3 illustrates how the AHP addresses the completion of the second stage. The final stage of our structural approach follows the completion of the first and second stages, as shown above. At this stage, the standard values obtained in the previous stage are used to estimate the optimal current account deficit balance. An economy's current account deficit balance is compared with its optimal values. This is the stage at which DLM undertakes its work.

Suppose this comparison reveals that the actual current account deficit exceeds the standard value of the current account deficit balance. In that case, it can be concluded that the current account deficit is unsustainable, and therefore, the country's economy cannot achieve external sustainability. However, suppose the current account deficit balance is lower than the standard. In that case, it can be said that the current account deficit is sustainable, and thus, the country's economy is on the right path toward external sustainability

The combination of AHP and DLM will, in the first stage, facilitate the identification of the relative weight impacts in the input layer, including the economic and behavioral variables it encompasses, to generate the sustainability hypothesis. In the second stage, the outputs from the first stage will be used to train DLM by sequentially introducing variables based on their explanatory power until the best model fit is achieved. Finally, the third stage will build on the operational outcomes of the previous two stages to determine the optimal current account balance. This will be achieved by continuously training deep learning models using the initial learning patterns established in earlier stages. The observed economic variables that constitute the layers of the DLM in the Egyptian economy have been identified using quarterly time series data covering the period from the first quarter of 1990 to the second quarter of 2024.

These variables will be expressed and input into the model layers as follows:

- The output layer, abbreviated as output, contains the current account balance CA_t, which is the internal variable that is interpreted from the model using the input layer, abbreviated as input, and contains the following explanatory variables: Inflation rate (Inf_t). It is expected that there will be an inverse relationship between the current account balance and Inf_t. An increase in the latter leads to a loss of export price advantage, one of the most critical determinants of their competitiveness.
- Exports become relatively more expensive from the perspective of foreign consumers, which reduces demand for them and decreases the current account balance. Additionally, high inflation rates may lead to a decline in the real exchange rate, which in turn reduces the volume of domestic exports and further decreases the current account balance.
- The fiscal deficit on a subscript base, $cap\ F$, $cap\ D$, end base, and $sub\ t$. It has a positive effect on the current account balance. An increase in subscript base $ap\ F\ cap\ D$, end base, and $sub\ t$ leads to a rise in aggregate demand due to higher public spending. This, in turn, increases the components of aggregate demand, including import spending, thereby widening the current account deficit. An increase in the deficit or surplus of the general state budget corresponds to a similar increase in the deficit or surplus of the current account. This relationship is known as the twin deficits hypothesis. The degree of economic openness, abbreviated as DEO_t, is measured by the percentage of the external sector relative to GDP. The relationship depends on the strength, diversity, and flexibility of the foreign trade structure.
- The Saving Investment Gap (SIG_t). It is expected that there will be a positive relationship between the current account balance and SIG_t. An increase in the latter (a negative savings gap), if not offset by public savings or a state budget surplus, will compel the economy to seek alternative sources of financing to bridge this gap. Consequently, this gap may result in a similar gap in foreign trade (a foreign resources gap). That occurs either directly through an increase in imports, leading to a current account deficit, or indirectly through external borrowing to address the disparity between the targeted investment needs required to achieve the desired growth rate and the available volume of national savings, given specific economic, social, and political conditions.
- An increase in the Economic Growth Rate (subscript base, E, G, R, end base, subscript t) Supports improved economic performance and enhances the effectiveness of implemented macroeconomic policies, thereby contributing to a higher current account balance. This is achieved through more significant capital accumulation, increased output, higher employment levels, increased volumes of commodity and service exports, and unilateral transfers. These factors help offset the decline in the current account balance caused by the increase in imports due to the higher economic growth rate.

An increase in Net Foreign Assets (NFA_t) may have a direct positive effect on CA_t through income or revenues transferred from abroad due to holding these assets. Additionally, an increase in the balance of net foreign assets may indirectly benefit the current account balance by providing the economy with the necessary capacity to finance its current account deficit using these assets. The direct relationship is evident in the impact of a rise in the real exchange rate RER_t on CA_t. As the real exchange rate increases, the relative prices of foreign goods in trade rise compared to domestic goods. This leads to higher external demand for domestic exports and reduced domestic demand for imports, thereby improving the current account balance.

In support of the new contribution of this approach and this study, a weighted dummy variable was added to express the effect of Actual Exchange Rate Regimes ($AERR_t$)s on CA_t. The actual exchange rate has weighted this dummy variable to capture the impact of $AERR_t$ through changes in the real exchange rate channel. It is expected that a direct relation will emerge between the current account balance and $AERR_t$The transition from traditional pegged and crawling peg to managed floating and floating exchange rate regimes involves an adaptation mechanism for absorbing external and internal shocks, including isolating the economy from the overall economic effects of these shocks and achieving financial stability. The input layer introduces an additional dummy variable. PCR_t to measure the impact of crises and political risks on the current account balance.

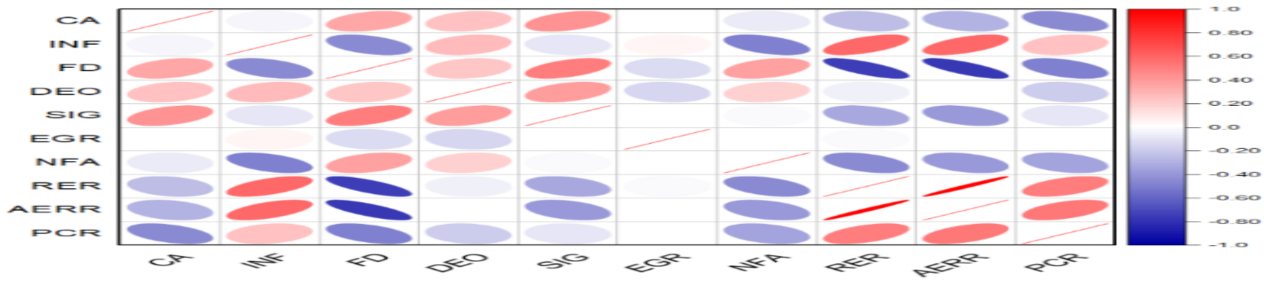


Figure 4: Parameters Correlation Matrix.

3. EXPERIMENTAL

A. Correlation Computation

Evaluating the effectiveness of each parameter is the first step; it is computed based on the correlation degree between each parameter. Figure 4 and **Error! Reference source not found.** represents the correlation results between each parameter and the other parameters. The real exchange rate vs. actual exchange rate regimes has the highest correlation, while net foreign assets show the lowest correlation with most parameters.

Table 3: Parameter's Correlations.

