

Dual-Method PLS-SEM and Artificial Neural Networks (ANN) for Women's Entrepreneurial Empowerment Role in Economic System

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Abstract: In this paper, we developed a model for the women entrepreneurs are advanced by social and infrastructural factors to determine their economic autonomy. The study employed a two-faceted method of analysis through the application of Partial Least Squares Structural Equation Modeling (PLS-SEM) to test hypotheses and Artificial Neural Networks (ANN) to validate the predictions. The mediation analysis proved that social capital intermediates the links between both market linkage and sociocultural interventions and access to finance which reveal that it plays a vital mediating role. Cronbach alpha values of 0.793 – 0.814 and the AVE values of more than 0.70 were used to ensure reliability and validity. In the case of ANN analysis, predictive accuracy, and model generalization were useful in validating the analysis, with R values of 0.842 to 0.862 in training, 0.789 to 0.794 in validation, and 0.831 to 0.840 in testing, and Mean Squared Error values of between 0.43 and 0.70 were used to confirm stabilized learning. The paper concludes that establishing trust-based community networks, market networks, and sociocultural support systems could be very important in augmenting financial autonomy and sustainable empowerment in rural women. It is based on the Social Capital Theory and it examines the role played by sociocultural intervention and market linkage infrastructure in the accessibility of finance by women mediated by social capital. Collectively, these results indicate that although PLS-SEM provides important linear causal associations, ANN supplements the former, because it can represent nonlinear interdependencies and enhance predictive strength.

Keywords: Gender-inclusive development, Social protection, Economic resources, ANN, Rural Entrepreneurship, Access to Finance.

1. Introduction

Empirical evidence that is presented by [1,2] suggests that women entrepreneurs have their working paths influenced by institutional barriers. These obstacles include limited access to capital, embedded social practices, and closed market systems. However, according to [3] the digital revolution and commercialization are providing new opportunities to women entrepreneurs by providing a host of platforms and adaptable models of business organizations. Enterprises owned by women are still experiencing systematic barriers that limit their capability to start and even to continue running. As the local economies have increased, institutions, most of which are rooted within patriarchal systems, continue to limit the opportunities of women and promote lapsed participation. The above barriers still hinder the employment of women into the labor market even with the current policy improvements [4,5] highlighting the need to adopt more accommodative and sustainable policies. The role of non-governmental organizations has been crucial towards enhancing empowerment in the situations which are characterized by scarcity of state resources [6,7,8]. Such efforts are committed to addressing problems that disproportionately impact women, such as poor access to healthcare, education, political representation, and economic resources [8]. To address the severity of these inequalities, governments of countries as well as the global organisations have established programmes aimed at increasing the participation and agency of women. Other programmes also focus on the essential support of women empowerment to reach sustainable development, including the United Nations Sustainable

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Development Goal [9,10,11,12].

A few investigations have combined social structural and computational viewpoints to comprehend the multifaceted character of entrepreneurship empowerment in rural South Asian environments, despite the expanding corpus of literature examining women's empowerment and financial inclusion. The majority of earlier research has either focused on sociocultural or financial accessibility separately, frequently ignoring the mediating function of social capital that links both areas. Although PLS-SEM is most widely used in terms of hypothesis testing and causal validation, few studies have further developed this paradigm by using the artificial neural networks (ANN) to understand nonlinear and non-compensatory relationships between empowerment determinants. As such, there is limited predictive and practical utility of existing models, due to methodological weaknesses which interfere with effective forecasting and practicality. The current study fills this gap by incorporating a mixed-methodology (PLS-SEM and ANN) approach to explain how a combination of social, cultural, and infrastructural factors contributes to the empowerment of women to become entrepreneurs in rural Pakistan, a scenario that is mostly filled with data and lacks empirical evidence. The crossroads between artificial intelligence (AI) and machine learning (ML) is a topical phenomenon in recent years, especially in regard to gender disparity recognition and mitigation of empowerment relationships. It has been empirically shown that predictive systems using AI can reveal undetected latent patterns and relationships as compared to traditional analytical tools, thus improving predictive accuracy and policy urgency. As an example, [13] utilized machine-learning algorithms, such as k -NN, decision tree, random forest, and Naive Bayes, to forecast the effects of micro-credit on empowerment of rural women in Bangladesh, with the decision-tree model obtaining the best model with a predictive score of 83.72%.

In [14] used a composite ensemble, which adopted PCA preprocessing, Support Vector Machine (SVM), a neural network, and AdaBoost, and a time-based model to predict the female participation in Egypt labour market. The AdaBoost part of this ensemble had the highest accuracy, which 100. On this methodological path, [15] compared Artificial Neural Network (ANN) and logistic regression models in the framework of financial inclusion program in India. Their results demonstrated ANN model had a greater accuracy of 82.8 percent, which implies its ability to represent non-linear relationship that empowerment results and financial behavior. [16] also explored women entrepreneurs in Kerala, India, using AI, while acknowledging the limitations of cost, digital literacy, and infrastructure, and confirmed that AI enables innovation, productivity, and marketing capabilities. AI can minimize gender differences in healthcare, education, and the workplace, stressing the need for inclusive and ethical systems to minimize algorithmic discrimination. [17] discussed the complex relationship between the inclusion of women and digital progress by discovering an inverse U-shaped relationship between the spread of AI and female entrepreneurship among EU countries in the general economic environment. The merits of hybrid AI models that integrate Factor Graph Neural Networks (F-GNN) and Adaptive eXtreme Gradient Boosting (AXGB) in advancing financial inclusion and women's economic autonomy were also demonstrated through complementary work by [18] which achieved a remarkable predictive accuracy of 97.2%.

The combination of artificial neural networks and Partial Least Squares structural equation modeling (PLS -SEM) is a methodology orientation in the empirical social research as presented by [19,20]. Digital finance and innovation could drive various industrial organization performances and outcomes [26]. Traditionally, women have challenged significant barriers to achieving equality, including limited access to education, healthcare, financial opportunities, and political contribution [27,28]. Although PLS-SEM is used to analyze the linear relationship between latent constructs, ANN models are used to identify the nonlinear, non-compensatory impacts thus improving the generalizability and prediction power. The hybrid method of the SEM-ANN model has already been used successfully in various fields such as behavioral sciences, health care, and entrepreneurship. The current research incorporates these methodological developments to focus on the role of socio-cultural interventions and market-linkage infrastructure on entrepreneurial empowerment of rural women in Pakistan with social capital having an intermediate role. The combination of explanatory and predictive analytics makes the research fill the gap between theoretical constructs and practical implementation by providing new information that policymakers and development practitioners can use to develop inclusive data-enabled empowerment mechanisms.

Motivation and Structure of the study

This study develops a two-fold analytical model to explore how social and infrastructural factors affect the economic independence of rural Pakistan women entrepreneurs. The research is also driven by the fact that there is a lack of empirical data which can be used to connect the development of social capital with access to finance based on effects of synergy between market-linkage infrastructure and socio-cultural interventions. Previous researches have mainly dealt with the independent variables only, without the interactive and mediating relationships existing between these factors having been developed in a complete way. In addition, traditional analytical approaches have been found to be inadequate in terms of nonlinear dynamics that exist in social systems. Therefore, the proposed study combines the uses of the Partial Least Squares Structural Equation Modeling (PLS-SEM) and the Artificial Neural Networks (ANN) in offering both confirmatory and predictive analyses. The hybrid approach increases the rigor of methods and helps more effectively detect complicated interdependencies which are often ignored by traditional models.

The outline of the manuscript presents the research background, aims and theoretical basis in Section 1: based on the Social Capital Theory. Section 2: outlines the research design, data collection methods and analysis methods, the combination of PLS-SEM and ANN. Section 3: reports the empirical findings based on both the statistical and the computation analysis, whereas Section 4: gives the comparative performance of the model when using Levenberg-Marquardt and Bayesian Regularization algorithms. Section 5: covers the main findings and implications of the findings to the financial empowerment of women and ends with conclusions and recommendations on future research. In conclusion, the article indicates that a combination of PLS-SEM and ANN is able to provide a deeper insight into the empowerment of women entrepreneurs. The results indicate that socio-cultural interventions and market connections are important to improve social capital which determines improved access to finance. The findings confirm the mediating influence of social capital and provide substantive recommendations to policymakers who may need to advance gender-reliant and sustainable entrepreneurship in the rural environment.

