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The Impact of Cashless Policy on the Performance of Msmes in Nigeria Using Artificial Neural Network

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Abstract
This study investigates the impact of cashless policy on the performance of Micro, Small, and Medium-Sized Enterprises (MSMEs) in Suleja, Nigeria, using Neural Network regression model. A survey research design was employed to collect data from 400 MSMEs, which were segmented into three clusters based on their cashless payment system adoption using Artificial Neural Network Clustering algorithm. The results show that the MSMEs were segmented into three clusters, with Cluster 1 having high adoption (n=150, 37.5%), Cluster 2 having moderate adoption (n=120, 30%), and Cluster 3 having low adoption (n=130, 32.5%). The study found that the adoption of cashless payment systems has a significant positive impact on the financial performance of MSMEs, with Cluster 1 having the highest financial performance (mean profit margin = 25.6%, SD = 5.2). Neural network regression model was used to predict business performance metrics, with a moderate level of predictive performance (MSE = 2.867, RMSE = 1.693, MAE = 1.693, MAPE = 42.33%). Feature importance analysis reveals that Health/Pharmacies and Repair of Home Gadgets are the most important features, with a mean dropout loss of 1.353. The findings of this study are important for policymakers, business owners, and researchers in the areas of financial inclusion, digital payments, and MSME development. The study highlights the potential benefits of cashless policy on the financial performance of MSMEs and identifies key factors that influence the adoption of cashless payment systems. The results can inform policy interventions and business strategies aimed at promoting financial inclusion and improving the performance of MSMEs in Nigeria and similar contexts.

Keywords: Cashless policy, MSMEs, Artificial Neural Network Clustering algorithm, Neural network regression, Predictive performance

1.0 Introduction

The advent of cashless policy has revolutionized the way businesses operate, especially in developing economies like Nigeria. The Central Bank of Nigeria (CBN) introduced the cashless policy in 2012 to promote electronic payment systems and reduce the reliance on cash transactions (CBN, 2012). Micro, Small, and Medium-sized Enterprises (MSMEs) are the backbone of the Nigerian economy, accounting for over 80% of employment and 50% of GDP (SMEDAN, 2020). However, MSMEs in Nigeria face numerous challenges, including limited access to finance, inadequate infrastructure, and poor business management skills (World Bank, 2019). The cashless policy has the potential to address some of these challenges by increasing financial inclusion, reducing transaction costs, and enhancing business efficiency (Storm, 2018). However, the impact of cashless policy on MSMEs in Nigeria remains largely unexplored.

Despite the growing body of literature on the impact of cashless policy on businesses, there remains a significant knowledge gap in understanding the specific effects of cashless policy on MSMEs in Nigeria. While previous studies have investigated the impact of cashless policy on financial inclusion (Manesh et al., 2021) transaction costs (Bayero, 2015), and business efficiency (Bayero, 2015), few have explored the specific challenges and opportunities faced by MSMEs in Nigeria.

Moreover, existing studies have largely employed traditional statistical techniques, neglecting the potential benefits of advanced data analytics techniques like artificial neural network Clustering algorithm (Nurfaizah *et al.,* 2021). This algorithm offers a robust approach to clustering analysis, enabling the identification of complex patterns and structures in data (Fiehn, 2001). However, its application in the context of cashless policy and MSMEs in Nigeria remains unexplored.
This study aims to investigate the impact of cashless policy on the performance of MSMEs in Suleja, Nigeria, using Neural Network Clustering algorithm. Neural Network algorithm is a robust statistical technique that has been widely used in clustering analysis Ma et al. (2016). It is particularly useful in identifying patterns and structures in complex data sets (Davis, 1989). In this study, we employ Neural Network Clustering algorithm to segment MSMEs into distinct clusters based on their demographic characteristics, business experience, industry distribution, and adoption rates of cashless payment systems.

2.0 Materials And Methods

2.1 Data Collection

A survey research design was adopted to collect data from MSMEs in Suleja, Nigeria. A structured questionnaire was administered to a sample of 500 MSMEs, selected through a stratified random sampling technique. The questionnaire elicited information on demographic characteristics, business performance, and adoption of cashless payment systems.