	Current Account	Inflation Rate	Fiscal Deficit	EconomicOpenness	Saving Investment Gap	Economic Growth Rate	Net Foreign Asset	Real Exchange Rate	Actual Exchange Rates Regimes	Political Crisis
Current Account	1.000000	-0.028447	0.358511	0.257972	0.420509	0.015773	-0.066947	-0.249575	-0.283284	-0.455008
Inflation Rate	-0.028447	1.000000	-0.443396	0.272393	-0.093113	0.052417	-0.483194	0.591363	0.586450	0.240632
Fiscal Deficit	0.358511	-0.443396	1.000000	0.234772	0.512696	-0.125660	0.379973	-0.758003	-0.777227	-0.484253
EconomicOpenness	0.257972	0.272393	0.234772	1.000000	0.385534	-0.147700	0.195285	-0.049454	0.015843	-0.184241
Saving Investment Gap	0.420509	-0.093113	0.512696	0.385534	1.000000	0.007159	-0.006935	-0.333836	-0.383047	-0.096282
Economic Growth Rate	0.015773	0.052417	-0.125660	-0.147700	0.007159	1.000000	0.007742	-0.007079	0.000380	0.015329
Net Foreign Asset	-0.066947	-0.483194	0.379973	0.195285	-0.006935	0.007742	1.000000	-0.451361	-0.381837	-0.350566
Real Exchange Rate	-0.249575	0.591363	-0.758003	-0.049454	-0.333836	-0.007079	-0.451361	1.000000	0.985309	0.502952
Actual Exchange Rates Regimes	-0.283284	0.586450	-0.777227	0.015843	-0.383047	0.000380	-0.381837	0.985309	1.000000	0.520327
Political Crisis	-0.455008	0.240632	-0.484253	-0.184241	-0.096282	0.015329	-0.350566	0.502952	0.520327	1.000000

B. Analytic Hierarchy Process Approach

The second step is to implement the AHP Approach for dataset parameters. From Table 3 and

Figure 4, the priority of each parameter is determined based on the correlation coefficient results for each parameter and its relationship with the others. Table 4, Table 5, Table 6, and Figure 5 show that the inflation rate is the most critical parameter, with a weight of 27%, while the political crisis is the least important, with a weight of 1%. The Random Index (RI) should also be considered when evaluating the results. The RI represents the average Consistency Index (CI) for many randomly generated matrices of the same order and can be viewed as an expected value of the RI. The ratio of the Consistency Index to the Random Index is called the Consistency Ratio (CR). A higher CR indicates poorer data quality based on this metric. It is essential to note that decision theory does not provide a precise measure of data quality. The Random Index Table shows that the RI is 1.24, and the CI value is 0.159877774.

Before proceeding to the second and third stages of the proposed algorithm for building and generating sustainability hypotheses — mainly external sustainability — the degree of persistence was calculated by dividing the Consistency Index (CI) by the Random Index (RI). The degree of persistence was found to be 0.11, which is considered satisfactory as it is less than or equal to 0.1.

Table 3: The Analytical Heroically Process Assumptions.

Size of correlation	**Interpretation**	**AHP Importance**
∓ (0.90 □□ 1.00)	Very high (positive and negative) correlation	8
∓ (0.70 □□ 0.89)	High (positive and negative) correlation	7
∓ (0.50 □□ 0.69)	Moderate (positive and negative) correlation	5,6
∓ (0.30 □□ 0.49)	Low (positive and negative) correlation	3,4
∓ (0.00 □□ 0.29)	Little, if any, correlation	2

Table 4: Priority for Each Parameter Vs. Another Parameter.

	Inflation Rate	**Fiscal Deficit**	**Economic Openness**	**Saving Investment Gap**	**Economic Growth Rate**	**Net Foreign Asset**	**Real Exchange Rate**	**Actual Exchange Rates Regimes**	**Political Crisis**
Inflation Rate	1	4	2	5	2	3	7	7	4
Fiscal Deficit	1/4	1	2	5	2	3	7	7	4
Economic Openness	1/2	1/2	1	3	2	3	2	2	2
Saving Investment Gap	1/5	1/5	1/3	1	2	2	3	2	2
Economic Growth Rate	1/2	1/2	1/2	1/2	1	2	2	2	2
Net Foreign Asset	1/3	1/3	1/3	1/2	1/2	1	2	3	3
Real Exchange Rate	1/7	1/7	1/2	1/3	1/2	1/2	1	9	5
Actual Exchange Rates Regimes	1/7	1/7	1/2	1/2	1/2	1/3	1/9	1	5
Political Crisis	1/4	1/4	1/2	1/2	1/2	1/3	1/5	1/5	1

Table 5: Weighted Values of Parameters.

Parameter	**AHP Wight**	**Percentage**
Inflation Rate	0.272820603	27.28 %
Fiscal Deficit	0.200559076	20.06 %
Economic Openness	0.125449065	12.54 %
Saving Investment Gap	0.08466773	8.47 %
Economic Growth Rate	0.083768868	8.38 %
Net Foreign Asset	0.068092741	6.81 %
Real Exchange Rate	0.079787421	7.98 %
Actual Exchange Rates Regimes	0.048863881	4.89 %
Political Crisis	0.035990615	3.60 %

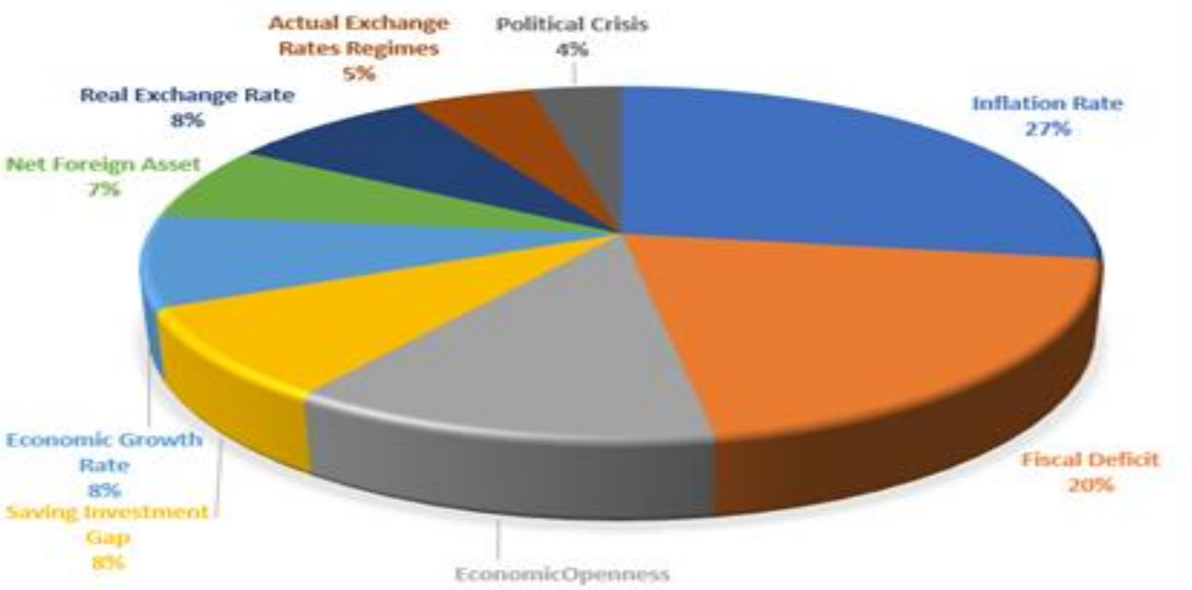


Figure 5: Parmeter's Wight.

C. Deep Learning Model

Deep learning models offer numerous advantages, one of the most significant being their ability to handle nonlinear relationships, which are common in real-world scenarios. These models can also process complex, non-stationary, fuzzy, noisy, and incomplete data. Additionally, they can manage many variables and model complex external relationships that do not conform to fixed patterns, such as those assumed by linear regression models. The solutions provided by neural network models are characterized by strong predictive power [31]. The explanatory and predictive capabilities of neural network models stem from the principle of Hebbian learning. Hebbian learning provides the theoretical foundation for repetitive neuron activation, thereby enhancing the effectiveness of connections between the input and output layers.