2. Materials and Methods

2.1 Research Approach

A quantitative research design has been used in the study as it is chosen because of its ability to be objective, replicable, and to generalize findings of the study. Quantitative designs permit the systematic-based data collection and statistical analysis so that they lower chances of researcher bias and increase the validity of the results. Earlier researchers, such as [21] have emphasized the relevance of quantitative research when conducting social research in large scale especially in testing hypothesized relationships between variables. Similarly, [22] argued that quantitative methods can be used to enhance the accuracy of results in a behavioral and social study design. It is based on these insights that the current study will use a systematic and data-driven approach to explore the determinants of entrepreneurial empowerment among women in rural Pakistan.

2.2 Study Design

It was conducted as a two-method quantitative study that combined the Partial Least Squares Structural Equation Modeling (PLS-SEM) of qualitative study together with the Artificial Neural Networks (ANN). By combining these tools of analysis, it will provide analytical validity and forecasting. The conceptualized model was tested with the help of PLS-SEM in the first phase to determine reliability and validity of measurement constructs and direct and mediating effects between the variables. SmartPLS version 4 was used to perform analysis.

At the second stage, ANN analysis was conducted to confirm and optimize the predictive results of the PLSSEM results. The ANN model was trained using the same data set, thus making it possible to explore nonlinear and non-compensatory interactions, which is impossible when using the traditional linear modeling methods. The hybrid approach PLS-SEM can be viewed as a confirmative instrument, and ANN can provide a predictive aspect of a dataset that is data-driven and adds more insight into the relationship between variables. The two-fold design has provided rigour of theory and robustness of computation to capture the multidimensionality of women entrepreneurial empowerment in rural Pakistan.

2.3 Data Collection Procedure

Data pertaining to this were gathered through a standardized questionnaire, which was given to the female entrepreneurs who had businesses in the rural areas of Punjab and Sindh in Pakistan. The convenience sampling method was used to make the method practical and collect data in time. Out of the 400 questionnaires sent, 386 of them were complete and usable giving a high response rate as far as the use of the questionnaire in structural modeling is concerned.

The tool used a five-point Likert scale of 1 = Strongly Disagree to 5 = Strongly Agree. It was constructed in a way that it captured perceptions in four main constructs including Market Linkages Infrastructure (MLI), Socio-Cultural Interventions (SCI), Social Capital (SC) and Access to Finance (AF). The validated items of the previous studies operationalised each construct, which were later adjusted to the local environment. The obtained data was an empirical foundation regarding the study of the interdependence of these variables and their combined impact on female entrepreneur empowerment.

2.4 Formulation of Data Analysis and Hypothesis Development for proposed model

We have the following hypothesis for analysis the data

H1: Market Linkages Infrastructure (MLI) has a positive and significant impact on Social Capital (SC).

H2: Socio-Cultural Interventions (SCI) have a significant and positive effect on Social Capital (SC).

H3: There is a significant and positive relationship between Social Capital (SC) and Access to Finance (AF).

H4: Market Linkages Infrastructure (MLI) has an indirect positive effect on Access to Finance (AF) through Social Capital

(SC).

H5: Socio-Cultural Interventions (*SCI*) have an indirect positive effect on Access to Finance (*AF*) through Social Capital (*SC*).

3. Material and Method

3.1 Market Linkages Infrastructure

The figure 1 illustrates the relationship between indicators of (*MLI2* & *MLI3*). Both indicators show a positive linear trend, suggesting that as one aspect of market linkage improves, the others also strengthen. This indicates that better infrastructure and connectivity are closely associated with enhanced market access and support for rural participants.

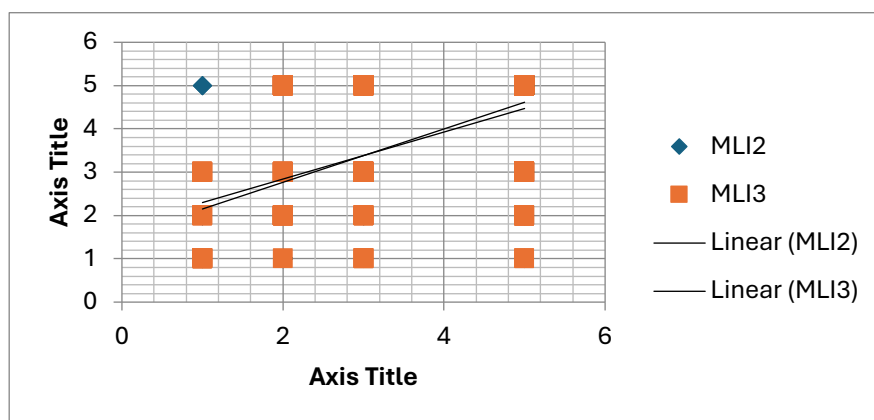


Fig. 1: Relationship between indicators

3.2 Socio-cultural Interventions

The figure 2 shows a moderate positive relationship between the variables as indicated by the trend line equation $y = 0.5439x + 1.9782$ and an R^2 value of 0.3299. This suggests that as socio-cultural factors improve, there is a corresponding increase in the associated outcome variable. However, the relatively low R^2 value indicates that other factors may also influence the results beyond socio-cultural interventions.

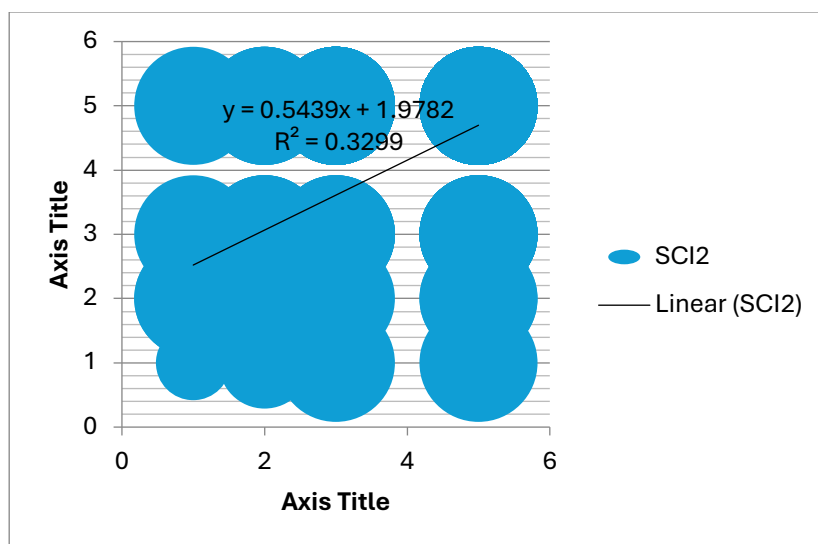


Fig. 2: Moderate positive relationship between the variables

3.3 Social Capital

The *SC* figure 3 compares two groups showing variations in the distribution of social connections and community

engagement. The left circle represents higher proportions of active participation, while the right indicates comparatively lower involvement. Overall, the figure highlights differences in social capital strength between the two groups, suggesting unequal access to social networks and support.

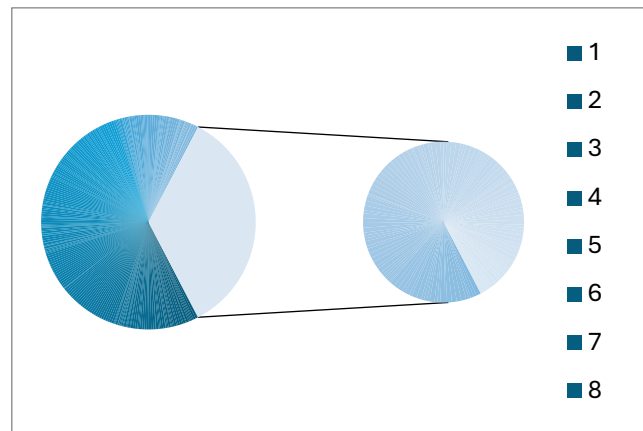


Fig. 3: Two groups variations

3.4 Access to Finance

The figure 4 below illustrates variations in access to finance across the three ($AF1, AF2, AF3$) show relatively higher fluctuations, indicating inconsistent access levels compared to ($AF1, AF2$). Overall, the results reveal uneven financial inclusion, suggesting disparities in how individuals or groups access financial resources.