This, in turn, improves the ability of artificial neural network models to adapt correlation weights, ultimately achieving optimal explanatory weights through network training. The study employs feedforward backpropagation neural network models. The backpropagation method is a systematic approach for training multilayer feedforward networks based on logical-mathematical methods and the chain rule for calculating derivatives in the error equation for the relative weights of the hidden and output layers. This process aims to identify the differences between the expected results and the actual results produced by the network. The network automatically uses these differences to adjust its internal weights until the errors are minimized.

This iterative process continues until the mean square errors reach the lowest possible level. At this point, the network achieves the optimal solution. Determining the optimal number of neurons in the hidden layer is crucial for enabling the network to interact effectively with its external environment. It also considers the transmission channels between the input and output layers, as well as their direct and indirect effects. Having fewer neurons than required may prevent the network from detecting signals in complex data, while using more neurons than necessary can increase training time. This study uses a trial-and-error method, supported by preliminary tests, as a clear and practical approach for determining the optimal number of neurons in the hidden layer.

The study began by selecting a small number of neurons, starting with only two in the hidden layer. The neural network was then trained and tested until the mean square error reached 1%, the target rate chosen by the study to minimize the mistakes as much as possible. After incrementally increasing the number of neurons in the hidden layer and repeating the training and testing process, the network achieved the optimal solution based on this target rate. It was concluded that the optimal algorithm for diagnosing the path of CAS. It consists of 9 neurons in the input layer, 10 in the hidden layer, and 1 in the output layer. DLM follows the functional form of the augmented feedforward backpropagation neural network. This model allows for the measurement of direct effects from the input layer to the output layer by estimating short–term relative weights ξ, as well as indirect effects from the input layer to the intermediate layer and then to the output layer by estimating long–term relative weights β.

$$
\begin{aligned}
CA_t = \gamma_0 + {} & \frac{\omega_1}{1 + e^{-(\alpha_{01} + \beta_{11} Inf_t + \beta_{21} FD_t + \beta_{31} DEO_t + \beta_{41} SIG_t + \beta_{51} EGR_t + \beta_{61} NFA_t + \beta_{71} RER_t + \beta_{81} AERR_t + \beta_{91} PCR_t)}} \\
& + \frac{\omega_2}{1 + e^{e^{-(\alpha_{02} + \beta_{12} Inf_t + \beta_{22} FD_t + \beta_{32} DEO_t + \beta_{42} SIG_t + \beta_{52} EGR_t + \beta_{62} NFA_t + \beta_{72} RER_t + \beta_{82} AERR_t + \beta_{92} PCR_t)}}} + \cdots \\
& \cdot + \frac{\omega_{10}}{1 + e^{-(\alpha_{10} + \beta_{110} Inf_t + \beta_{210} FD_t + \beta_{310} DEO_t + \beta_{410} SIG_t + \beta_{510} EGR_t + \beta_{610} NFA_t + \beta_{710} RER_t + \beta_{810} AERR_t + \beta_{910} PCR_t)}} \\
& + \begin{bmatrix} \xi_1 \\ \xi_2 \\ \xi_3 \\ \xi_4 \\ \xi_5 \\ \xi_6 \\ \xi_7 \\ \xi_8 \\ \xi_9 \end{bmatrix} \begin{bmatrix} Inf_t \\ FD_t \\ DEO_t \\ SIG_t \\ EGR_t \\ NFA_t \\ RER_t \\ AERR_t \\ PCR_t \end{bmatrix} \qquad (7)
\end{aligned}
$$

Figure 6, illustrates the proposed algorithm for training and estimating neural network models. It demonstrates how the direct effect is transferred from the input layer to the output layer, as well as the indirect effect from the input layer to the intermediate layer and then to the output layer. The network was trained using the TRAINLM function and the adaptation learning function LEARNGD. These functions adjust the relative weights until the network achieves the desired outputs. The training process begins with the selection of small initial relative weights. Each pair of network outputs is then compared with the target output, and the error is calculated. The weighted inputs are modified through backpropagation, enabling the learning function to minimize the mistakes between the network outputs and the actual output layer. At each learning stage, the network's training models progress sequentially, layer by layer, until the output layer is reached. The deviations between the output and target output layers are estimated, and the residuals are used in the network's feedback processes. The relative weights are adjusted layer by layer until the optimal weights and target outputs are achieved.

The data was divided according to the default ratios for neural network models, with 70% allocated to the training sample, 15% to the validation sample, and the remaining 15% to the preliminary test sample. The study selected the sigmoid function as the activation function, specifically chosen to stimulate the explanatory variables in the input layer and the hidden layer to achieve the best estimation for the neural network. The sigmoid function denoted in the proposed algorithm for training and estimating the neural network is one of the most important and widely used types of nonlinear logistic activation

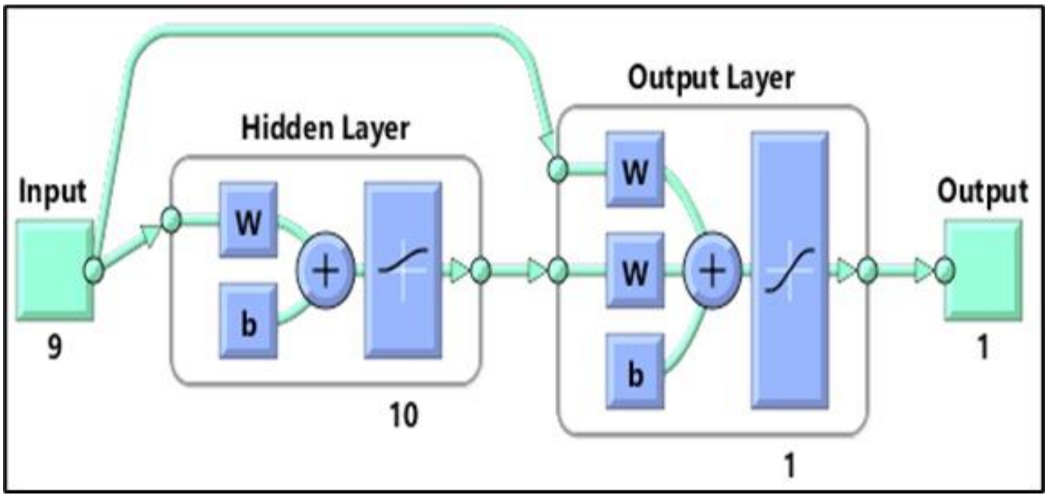


Figure 6: Deep Learning Model Architecture.

functions for activating explanatory variables in the input layer or the units of hidden layers.

By training the neural network as previously described it becomes evident that the results of the training and estimation were as follows:

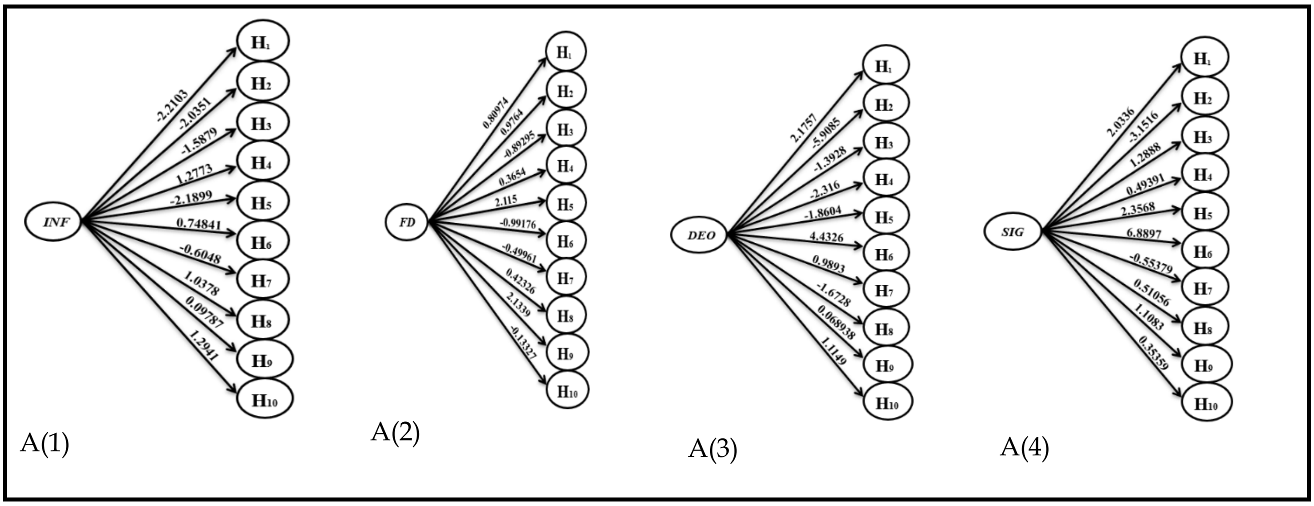
$$CA_t = -0.32 + \frac{2.3263}{1 + e^{-(2.47 - 2.21\,Inf_t + 0.81\,FD_t + 2.17\,DEO_t + 2.03\,SIG_t + 0.09\,EGR_t - 0.56\,NFA_t - 0.01\,RER_t - 2.21\,AERR_t - 1.40\,PCR_t)}} + \frac{1.6046}{1 + e^{-(2.34 - 2.04\,Inf_t + 0.97\,FD_t - 5.90\,DEO_t - 3.15\,SIG_t - 0.14\,EGR_t - 3.03\,NFA_t + 2.59\,RER_t - 0.19\,AERR_t - 2.52\,PCR_t)}} + \cdots \cdot + \frac{-0.31712}{1 + e^{-(3.31 + 1.29\,Inf_t - 0.13\,FD_t + 1.11\,DEO_t + 0.35\,SIG_t - 1.51\,EGR_t + 1.85\,NFA_t - 1.65\,RER_t - 0.85\,AERR_t - 1.58\,PCR_t)}} + \begin{bmatrix} -0.12 \\ 0.55 \\ 0.37 \\ 0.41 \\ 0.64 \\ 0.28 \\ 0.72 \\ 0.89 \\ -0.46 \end{bmatrix} \begin{bmatrix} Inf_t \\ FD_t \\ DEO_t \\ SIG_t \\ EGR_t \\ NFA_t \\ RER_t \\ AERR_t \\ PCR_t \end{bmatrix} \quad (8)$$

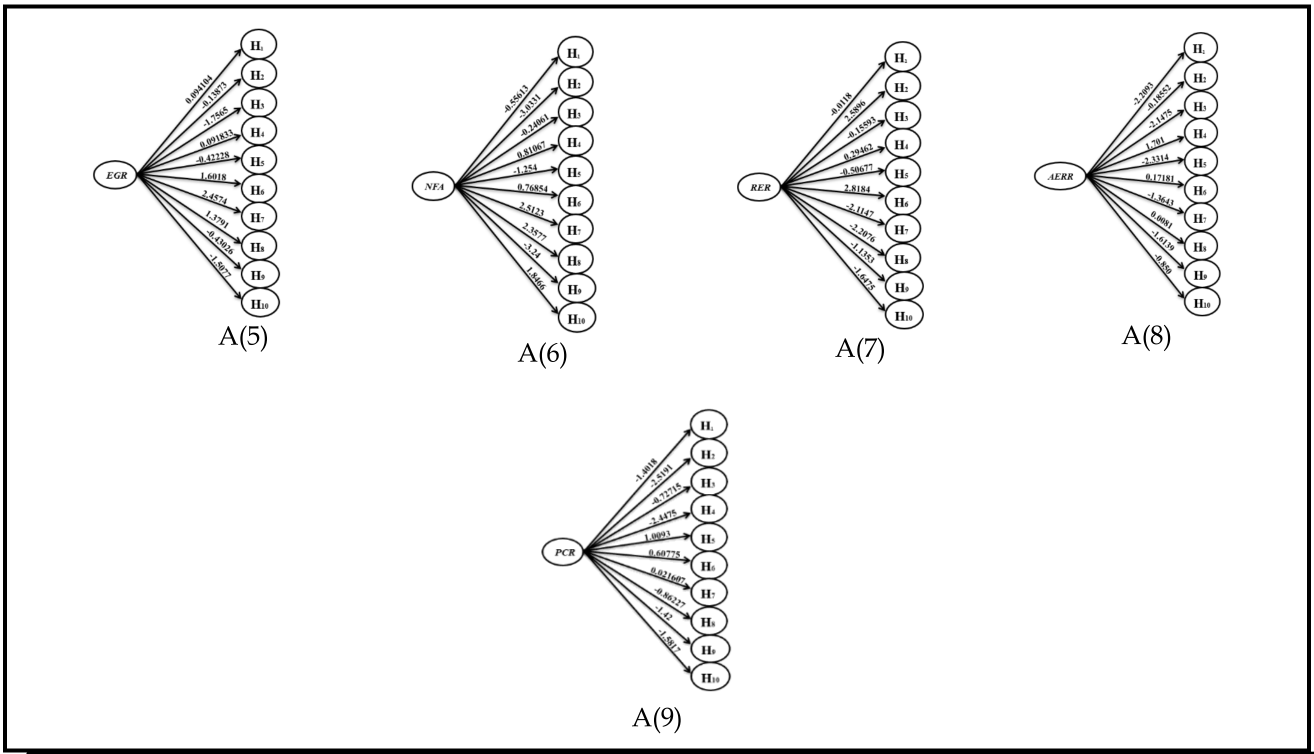
3.1. Experimental Results

By examining the results of the neural network's training and estimation presented above, it becomes evident that there is a significant direct positive relationship between the seven main variables in the input layer and the Egyptian current account balance during the study period. These results are consistent with the previously mentioned hypotheses and literature.

Notably, the actual exchange rate regimes variable emerged as the top performer, surpassing others, and rightly so, as the exchange rate regimes reflect the relative strength of the economic policies applied within the economic framework. This result supports the validity and logic of the proposed structural approach to explaining sustainability, mainly through the extent to which changes in the path of structural variables affect the robustness of the external economic system and its ability to withstand potential external shocks and crises. On the other hand, the results revealed a significant inverse relationship between the Egyptian current account balance and the negative repercussions of the crises and external economic shocks experienced by the Egyptian economy.

An increase in these negative repercussions by 1% led to a decrease in the Egyptian current account balance by 0.46% respectively, as shown in Figure 7. C, the study relied on estimating, the long-term elasticities mentioned in the estimation results presented in Figure 7. A and Figure 7. B; in addition to the direct and short-term effects previously discussed. Regarding the diagnostic testing stage of the neural network model, the proposed algorithm for training and estimating DLM required minimal time to achieve its primary goal: achieving a mean squared error of 1%.





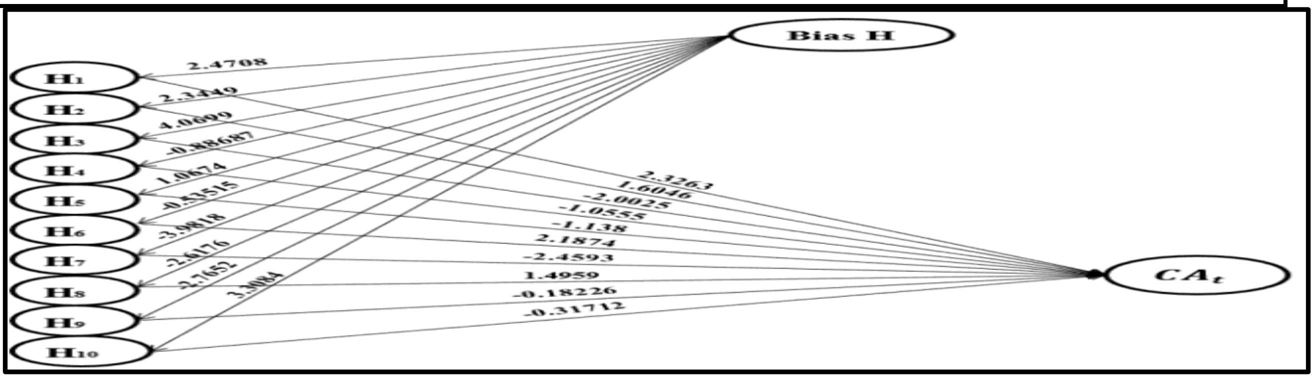


Figure 7 (B)

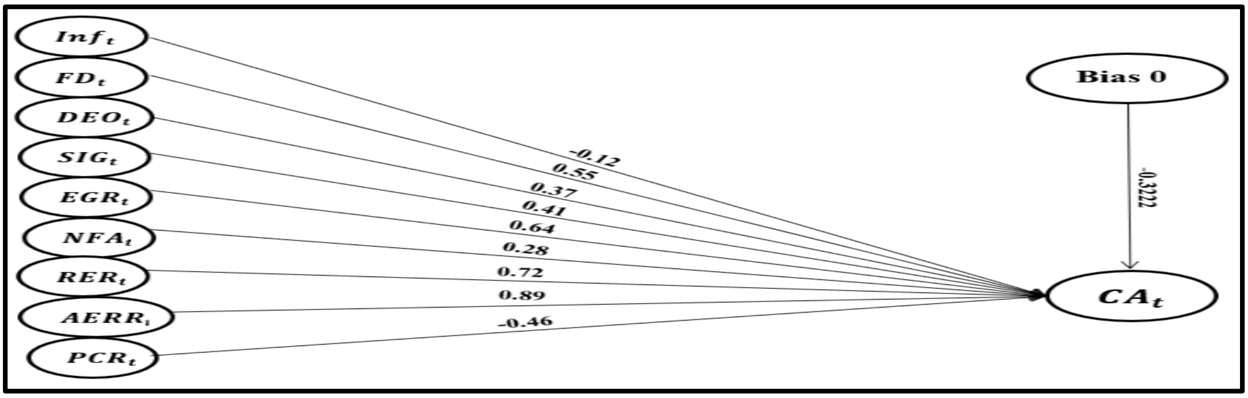


FIGURE 7 (C)

FIGURE 7. Deep Learning Result. (A) The study relied on estimating; (B) the long-term elasticities mentioned in the estimation results (C) the long-term elasticities mentioned in the estimation results

As evident in Figure 8 and Figure 9, the slope of the gradient errors or residual curve rapidly approached this target, even surpassing it, ultimately recording a value insignificantly different from zero by attempt No. 671. This achievement, if any, underscores the model's goodness-of-fit across the testing, validation, and training stages.

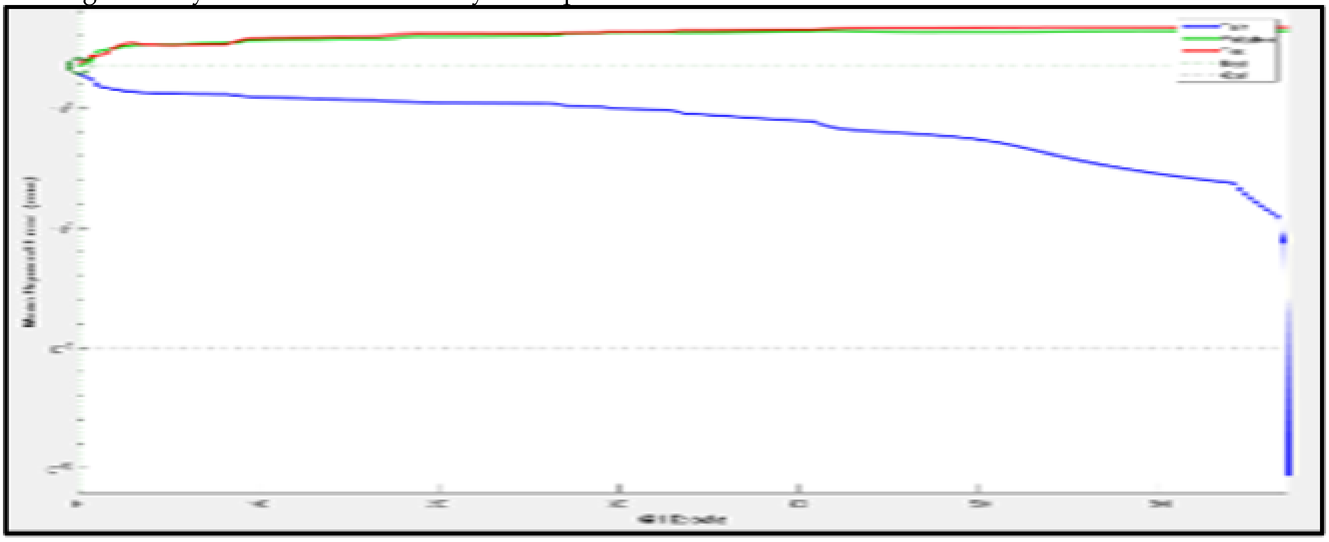


Figure 8: Mean Square Error.

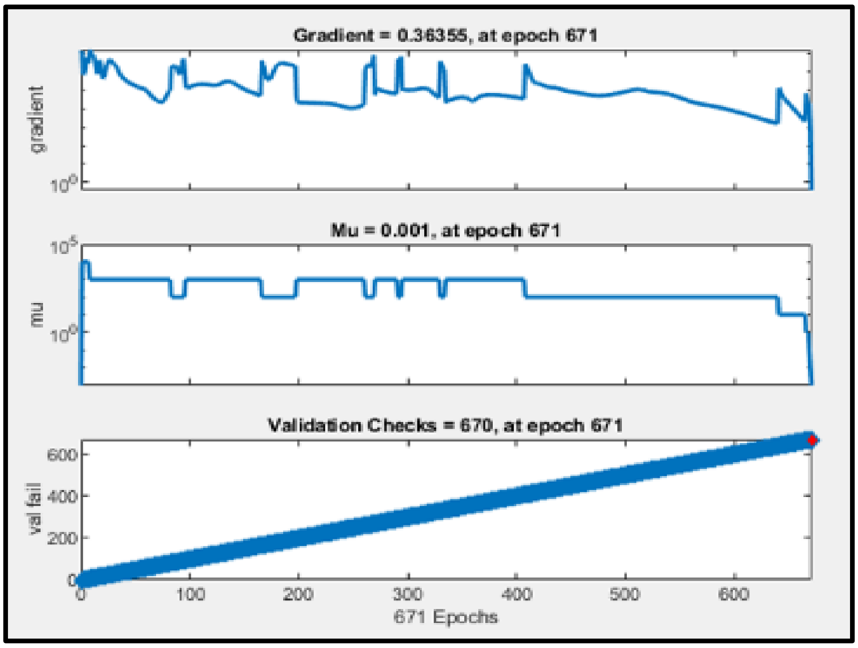


Figure 9: Validation, Gradient, And Mu. Performance

Moreover, Figures 10,11 are representing the highlights of strong correlation between the actual Egyptian current account balance CA_t—which represents the output layer in the neural network model and the estimated optimal Egyptian current account balanceCAF_t. This estimation is achieved by weighting the long-run elasticities in Figures 7a and 7b, with the possible values of the economic variables in the input layer. The correlation coefficient between the actual and estimated Egyptian current account balance was 0.902 across all models. This indicates that the residuals or deviations between the output layer and the target did not exceed 0.098. In the training sample, the correlation coefficient between CA_t and CAF_t reached 0.926, confirming that the residuals or deviations between the output and target layers did not exceed 0.074.