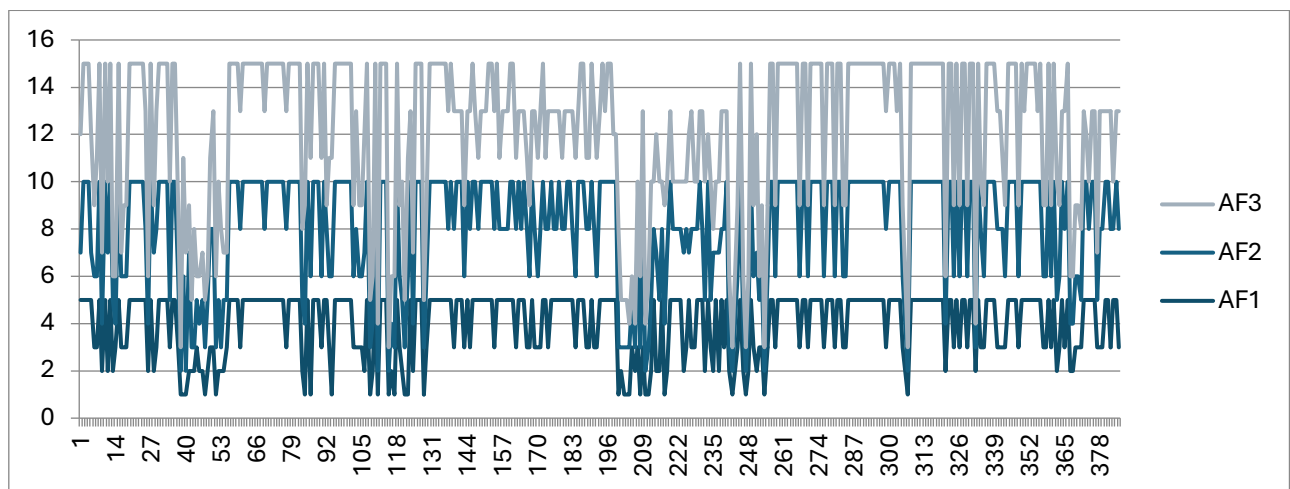


Fig. 4: Variations in access to finance

3.5 Construct Reliability

Internal consistency was assessed through the use of Cronbach alpha as well as composite reliability. All constructs had alpha coefficients that were above the acceptable value (0.70), which ranged between 0.793 (SC) and 0.814 (MLI) and thus, resulted in high internal reliability. Composite reliability indices (ρ_a and ρ_c) also were higher than 0.70 across all the constructs, which verified measurement consistency. Convergent validity was evaluated in terms of the Average Variance Extracted (AVE); all the c-values were more than 0.70 which implies that each construct explains a significant percentage of the variance in the indicators. These results in table 1 support the discriminant validity of each of the constructs reinforcing the uniqueness of the different aspects of women empowerment.

Table 1: Construct Reliability and Validity

Construct	Cronbach's Alpha	ρ_a	ρ_c	AVE
AF	0.803	0.804	0.884	0.817
MLI	0.814	0.816	0.890	0.729
SC	0.793	0.797	0.879	0.708

<i>SCI</i>	0.795	0.800	0.879	0.709
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3.6 Discriminant Validity (HTMT)

Discriminant validity was assessed through the HTMT criterion. Referring to the table 2, all constructs recorded values lower than 0.09; thus, they are distinct empirically. The highest value was between access to finance and socio-cultural interventions, showing a strong yet acceptable relationship.

Table 2: Heterotrait-Monotrait Ratio (*HTMT*)

<i>Construct</i>	<i>AF</i>	<i>MLI</i>	<i>SC</i>	<i>SCI</i>
<i>AF</i>				
<i>MLI</i>	0.760			
<i>SC</i>	0.741	0.706		
<i>SCI</i>	0.820	0.792	0.725	

3.7 Collinearity Statistics (VIF)

Possible collinearity between the indicators was evaluated by the Variance Inflation Factor (VIF) values. All the tested variables showed VIF values significantly lower than the critical threshold for the indicators. The threshold is 5, varying from 1.584 to 2.046, thus confirming that multicollinearity is not a problem in the measurement model. The highest *VIF* values were observed for *AF2* (2.046) and *SCI* (2.046), indicating slightly strong shared variance within their respective construct yet remaining within acceptable limits. The table 3 shows Lower VIF values, such as *AF3* (1.584) and *SCI3* (1.584), suggest minimal redundancy among indicators. Overall, these results confirm that the outer model is free from collinearity issues, supporting the robustness and stability of subsequent structural analysis.

Table 3: Outer Model Collinearity (VIF values)

<i>Construct</i>	<i>Indicator</i>	<i>VIF</i>
<i>AF</i>	<i>AF1</i>	1.779
	<i>AF2</i>	2.046
	<i>AF3</i>	1.584
<i>MLI</i>	<i>MLI1</i>	1.689
	<i>MLI2</i>	1.930
	<i>MLI3</i>	1.810
<i>SC</i>	<i>SC1</i>	1.598
	<i>SC2</i>	2.011
	<i>SC3</i>	1.654
<i>SCI</i>	<i>SCI1</i>	1.779
	<i>SCI2</i>	2.046
	<i>SCI3</i>	1.584

3.8 Direct Path Coefficients

The structural model results in the table 6 indicate that all hypotheses' direct relationship is positive and statistically significant. Market Linkages Infrastructure (*MLI*) has a significant effect on Social Capital (*SC*) ($\beta = 0.068, t = 4.950, \rho < 0.001$), suggesting that improving market access enhances women's social networks and connections. Similarly, Socio-Cultural Interventions (*SCI*) show a significant positive relationship with (*SC*) ($\beta = 0.068, t = 5.300, \rho < 0.001$), indicating that supportive cultural initiatives strengthen social cohesion in table 4. Finally, (*SC*) significantly influences Access to Finance (*AF*) ($\beta = 0.044, t = 13.305, \rho < 0.001$), confirming that strong social networks facilitate better financial access for women entrepreneurs. Overall, the direct paths are supported, validating the proposed relationships in the model.

Table 4: Direct Path Coefficients

<i>Path</i>	β	<i>t - value</i>	<i>P - value</i>	<i>Result</i>
<i>MLI</i> → <i>SC</i>	0.068	4.950	0.001	<i>Supported</i>
<i>SC</i> → <i>AF</i>	0.044	13.305	0.001	<i>Supported</i>
<i>SCI</i> → <i>SC</i>	0.068	5.300	0.001	<i>Supported</i>

3.9 Indirect (Mediated) Effects

It was also established in the analysis that there exist important indirect effects. The Access to Finance (*AF*)- Market Linkages

Infrastructure (MLI) result was determined to have a negative impact upon social capital (SC) ($0.044, t=4.519, p=0.001$) meaning that better access to the market may lead to greater financial inclusion indirectly because of stronger social networks with women. Likewise, Socio cultural Interventions (SCI) showed an important indirect influence on AF via SC ($\beta=0.048, t=4.509, p=0.001$), which indicates that conceivable cultural setups enhance financial access by creating a firmer bond to the community. These results in the table 5 highlight the mediating effect of social capital in the relation of market and socio-cultural factors to financial empowerment.

Table 5: Indirect (Mediated) Effects

<i>Path</i>	β	<i>t – value</i>	<i>p – value</i>	<i>Mediation Type</i>
<i>MLI → AF</i>	0.044	4.519	0.001	<i>Supported</i>
<i>SCI → AF</i>	0.048	4.509	0.001	<i>Supported</i>

The structural model shows the relationship among (*MLI, SCI, SC*) and (*AF*). Both (*MLI*) ($\beta = 0.338$) & (*SCI*) ($\beta = 0.362$) have a positive effect on (*SC*), indicating that improved infrastructure and supportive social interventions strengthen social capital. In turn, (*SC*) strongly influences (*AF*) ($\beta = 0.592$), showing that stronger community networks and trust enhance access to financial resources. The values ($SC = 0.401, AF = 0.350$) suggest that the model explains a substantial portion of the variance, confirming the interconnected role of social and infrastructural factors in improving financial access.

4. Levenberg Marquardt Neural Network (LBMNN) Approaches

This is a mathematical concept which is used in all the learning models to study and improve functions.

$$\nabla \delta(z_1, z_2, \dots, z_n) = \begin{bmatrix} \frac{\partial \delta}{\partial z_1}(z_1, z_2, \dots, z_n) \\ \frac{\partial \delta}{\partial z_2}(z_1, z_2, \dots, z_n) \\ \vdots \\ \frac{\partial \delta}{\partial z_n}(z_1, z_2, \dots, z_n) \end{bmatrix}$$

Definition 1: (Performance): Performance in the context of a neural network that is artificial refers to the effectiveness and dependability of its objectives. Measures of assessment comprise accuracy, mean squared error (MSE), loss/error, and precision, and the recall. In order to improve performance, it might be necessary to alter the network architecture, hyper parameters, and training processes.

Definition 2: (Mu (μ)): The parameter denoted by the symbol " μ " is the learning rate or step size in training a neural-network. It controls the size of changes made to biases and weights in training. Values used as initial or default values 1×10^{-8} or 1×10^{-9} are not necessarily the most optimal. Depending on the data scale and the model parameters and complexity of the task, the required value of " μ " is different.