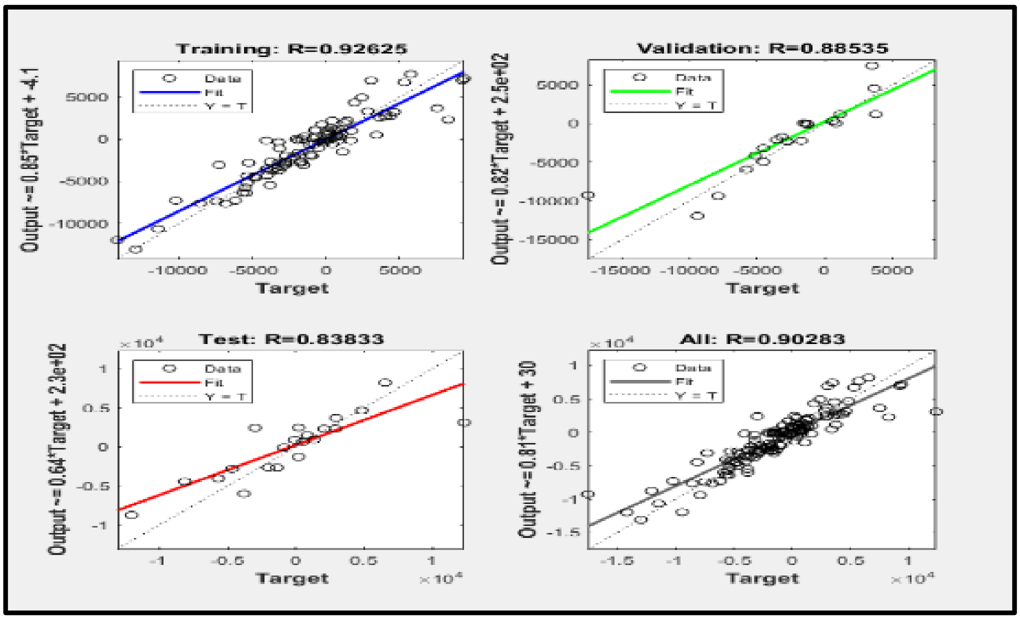


Figure 10: Regression Coefficients Between the Actual and Estimated Output Layer of Deep Learning Model.

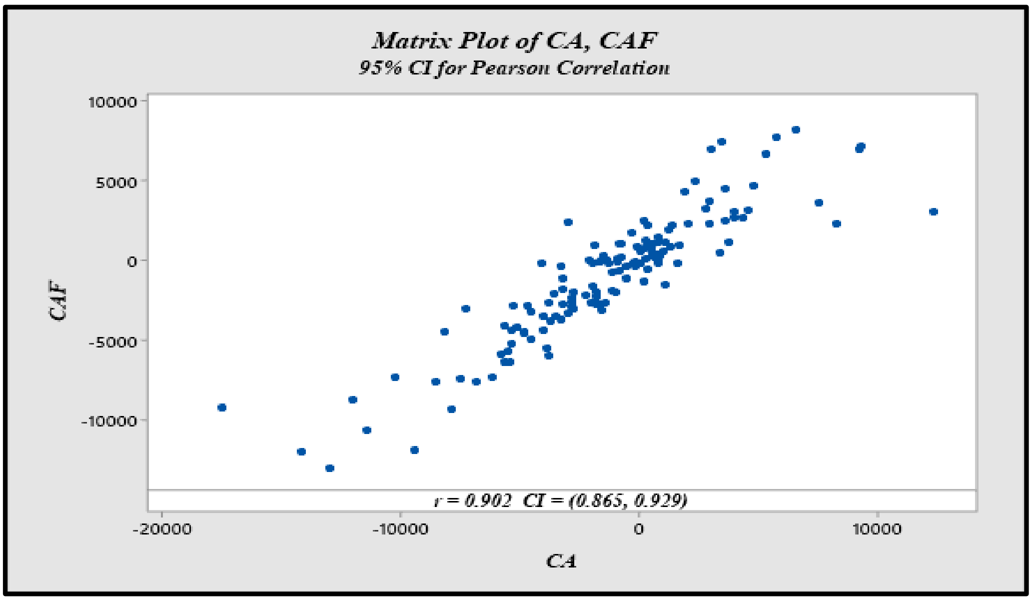


Figure 11: Correlation Between the Actual and Estimated Output Layer of Deep Learning Model.

Although the correlation coefficient in the test dataset is slightly lower than that of the training dataset, the TRAINLM and LEARNGD algorithms demonstrate strong predictive performance, achieving a correlation coefficient of approximately 88.5% in the validation sample. This indicates a high degree of agreement between the predicted and actual outputs and contributes to the overall robustness of the model. The combined regression result R ≈ 90.2% confirms the good overall fit of the deep learning model, reflecting its ability to generalize effectively across training, validation, and test datasets.

After confirming the goodness of fit and the accuracy of the results obtained, it is possible to accept this model and proceed to the next stage, which involves predicting the CAF_t for future periods. Before using our algorithm in the forecasting process, a future value of CAF_t was generated for a later period by comparing these estimates with actual data and recording the deviations. It turns out that there is a small deviation between CA_t and CAF_t which may not exceed 0.01, with both following the same upward trend. The results obtained from this model can be visualized in Figure 12.A and 12.C, which show that the actual and estimated current account balances are very close to each other. This indicates the accuracy of the results achieved by applying our algorithm Figure 12.D, confirms the extent of the match between the actual outputs that were entered into the neural network model that represents CA_t and CAF_t which were predicted by the proposed algorithm, as this trend line between them shows the extent of the complete correlation between the actual and estimated outputs and that all observations fall on the line of complete correlation between them. There are only 5 observations that are far from the trend line.