Definition 3: (Epoch): In artificial intelligence, an “epoch” is a full training operation through the dataset. It involves data transmission into the network, calculating the errors, and revision of the model parameters. Several epochs are run in order to enhance model accuracy and convergence.

Definition 4: (Training): Training entails the neural network training on a labelled data so as to tune its parameters. Its main goal is to maximize the performance of the network through the minimization of a prespecified loss. The training is continued until convergence is achieved and the number of iterations is predefined.

Definition 5: (Validation): Validation plays an important role in determining the capacity of a model to generalize. The network performance is evaluated on a separate set known as the validation set. The model analyses the validation data and then makes predictions that are compared with the actual target values. The “Num parameter” is not a specific definition in neural networks, and it simply describes the number of network parameters, which include biases and weights. The size of these parameters affects the complexity and the computational efficiency of the model.

Definition 6: Mean Square Error (MSE) [23]: MSE is a statistical index that calculates the mean squared error between the estimated outputs $\hat{x}_i$ and desired outputs x_i . It measures the general validity of network predictions:

$MSE = \frac{1}{n} \sum_{i=1}^n (Y_i - \hat{Y}_i)^2$ where n represents the data points of the set.

Definition 7: R – Squared [24]: R^2 is a statistical measurement that is used in a regression equation to estimate what percentage of the variance in the dependent variable can be attributed to the independent variable. It can be computed as.

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

And where n is the number of observations Y_i , $\bar{Y}$ is the actual value of the dependent variable at the i th observation, $\hat{Y}_i$ is the predicted value under the regression model, and $\bar{Y}$ is the average of the observed values. A horizontal line in a plot means that there is no change in the forecast or system efficiency so the horizontal line that fits best needs to be the one that is closest to the lowest MSE, which means the most accurate results throughout the data. The best vertical line has been determined by the MSE values that are the lowest in all models implying greater accuracy and minimized forecasting errors. The research process started with the creation of a conceptual framework, which was then followed by data gathering, preparation, and coding shown in table 6.

Table 6: Levenberg Marquardt Neural Network

The pseudo-code of the developed ANN
Levenberg Marquardt Neural Network
Step 1: This is done by preparing the input of the neural-network technique in model (1) using the ABMT. Step 2: The given data set should be in a form of a matrix or a vectors. Step 3: partition the data by using hidden neurons: (a) Hidden neurons – 10 (b) Testing data – 15 % (c) Validation data – 15 % (d) Training data – 70 % Step 4: Add both the input data and different weights and biases. Step 5: As a culmination of the process, the following are required: (a) The limit to repeating it has been reached. (b) The maximum (μ) has been achieved. (c) The error must be small. (d) The gradient calculated is sufficiently small. Once these anticipated results are reached then the process was complete, otherwise continue. Step 6: Retrain the system or change the settings of the parameters keeping the results the same thus completing the LMBNN process. Step 7: Conserve the plots created. End of LMBNN and Comparisons with Bayesian Regularization had the performance

Finally, results were interpreted to draw meaningful conclusions, providing insights into the impact of market linkages infrastructure, socio-cultural interventions, social capital, and access to finance on women's empowerment in Figure 5.

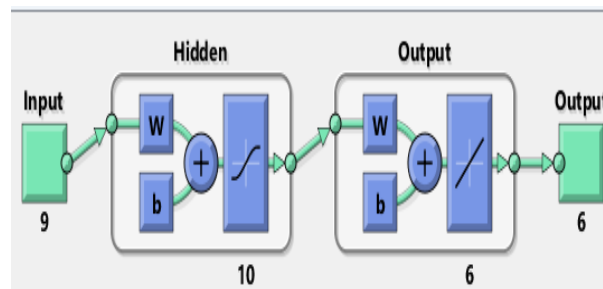


Fig. 5: Neural network of the proposed model

To validate the PLS-SEM findings and capture potential complex, non-linear relationships between the constructs, an Artificial Neural Network (ANN) analysis was performed. We developed a computational framework that incorporates a stochastic procedure using Artificial Neural Networks with Levenberg-Marquardt backpropagation (ANNLMB). A multilayer perceptron (MLP) network was designed with the following architecture: **Input layer**, the neurons corresponding to the latent variable scores of the three predictors: Market Linkages Infrastructure (MLI), Socio-Cultural Interventions (SCI),

and Social Capital (SC). The layer that is hidden. They used a single concealed layer. A trial-and-error procedure aimed at reducing the prediction error on the validation set led to the ideal configuration, which involved setting the number of neurons in this layer at 10. The output layer. The aim variable, Access to Finance (AF), is represented by a single neuron. A minimum-maximum scaler was used to normalize the dataset to a $[0, 1]$ range in order to guarantee reliable and effective network training. Three subsets of the data were then randomly selected: 70% for model training, 15% for validation (to avoid overfitting and stop training at the generalization point), and the remaining 15% for testing to give an objective assessment of the predictive performance of the finished model.

Because of its quick convergence characteristics, the Levenberg-Marquardt (trainlm) algorithm was used to train the network. Mean Squared Error (MSE), which tracks the training error history over epochs, was used to assess the network's performance. In order to verify the validity of our results, we provide numerical calculations in four different versions (Case 1-4) of the ANNLMB framework, which enables a thorough examination of the stability and functionality of the model. R-values for regression are the main criteria for checking the relationship of a network's predictions with the real targets, besides error histogram distributions and the mean square error (MSE) for training, validation, and testing sets results shown in table 6, 7 and 8 of the model. The simulation results of are shown in figure 6 (performance measure), figure 7 (validation check), figure 8 (error histogram) and figure 9 (regression analysis) for different cases of proposed model.

This diagram shows a feedforward neural network with 9 input neurons, one hidden layer of 10 neurons, and an output layer of 6 neurons. Each layer applies weighted connections, biases, and activation functions to process data.

Table 7: (ANN) Approach for performance and gradient measure

Model	Case 1	Case 2	Case 3	Case 4
Epuroach	0.21	0.21	10	12
Time	0.001	0: 00: 00	0: 00: 0	0: 00: 00
Performance	0.914	0.697	0.430	0.393
Gradient	0.0153	0.211	0.0583	0.601
Mu	0.001	0.000100	0.00100	0.000100
Validation Check	6	6	6	6

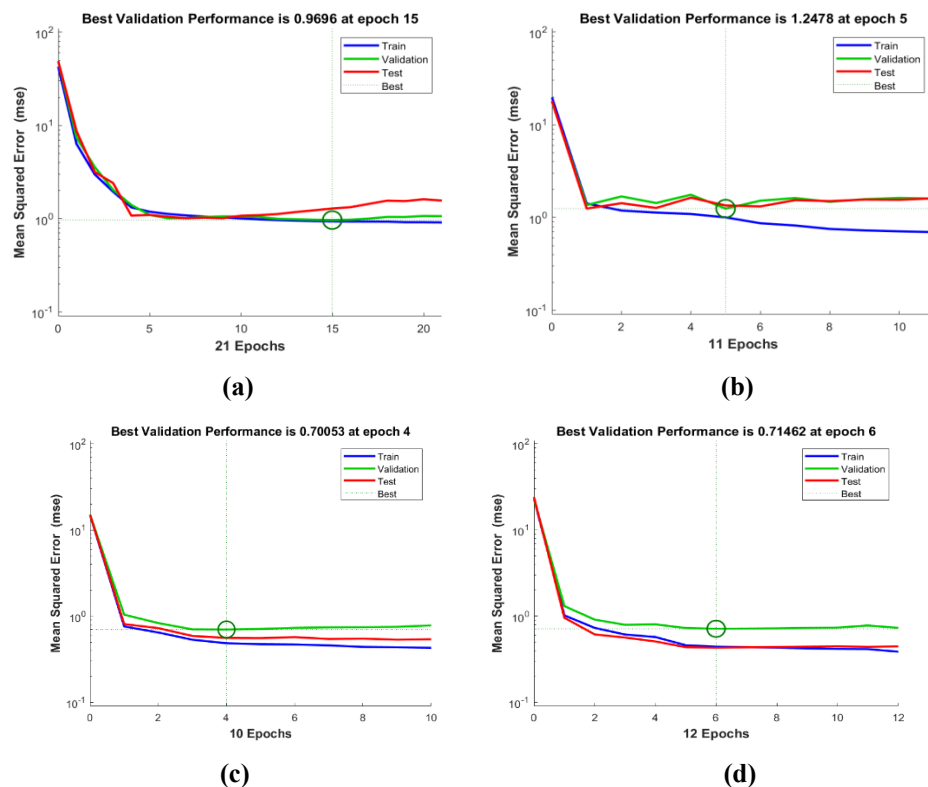


Fig. 6: Best value performance for (a) Case I, (b) Case II, (c) Case III, (d) Case IV

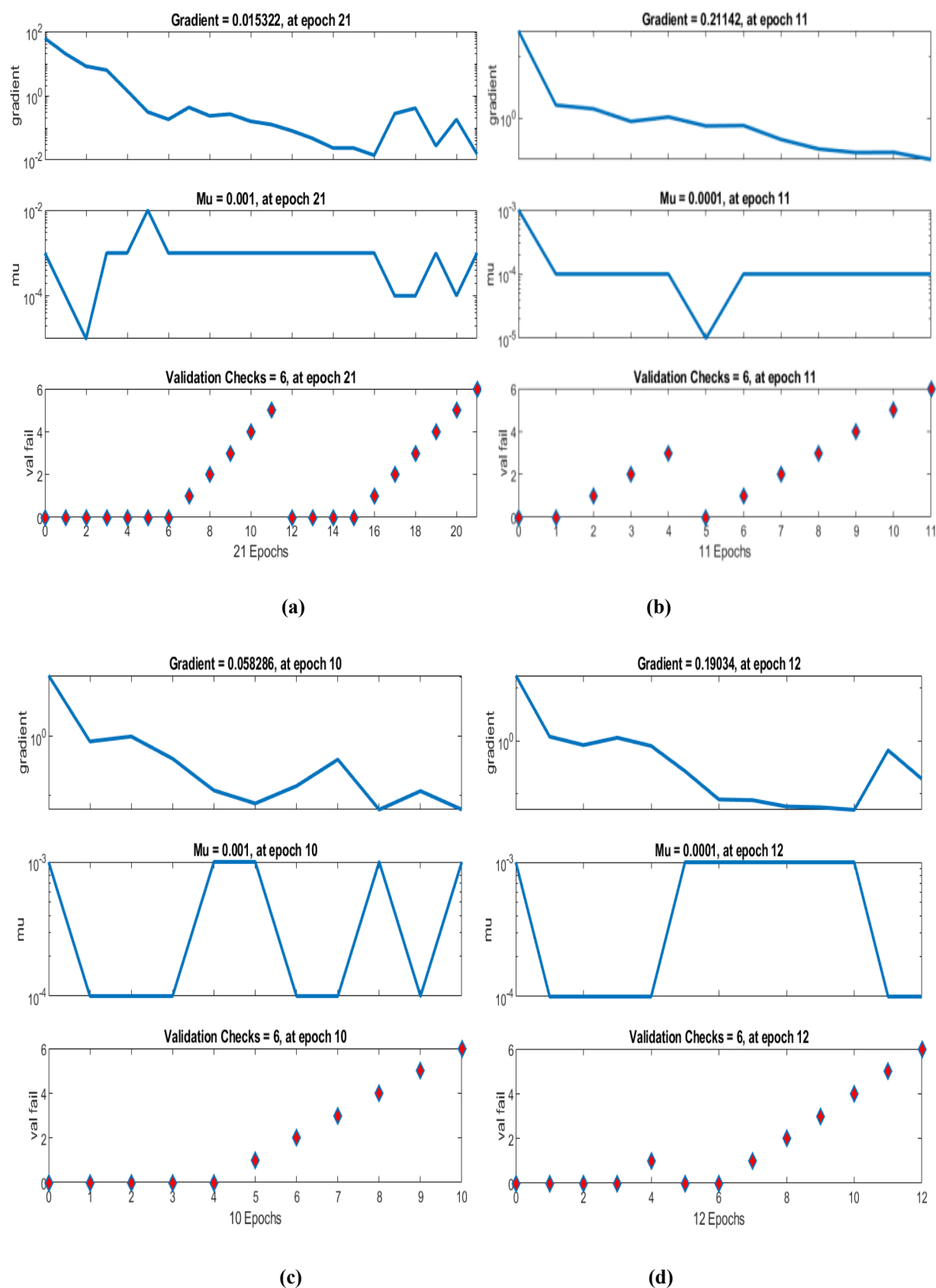
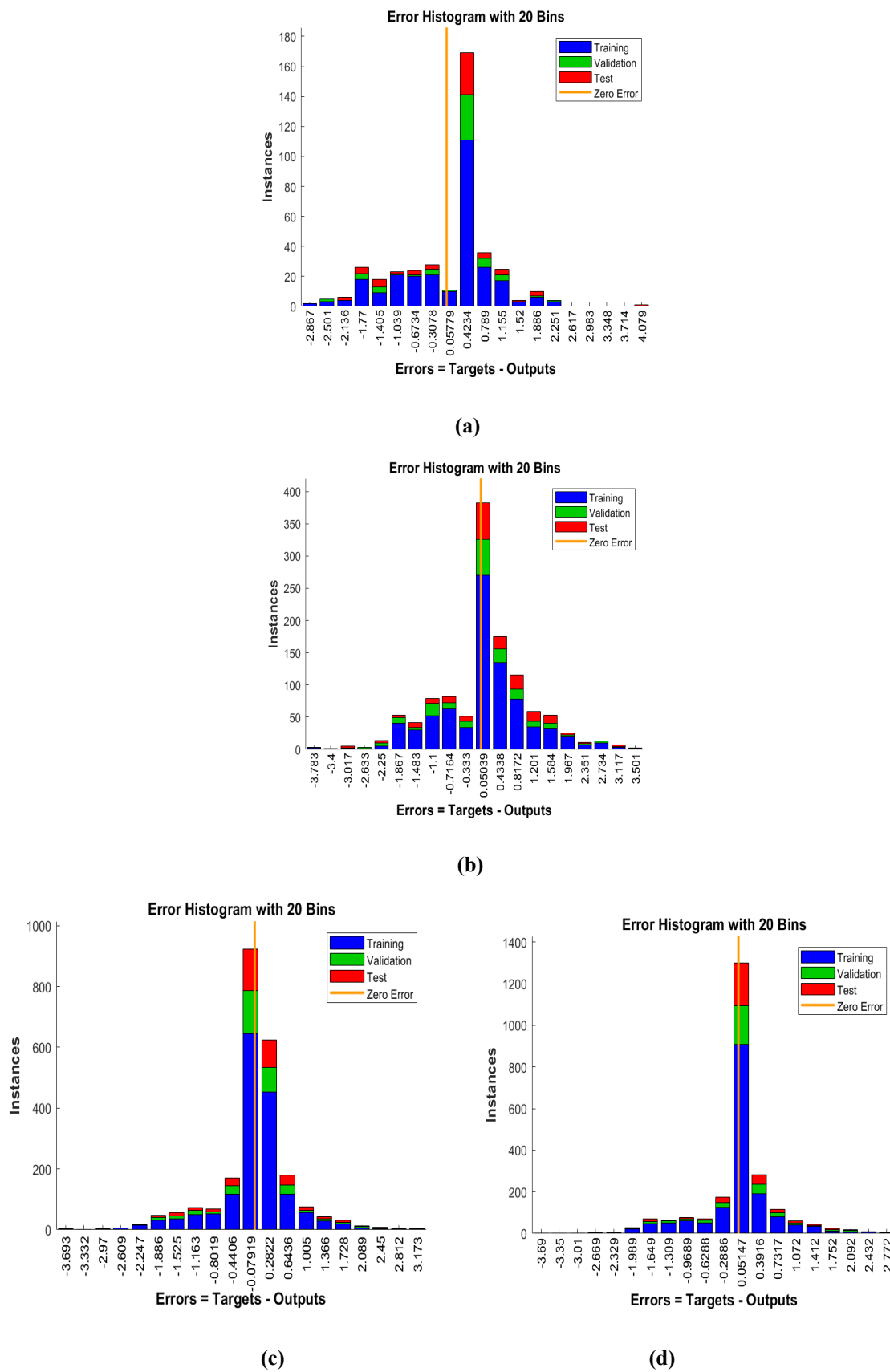