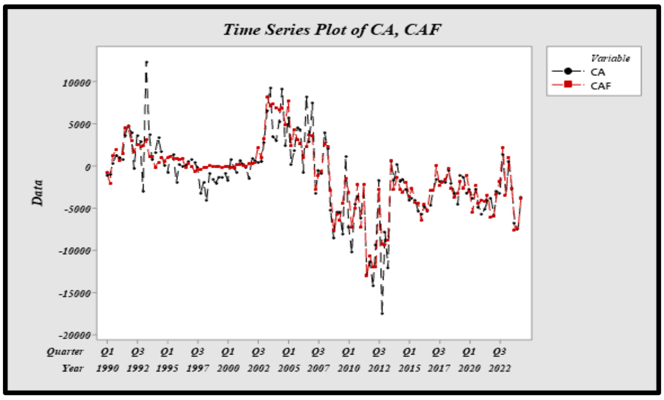


Figure 12(A)

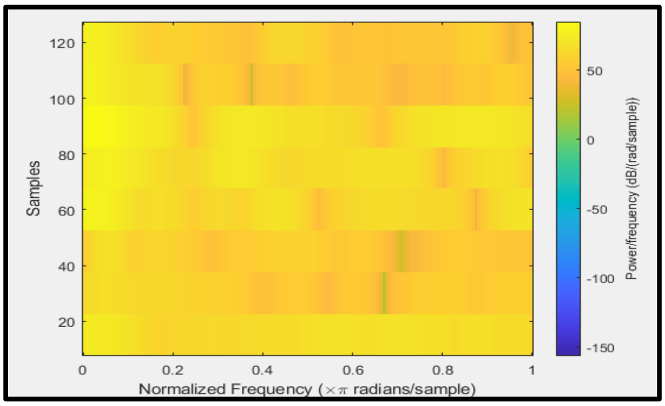


Figure 12(B)

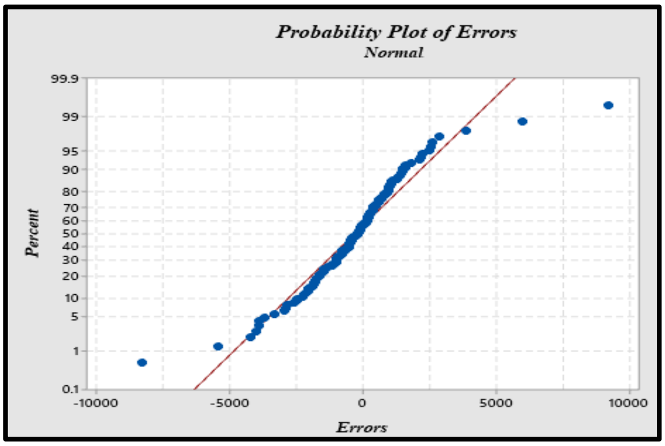


Figure 12(C)

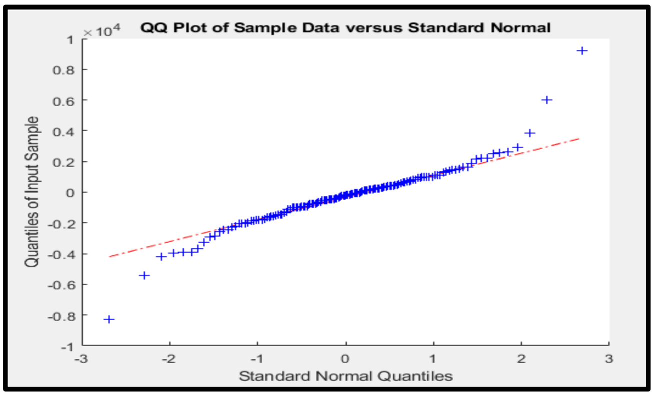


Figure 12(D)

Figure 12. Harmonic Distribution Between CA_t And CAF_t

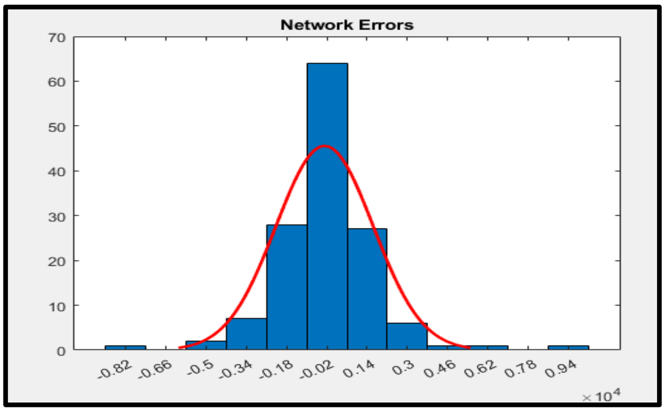


Figure 13(A)

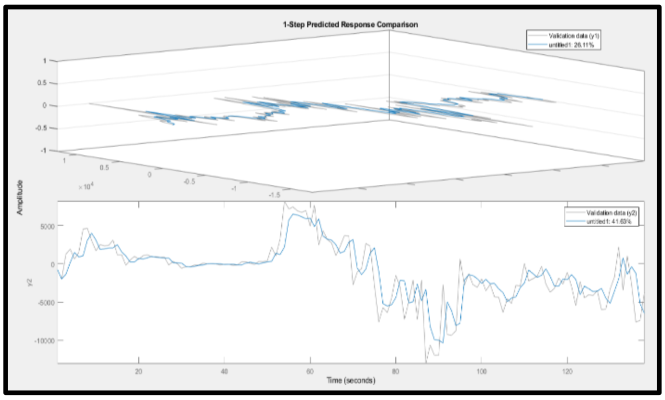


Figure 13(B)

Figure 13: Residuals Distribution.

This match between CA_t and CAF_t was verified in Figure 13, which shows the blending of the blue color, representing the actual outputs, with the yellow color, representing the predicted output layer via the proposed algorithm. The two colors merge completely, making each color indistinguishable on its own, thus demonstrating the extent of the perfect match between the actual and predicted outputs.

In the Diagnostic Checks stage, the goodness of fit and accuracy of estimation results obtained through our DLM approach for diagnosing the path of CAS are judged by identifying the Ljung–Box statistic ($\mathcal{Q}$), which depends in its calculation on the residuals generated from our algorithm.

This statistic is used to test the following hypotheses, and calculated using the following equation:

$$\begin{cases} H_0: all\ \rho_k = 0, & if\ \mathcal{Q} \leq x^2(k) \\ H_1: not\ all\ \rho_k = 0, & if\ \mathcal{Q} \leq x^2(k) \end{cases} \quad (9)$$

$$\mathcal{Q}(P) = \mathcal{T}(\mathcal{T}+2)\sum_{i=1}^{P}\frac{\rho_i^2}{\mathcal{T}-i} \sim x_P^2, \quad i = 1,2,\ldots,P, \quad (10)$$

Where $\mathcal{T}$ is the time series length, and ρ_k is the residuals autocorrelation coefficient from order k. The null hypothesis in this test challenges the assumption that all autocorrelation coefficients of residuals or errors are not significantly different from zero, implying that the error time series follows a purely random or white noise process. If confirmed, this indicates the quality of the model's fit. Conversely, the alternative hypothesis whether at least one of the autocorrelation coefficients of the residuals or estimated errors is significantly different from zero, which would confirm the inaccuracy of the estimation results obtained from this model and necessitate refitting. Examining the calculated Chi–Square values at different lag periods, all values were lower than their critical values, indicating significance at any significance level. This finding is further supported by the P–value at each period, all of which were greater than 0.05, allowing us to accept the null hypothesis that the residuals or estimated errors from our algorithm are not significantly different from zero. This validation is illustrated in Figure 11, which shows how the errors are distributed along the zero line and how minimal the recorded deviations of the residuals are from the zero line. The probability of errors that follow a normal distribution with a 95% confidence level and that they all revolve around the zero value.

At this stage, the study aims to interpret the structural approach to sustainability hypothesis generation in the Egyptian economy, following the successful completion of the first stage by neural network models. The first stage involved identifying the determinants of the Egyptian current account, estimating short-term relative weights, testing the significance of short-term parameters, and estimating long-term parameters. This approach considers these values crucial for determining the optimal current account deficit size to ensure the economy follows a sustainable external path.