Fig. 7: Validation checks for (a) Case I, (b) Case II, (c) Case III, (d) Case IV

**Fig. 8:** Error histograms with 20 bins for (a) Case I, (b) Case II, (c) Case III, (d) Case IV

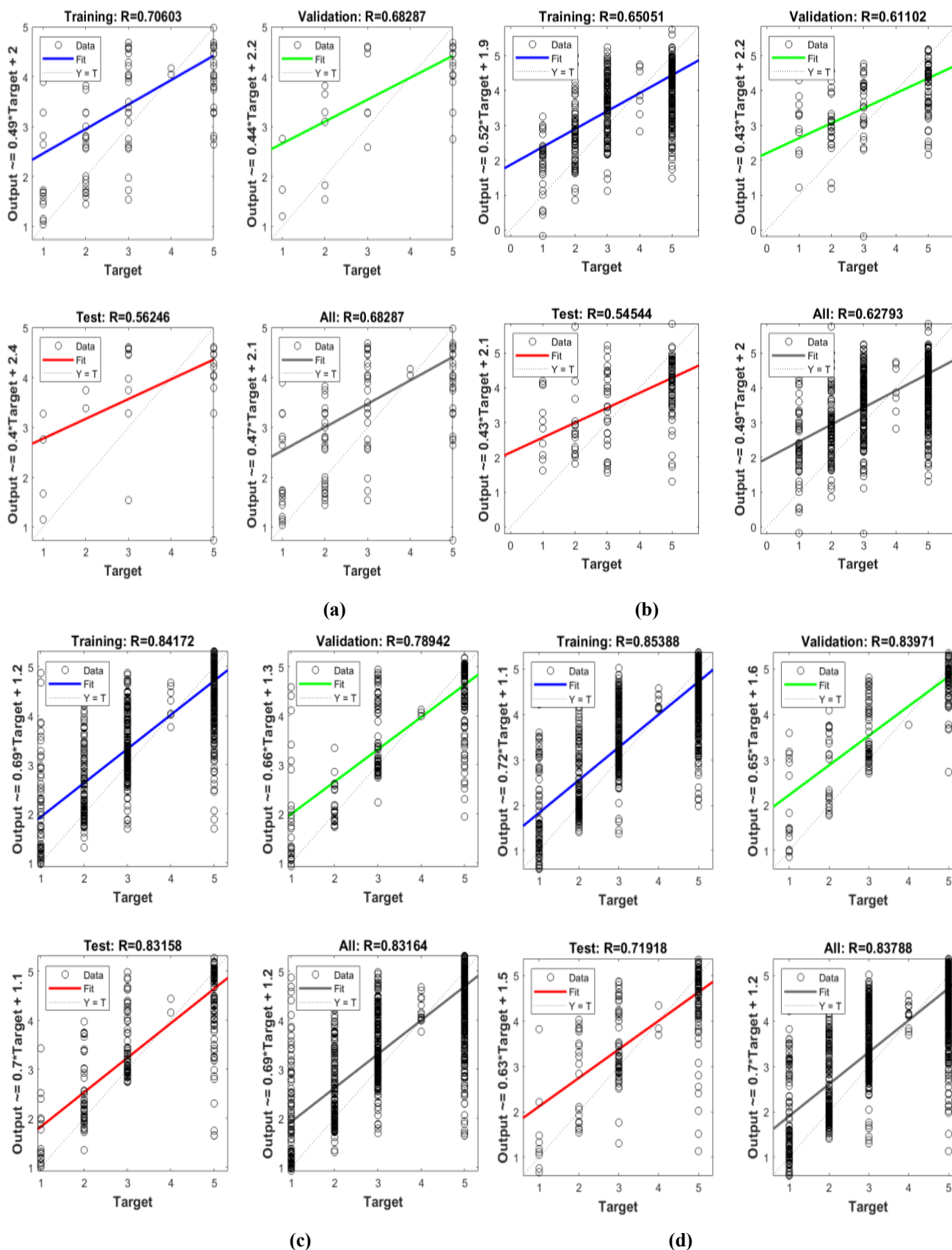


Fig. 9: Testing of Regression analysis for (a) Case I, (b) Case II, (c) Case III, (d) Case IV

Table 8: MSE and Regression analysis of the proposed model

<i>Cases</i>	<i>Samples</i>	<i>MSE</i>	<i>R</i>
Training Sample	274	$4.85127e - 1$	$8.41724e - 1$
Validation	59	$7.00525e - 1$	$7.89415e - 1$
Testing	59	$5.59455e - 1$	$8.31575e - 1$
Training Sample	274	$4.43554e - 1$	$8.61873e - 1$
Validation	59	$7.14620e - 1$	$7.94316e - 1$
Testing	59	$4.30018e - 1$	$8.40241e - 1$

4.1 Model Performance Comparison of Levenberg-Marquardt (trainlm)

The comparison of the Bayesian Regularization and Levenberg Marquardt algorithm shows that there are apparent discrepancies in the performance and computational efficiency. The Bayesian Regularization had the performance of 0.312 with a gradient of 0.00641, Mu 5.00×10 to the 10 and took 7s to do 830 iterations which had a consistent convergence but no validation checks. On the other however, Levenberg-Marquardt algorithm achieved a performance of 0.914 and a gradient of 0.0153, Mu of 0.00100, and needed fewer than 1s to make 21 iterations, and six validation checks, meaning that it is more computationally fast and more stable in validation. In general, Bayesian Regularization was a more precise and smooth learning process, but Levenberg Marquardt obtained the results faster with a greater level of validation reliability shown in figure 10 and 11.