This stage also begins after the completion of the second stage, in which the standard relative weights obtained in the previous stage are used to estimate the optimal Egyptian current account deficit balance. Before proceeding to the third stage, the estimated optimal Egyptian current account balance was obtained for the period from the second quarter of 1990 to the second quarter of 2024. These estimates were then compared with actual data, and deviations were recorded.

In this third stage, the actual deficit in the Egyptian current account is compared with its optimal values. If the actual current account deficit exceeds the standard value, it indicates that the deficit is unsustainable, meaning the Egyptian economy cannot achieve external sustainability. Conversely, if the actual deficit is lower than the standard balance, the deficit is considered sustainable, suggesting that the Egyptian economy is on the right path toward external sustainability. The results showed that during the first period (1991–1999), when the Egyptian economy adhered to traditional peg regimes, the current account deficit reached stages of external unsustainability. The most critical period occurred from the last quarter of 1997 to the third quarter of 1998, when the actual Egyptian current account deficit exceeded its optimal counterpart. With monetary authorities introducing some flexibility in exchange rate movements and the Egyptian economy shifting to crawling peg regimes during the second period (2000–2002), progress was made toward external sustainability. However, this period was not entirely free from instances of external unsustainability, particularly in the fourth quarter of 2000 and the third quarter of 2001, when the actual current account deficit exceeded its optimal level by 1,462 million USD and 4.60 million USD, respectively. During the third period (2003–2015), under the actual exchange rate regime and with monetary authorities allowing greater flexibility in the Egyptian pound's exchange rate against foreign currencies, the economy also experienced instances of external unsustainability in certain quarters where the actual current account deficit exceeded its optimal balance. The gradual and orderly transition toward a flexible exchange rate in the fourth period (2015–2024) provided a lifeline for the Egyptian economy to overcome external unsustainability. During this period, instances of external unsustainability in the Egyptian current account occurred in 24% of the total timeframe.

4. DISCUSSION

This study proposes a new hypothesis to test and evaluate sustainability by presenting a novel vision for designing a structural approach. This approach will assess and correct the path of external sustainability in the Egyptian economy through quarterly data from the first quarter of 1990 to the second quarter of 2024. This hypothesis enables the assessment of the path and status of sustainability, both in general and in particular, with respect to external sustainability. The proposed structural approach, designed to evaluate the status of sustainability, relies on three fundamental stages to achieve its goal.

Deep learning is utilized as a tool to study decision-making, with a specific focus on how economists identify sustainable paths. The AHP contributes to the generation of sustainability hypotheses, aiming to maintain well–anchored expectations.

We also provide suggestive evidence of the limitations of current economic measurement approaches. First, economists often rely on overly simplistic models to predict and assess sustainability. These models fail to adequately account for sudden and adverse economic shocks and their impacts on the economy. Second, we demonstrate how policies that focus solely on economic factors while neglecting political and structural factors can lead to significant inefficiencies. Although several studies examine CA sustainability, there is a lack of sustainability analysis at the structural level. We fill this gap by utilizing DLM as a tool for generating sustainability hypotheses.

The combination of AHP and DLM in the first stage facilitated the identification of the relative weight effects in the input layer, including the economic behavioral variables, to generate a sustainability hypothesis. In the second stage, the outputs from the first stage were used to train the deep learning model by sequentially introducing variables based on their explanatory power until the best model fit was achieved. Finally, the third stage utilized the operational results of the previous two stages to determine the optimal current account balance. This was accomplished by continuously training the deep learning models using the initial learning patterns generated in the earlier stages. Our estimation of the errors and residuals resulting from econometric models used to predict the path of CAD and set its target rates provides the opportunity for deep learning models to absorb these errors, as well as successive and opposite shocks, when setting the optimal current account balance, ensuring sustainability is automatically revised through this rate. This approach enables us to precisely characterize inefficiencies and the necessary revision of economic policy tools to accommodate unexpected and emerging random changes in the economic arena.

Our first conclusion confirms the validity of the empirical analysis by accepting the hypothesis consistent with the historical development of the Egyptian current account's behavior and path under various exchange rate regimes. Specifically, the hypothesis states that the Egyptian economy, during the actual adoption of various exchange rate regimes, has witnessed cases of external unsustainability throughout the study period. The results of the proposed structural approach revealed 79 instances of external unsustainability, representing 57.24% of the total study sample. The estimates from this scenario also indicate that the Egyptian economy will continue on a path of external unsustainability in the future. This is due to the prevailing decline in Egyptian economic performance and the limited effectiveness of the economic policies currently applied in the Egyptian economy.

The urgent need for the Egyptian economy to transition albeit gradually and in an unorganized manner toward a floating exchange rate regime necessitated a framework to absorb and neutralize the negative effects of economic shocks, crises, and unexpected political risks on the path to external sustainability. This previous scenario aligns with the results of our structural model, which identified 19 cases of unsustainability during the period of successive internal and external shocks to the Egyptian economy, spanning from first quarter of 2016 to second quarter 2024. These cases occurred at a rate of up to 24% during a period that accounted for 24.63% of the total study sample. This supports the hypothesis of an equal and symmetrical distribution of unsustainability cases over the entire study period.

If only the first reference result of this previous scenario is accepted, this result alone is sufficient to necessitate radical and structural changes in the applied real exchange rate systems, as well as corresponding adjustments to the economic policies implemented in the Egyptian economy.

Finally, our findings suggest that external sustainability depends on the state's ability to finance the current account deficit through available funding sources without requiring drastic changes to the existing economic policies. However, in cases of external unsustainability experienced by the Egyptian economy, particularly when accepting the results of the alternative reference scenario, which highlights the decline in Egypt's economic performance and the limited effectiveness of its applied economic policies, it becomes necessary to adopt and implement a set of sustainable economic policies under the framework of a sustainable exchange rate regime. These regimes aim to achieve the desired convergence between the current deficit in Egypt's current account and the balance required to attain external sustainability in the medium term.

5. CONCLUSION

This study proposes a new structural approach to assess and enhance external sustainability in the Egyptian economy, utilizing the deep learning model (DLM) and the analytic hierarchy process (AHP) to generate sustainability hypotheses. The approach identifies 79 instances of external unsustainability, representing 57.24% of the study period from first quarter of 1990 to second quarter of 2024, and predicts a continued trend of unsustainability due to declining economic performance and ineffective policies. The findings underscore the pressing need for structural reforms in exchange rate regimes and economic policies to mitigate inefficiencies and absorb external shocks, particularly during periods of economic and political instability. The study emphasizes that achieving external sustainability requires financing current account deficits without drastic policy changes. However, in cases of persistent unsustainability, adopting sustainable economic policies and exchange rate frameworks is essential to align Egypt's current account deficit with medium-term external sustainability goals. The results underscore the importance of integrating political and structural factors into economic models to improve policy effectiveness and ensure long—term stability.

6. LIMITATIONS

Modeling a general hypothesis for sustainability testing is a challenging task that requires the use of diverse datasets from machine learning and deep learning, particularly due to the difficulty of determining the optimal current account balance. The structural approach and its design are critical issues for policymakers, necessitating new construction criteria to characterize the complex relationships between the structural variables layer and the output layer. Additionally, the application of multi-criteria decision—making is inherently challenging, and the analysis is highly complex. Training machines using diverse datasets and formats represents an innovative approach in the field of sustainability, enabling the updating of hypotheses used in testing. Finally, we recommend leveraging deep learning models and the Analytic Hierarchy Process to describe complex and intelligent decision-making behaviors for external sustainability. This approach is particularly crucial when researching sustainability testing in general and external sustainability in particular.

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