**Fig. 10:** Comparison with Levenberg Marquardt algorithm and Bayesian Regularization had the performance

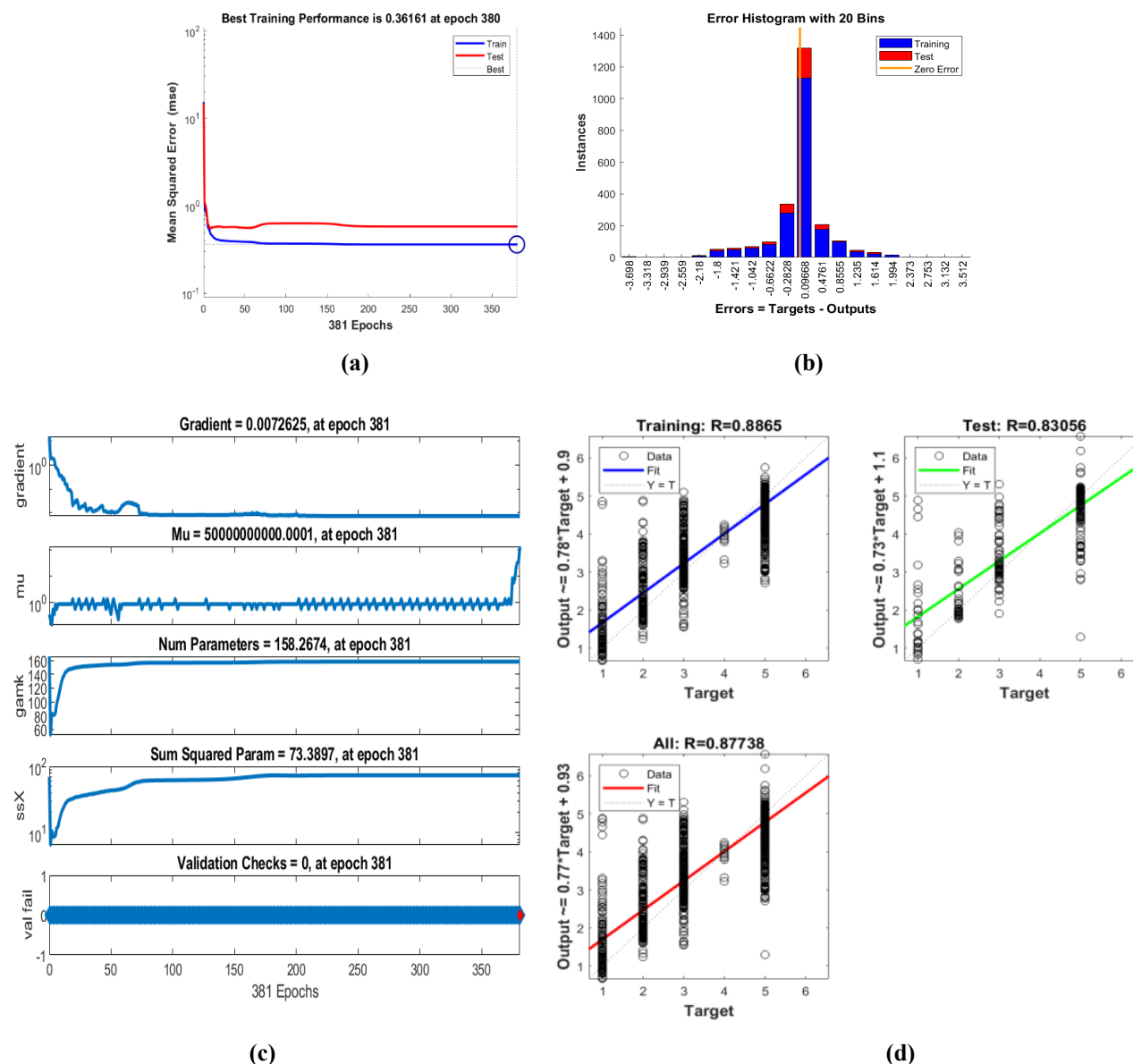


Fig. 11: Model Performance with Bayesian Regularization

5. Validity of the Results and Discussion

Both PLS-SEM and ANN analyses validated the results by means of rigorous statistical evaluation. In the case of the PLS-SEM step, the measurement model exhibited high internal consistency with Cronbach 0.793 -0.814 and composite reliability of over 0.70, which meets the requirements of other reliability standards [22]. The convergent and discriminative validities were obtained and confirmed by the values of the Average Variance Extracted (AVE) more than 0.70 and HTMT ratios lower than 0.90, respectively, and the specificity of every construct. Also, the Variance Inflation Factor (VIF) ranged between 1.584 and 2.046, which showed that there was no multicollinearity which proves the model of measurement was stable and robust. The structural model had a high explanatory variable, as indicated by significant path coefficients (all $p < 0.05$) showed that the variable Market Linkages Infrastructure (MLI), Socio- Cultural Interventions (SCI), and Social Capital (SC) combinedly explained a significant percentage of the variance of the Access to Finance (AF). These results justify the theoretical validity and the empirical power of the suggested relationships.

In the case of ANN analysis, predictive accuracy and model generalization were taken as the indicators of validity. In four network cases, the R values of training were 0.842 to 0.862, validation 0.789 to 0.794, and testing 0.831 to 0.840 which are relatively high values of correlation between the predictive and actual results. The values of the corresponding Mean Squared error (MSE) of 0.43-0.70 supported low prediction error and stable behavior during learning. The close relationship between

training and validation errors prove a low level of over-fitting and high level of generalization. These pointers, combined, would confirm that the PLS-SEM and ANN analyses have produced statistically viable, internally reliable, and predictive outcomes that prove the stability of the entire analytical framework of the two-method analysis.

The findings obtained with the use of PLS-SEM and ANN have shown the effectiveness and predictive ability of the hybrid model in explaining the entrepreneurial empowerment of women. The PLS-SEM results confirmed all the hypothesized direct and mediate relationships showing that both Market Linkages Infrastructure (MLI) and Socio-Cultural Interventions (SC) can have a significant and positive impact on Social Capital (SC) that subsequently has a strong impact on Access to Finance (AF). These findings confirm the fact that the improvement of infrastructure and cultural settings both contribute to the social capital formation and financial inclusion, as the Social Capital Theory proposes [25,21].

These findings were extended by the ANN findings that determined nonlinear, non-compensatory relationships between the constructs. Strong predictive reliability and effectiveness the large R-values (0.79-0.86) and small MSE-values (0.43-0.70) are indications of a strong predictive reliability and effectiveness of the model even using multiple partitions of the data. The training, validation and test stability values show that the ANN model was very effective in capturing nonlinear complex interactions that would otherwise be missed by the traditional linear modelling. Further, the ANN sensitivity analysis showed that the most important predictors were the Socio-Cultural Interventions, which has the strongest normalised importance of predictors, thus indicating the critical influence of cultural and attitudinal transformation under producing better financial access and empowerment outcomes in women.

The study's conclusions demonstrate the crucial mediating function of social capital in bridging market connections and sociocultural interventions to rural women's empowerment and access to finance. According to the PLS-SEM results, social capital reinforces the proposed mediation pathways by considerably transmitting the impacts of cultural and support for infrastructure towards financial inclusion. As [19,20] argue, the study is situated in an analytical innovation that contains a promising trend of hybrid AI research with the merits of computational precision of ANN and theoretical validity of SEM in the explanation of complex social processes. Besides, AI is turning out to be a significant reason behind the world evolving female empowerment as evidenced by several researches. [18] imply that hybrid AI models can provide accurate predictions of the results of financial inclusion, which will help policymakers to develop specific interventions. Similarly, [16] discovered that female entrepreneurs who face financial and literacy issues and embrace the use of AI-driven innovation enjoy higher productivity and market penetration.

The overall results of the ANN and the PLS-SEM analyses suggest that the empowerment of women is not dependent on an access to financial resources only, but on the sociocultural and structural ones, to a significant degree. The results of ANN in Table 7 indicate that the best convergence was observed in Case 1, which obtained the best performance (0.914) and the least gradient (0.0153). Later cases had worse performance and bigger gradients indicating more complicated learning processes. These observations are also supported by Table 8 that presents acceptable mean squared error (MSE) values during training (0.48 0.44), validation (0.70 0.71), and testing (0.55 0.43) stages and strong regression coefficients (R 0.78 0.86) that all illustrate the stability and reliability of the model.

The best performance scores were obtained at different training epochs in each of the cases: Case I (0.9696 at epoch 15), Case II (1.2478 at epoch 5), Case III (0.70053 at epoch 4), and Case IV (0.71462 at epoch 6), thus illustrating differences in the convergence speed of the model. Figure 7 validation checks support the consideration of consistent learning efficiency, where the lowest gradient was achieved in Case 1, (0.015322 in epoch 21). Figure 9 gives the results of the regression analysis of all cases the R-values lie between 0.62793 and 0.83788 hence showing a very strong relationship between the predicted and actual data.

Lastly, Figure 11 shows model performance with Bayesian Regularization, where the highest training performance that was achieved was 0.36161 at epoch 381 and the gradient at 0.0072625, which is a high convergence. The results of the regression (training R = 0.8865, testing R = 0.83056 and R = 0.87738 in total) indicate the great predictive power of the model. In totality, the findings substantiate that ANN and PLS-SEM models have effectively represented both the linear and nonlinear mechanisms of empowerment and hence the importance of sociocultural and infrastructural factors in the improvement of the outcomes of women empowerment.

Theoretical Implications

- The results contribute to the theoretical understanding of the Resource-Based View (RBV), the Social Investment Theory, and the Empowerment Theory showing that the joint access to the financial resources and culturally competent interventions increases the entrepreneurial potential of women in rural Pakistan.
- It clarifies that social capital is both a resource and a mechanism causing easier access to finance, institutional support and entrepreneurship opportunities.

- Lastly, the paper places the empowerment of rural women into the framework of sustainable development and advances the purpose of integrating the Resource-Based View, Social Capital Theory and gender-sensitive approaches to empowerment in an effort to facilitate entrepreneurship under resource limited conditions.

Practical Implications

- As has been shown by the empirical study, the empowerment of the rural women entrepreneurs brings great benefits to various stakeholders, who include the government agencies, non-governmental organizations, financial institutions, and the local communities.
- Findings suggest that Social Capital (SC), Socio-Cultural Interventions (SCI), and Financial Accessibility (FA) are interdependent elements therefore; interventions should be heterogeneous and context-specific to reach efficacy.
- The findings indicate that inclusive financial systems need to focus on micro-loans, savings products, and flexible lending provisions that are tailored to the needs of women and which are complemented by financial literacy programs which enhance their ability to use resources well.
- The paper highlights the critical role of Social Capital, in which the peer organisations, cooperatives, and self-help groups will give access to the market, support institutions, and self-confidence of rural women.

6. Conclusion

In general, the fact that the PLS-SEM confirmatory findings are consistent with the ANN predictive analysis proves the usefulness of the dual-methodology. The hybrid paradigm also adds not only summative theoretical rigor but also practical predictive precision in that infrastructural and sociocultural intervention coupled with mediating through social capital greatly increases financial empowerment of rural women entrepreneurs. The findings have created a strong methodological base of future empowerment studies using mixed structural and computational analytics. The study examined mediating role of social capital in the association between sociocultural interventions, financial accessibility and entrepreneurial empowerment amongst rural women in Pakistan. The application of the PLS Structural Equation Modeling (PLS-SEM) and Artificial Neural Networks (ANN) together provided not only the level of explanations but also the level of prediction and proved that the social capital plays a significant role in mediating the relationship between women access to finance and the cultural and infrastructural determinants of empowerment. Case 1 (0.914) of the ANN model gave the best performance with a low gradient (0.0153) and least computation time but the performance in the latter cases (as low as 0.393) and with increasing gradient. Mu parameter was kept within optimum ranges and consistency in the model stability was reflected in the validation checks where the value of the parameter was always six. These findings confirm the premise that the effects of empowerment take nonlinear courses influenced by sociocultural and infrastructural forces, and social capital is an important moderating variable in empowering women to become entrepreneurs. Integrating AI-based analytical tools like ANN and machine-learning models into empowerment efforts should be introduced by development professionals to find out how most responsive communities are and tailor-crafted interventions. For future recommendations are:

- Policymakers need to cultivate digital and AI literacy in rural women to increase financial inclusion levels, entrepreneurial productivity, and self-efficacy.
- Placing governments should implement ethical and gender-isolating AI systems to decrease the level of algorithmic prejudice and avoid unfair methodologies in the decision-making procedure.
- Social capital building should be coupled with digital empowerment, and NGOs and microfinance institutions should promote learning and collaboration on a network of rural women entrepreneurs.

Some limitations are follows for different types of data

- Develop methodological innovation, researchers are invited to replicate and generalize hybrid methods with PLS-SEM and ANN in other contexts are not fruitful for existing data.
- The national and regional development programs are not organized for the development of data with AI and financial inclusion programs.

Conflicts of Interest Statement

Authors have no conflict of interest

References

- [1] Aiswarya, S., & Sangeetha, S. (2023). Augmenting Innovation: Artificial Intelligence among Women Entrepreneurs. Ramanujan International Journal of Business and Research, 8(2), 40-

- 49.,doi: <https://doi.org/10.51245/rijbr.v8i2.2023.1366>
- [2] Albahri, A. S., Alnoor, A., Zaidan, A. A., Albahri, O. S., Hameed, H., Zaidan, B. B., ... & Yass, A. A. (2022). Hybrid artificial neural network and structural equation modeling techniques: a survey. *Complex & Intelligent Systems*, 8(2), 1781-1801., <https://doi.org/10.1007/s40747-021-00503-w>
- [3] Alkire S. Foster, J. (2011) Counting and multidimensional poverty measurement. *J Public Econ*, 95(7-8):476--87., <https://doi.org/10.1016/j.jpubeco.2010.11.006>
- [4] Chauhan, P. R., Vanitha, P., Agnihotri, K., Praveen, R. V. S., Kumar, S., & Praveena, S. (2025). Analyzing Social Entrepreneurship and Financial Inclusion for Women Empowerment Using an F-GNN and AXGB Hybrid Approach. In the 2025 Global Conference in Emerging Technology (GINOTECH) (pp. 1-6). IEEE. DOI: [10.1109/GINOTECH63460.2025.11077069](https://doi.org/10.1109/GINOTECH63460.2025.11077069)
- [5] Coleman, J. S. (1988). Social capital in the creation of human capital. *American Journal of Sociology*, 94, S95–S120.
- [6] Cornwall Andrea, Rivas Althea-Maria. From ‘gender equality and ‘women’s empowerment’to global justice: reclaiming a transformative agenda for gender and development. *Third World Q* 2015;36(2):396--415. <https://doi.org/10.1080/01436597.2015.1013341>
- [7] Creswell, J. W. (2014). *Research design: Qualitative, quantitative, and mixed methods approaches* (4th ed.). SAGE Publications.
- [8] Duflo Esther. Women empowerment and economic development. *J Econ Lit* 2012;50(4):1051--79. DOI:10.1257/jel.50.4.1051
- [9] Gawel, A. (2024). Female entrepreneurship facing artificial intelligence in the European Union countries. In D. Crowther & S. Shahla (Eds.), *Social Responsibility, Technology and AI: Developments in Corporate Governance and Responsibility* (Vol. 23, pp. 163-182). Emerald Publishing. DOI:10.1108/S2043-052320240000023009.
- [10] Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2020). *A primer on partial least squares structural equation modeling (PLS-SEM)* (3rd ed.). SAGE Publications. https://doi.org/10.1007/978-3-319-57413-4_15
- [11] Huang, J., Krivkovich A. Starikova I., Yee L., Zanoschi D. (2019). *Women in the workplace 2019*. San Francisco. Retrieved from McKinsey Co. website: <https://www.mckinsey.com/featured-insights/genderequality/women-in-the-workplace,2019>
- [12] Naila Kabeer (2005) Gender equality and women's empowerment: A critical analysis of the third millennium development goal 1, *Gender & Development*, 13:1, 13-24, DOI: 10.1080/13552070512331332273
- [13] Klasen Stephan, Schüler Dana. Reforming the gender-related development index and the gender empowerment measure: implementing some specific proposals. *Fem Econ* 2011;17(1):1--30. <https://doi.org/10.1080/13545701.2010.541860>
- [14] Kumar, R. M., Delina, G., Kumar, R. S., & Devi, S. S. (2022). Logistic regression vs. artificial neural network model in prediction of financial inclusion: empirical evidence from PMJDY program in India. *International Journal of Financial Services Management*, 11(3), 245-267. <https://doi.org/10.1504/IJFSM.2022.126865>
- [15] Mahadew, B. (2024). Gender equality and the empowerment of women and girls: the organization for economic co-operation and development’s (OECD’s) guidance for development partners—a critical assessment of its relevance to combat entrenched gender bias. In: *From entrenched gender bias to economic empowerment: undermining the patriarchy*. Cham: Springer Nature Switzerland; 2024. p. 71--88. https://doi.org/10.1007/978-3-031-57212-8_6
- [16] Nations United. *Transforming our world: the 2030 agenda for sustainable development*. Department of economic and social affairs, vol. 1. New York: United Nations; 2015. p. 41.
- [17] Nguyen, P. H., Tsai, J. F., Lin, M. H., & Hu, Y. C. (2021). A hybrid model with spherical Fuzzy-AHP, PLS-SEM, and ANN to predict vaccination intention against COVID-19. *Mathematics*, 9(23), 3075. <https://doi.org/10.3390/math9233075>
- [18] Polin, J. A., Sarker, M. F. H., Dolon, M. D. K., Hasan, N., Rahman, M. M., & Vasha, Z. N. (2024). Predicting the effects of microcredit on women’s empowerment in rural Bangladesh: using machine learning algorithms. *Bulletin of Electrical Engineering and Informatics*, 13(4), 2699-2706. DOI: <https://doi.org/10.11591/eei.v13i4.7169>
- [19] Putnam, R. D. (1993). *Making Democracy Work: Civic Traditions in Modern Italy*. Princeton University Press. <https://doi.org/10.2307/j.ctt7s8r7>

- [20] Ridgeway, C. L. (2011). *Framed by gender: How gender inequality persists in the modern world*. Oxford University Press. <https://doi.org/10.1093/acprof:oso/9780199755776.001.0001>
- [21] United Nations Girls' Education Initiative. *Teaching and learning. Achieving quality for all; EFA global monitoring report, 2013-2014 gender summary (ARA)*; 2014.
- [22] Women UN. *Turning promises into action: gender equality in the 2030 agenda for sustainable development*. UN, 2018.
- [23] World Bank Group. *Global financial development report 2014: financial inclusion, vol. 2*. World Bank Publications; 2013.
- [24] Dikov, G., Bayer, J., (2019). Bayesian learning of neural network architectures. In: *The 22nd International Conference on Artificial Intelligence and Statistics*. PMLR, pp. 730–738. PMLR 89:730-738, 2019.
- [25] Qi, J., Du, J., Siniscalchi, S.M., Ma, X., Lee, C.H., (2020). On mean absolute error for deep neural network based vector-to-vector regression. *IEEE Signal Process. Lett.* 27, 1485–1489., doi: 10.1109/LSP.2020.3016837.
- [26] Abueid, A. I., Mohammad, S. I., Mohammad, A. A. S., Vasudevan, A., Al Sarayreh, A., Alrfai, M. M., ... & Saraireh, S. (2025). Digital Finance and Fintech Innovations Towards Disrupting Finance Innovation. In *Artificial Intelligence, Sustainable Technologies, and Business Innovation: Opportunities and Challenges of Digital Transformation* (pp. 17-31). Cham: Springer Nature Switzerland. https://doi.org/10.1007/978-3-031-77925-1_2
- [27] Al-Assaf, K. T., Foriki, M. S. M., Samarah, T., Hindieh, A., Mohammad, S. I. S., Vasudevan, A., and Al Kurdi, B. (2025). Impact of digital marketing on promoting the local pharmaceutical products in Jordan. *IRMM.*, 15(1), 137, DOI: <https://doi.org/10.32479/irmm.17707>
- [28] Khalufi, N. A. M., Sheikh, R. A., Khan, S. M. F. A., and Onn, C. W. (2025). Evaluating the impact of sustainability practices on customer relationship quality: an SEM-PLS approach to align with SDG. *Sustainability*, 17(2), 798. <https://doi.org/10.3390/su17020798>