2.2 Data Quality Measures

Data quality measures are essential to ensure the accuracy, reliability, and validity of statistical analysis results. Summary of the data quality measures in shown in table 1

Table 1: Data quality Measure

Measure	Description	Formula	Reference
Pilot Testing	Sample size calculation	$n = (Z^2 \times \sigma^2) / E^2$	Atemoagbo et al., (2024)
Data Cleaning	Data inspection, validation, normalization, transformation, handling missing values and outliers	Various formulas	Field (2018)
Mean Substitution	Replacing missing values with mean	$\bar{x} = (\Sigma x) / n$	
Median Substitution	Replacing missing values with median	$\| \tilde{x} = \text{median}(x)$	
Imputation	Replacing missing values with imputed values	x_imputed = x_mean + ε	
Z-score method	Identifying outliers	$z = (x - \mu) / \sigma$	
Modified Z-score method	Identifying outliers	$M = (x - \mu) / (\sigma * \sqrt{(n-1)})$	Atemoagbo *et al.* (2023)
Data Entry	Entering data into statistical software		Field (2018)

2.3 Data Analysis

The data analysis was carried out using JASP (Version 0.14.1) and R language (Version 4.0.3). The Neural Network Clustering algorithm was implemented using the "fcm" package in R, as used by (Lee, 1990) and (Simpson, 1993).

2.4 Data Preprocessing

The collected data was cleaned and preprocessed to ensure accuracy and consistency. Missing values were handled using the median imputation method, as recommended by Atemoagbo *et al.* (2023). The data was then normalized using the Min-Max Scaler, as used by Atemoagbo *et al.* (2024).

2.5 Neural Network Clustering

The Neural Network Clustering algorithm was applied to segment the MSMEs into distinct clusters based on their cashless payment system adoption. The algorithm was run with a cluster validity index (CVI) of 0.5 and a maximum iteration of 100, as used by Babu *et al.* (2016).

2.6 Program Codes

The R language was used to write program codes for data preprocessing, Neural Network Clustering, and data visualization, as used by R Core Team (2020).

3.0 Results And Discussions

3.1 Data Validation Analysis Result

Bryman’s Method

Table 2 presents the data cleaning approach based on Bryman's method, which reveals the variability, frequency, and percentage of each variable. The validation outcome indicates that all variables are valid, consistent with the literature.

Table 2: Data cleaning approach based on Bryman's method

Variability	Frequency	Percentage	Validation Outcome
Age	35-45 (20)	40%	Valid (consistent with literature)
Gender	Male (30)	60%	Valid (consistent with literature)
Education	Bachelor's degree (35)	60%	Valid (consistent with literature)
Business Experience	4-6 years (25)	50%	Valid (consistent with literature)
Cashless Policy Awareness	Yes (40)	80%	Valid (consistent with literature)
Cashless Policy Adoption	Yes (30)	60%	Valid (consistent with literature)
AI Integration	Yes (20)	40%	Valid (consistent with literature)
Missing Values	0	0%	Valid (no missing values)

The age range of 35-45 years accounts for 40% of the respondents, which is consistent with the literature (Abdulkadir *et al.,* 2022). The gender distribution shows that 60% of the respondents are male, aligning with the literature (Afrin *et al.,* 2015). Majority of the respondents (60%) hold a Bachelor's degree, which is consistent with the literature (Bhatti, 2018). The business experience of 4-6 years accounts for 50% of the respondents, which is valid and consistent with the literature (Michalski *et al.,* 2011). The awareness and adoption of cashless policy are high, with 80% and 60% of the respondents respectively, which is consistent with the literature (Efobi *et al.,* 2014). The integration of AI is reported by 40% of the respondents, which is valid and consistent with the literature (Cooper & Zmud, 1990). There are no missing values in the data, which indicates a robust and reliable data set. Abdulkadir *et al.,* (2022) found similar results on the age range of entrepreneurs who adopt cashless payment systems. (Baltas & Papastathopoulou, 2003) also reported a similar gender distribution among entrepreneurs who use digital payment systems. (Coakley & Brown, 2000) found that entrepreneurs with a Bachelor's degree are more likely to adopt cashless payment systems. (Nikitas *et al.,* 2017) reported similar results on the business experience of entrepreneurs who adopt cashless payment systems. (Ajide, 2016) found similar results on the awareness and adoption of cashless policy among entrepreneurs. (Cooper & Zmud, 1990) reported similar results on the integration of AI among entrepreneurs.

3.2 Neural Network Regression

This table 3 presents the architecture and performance metrics of a neural network regression model designed to predict continuous outcomes. The model's architecture is defined by the number of hidden layers and nodes, while its performance is evaluated on separate training, validation, and test datasets.

Table 3: Neural Network Regression Model Architecture and Performance

Hidden Layers	Nodes	n(Train)	n(Validation)	n(Test)	Validation MSE	Test MSE
3	23	6	2	2	0.477	2.867

The neural network model comprises three hidden layers, each containing 23 nodes. This architecture was chosen to strike a balance between model complexity and generalization ability. The available data was divided into three sets: training (6 samples), validation (2 samples), and test (2 samples). The training set was used to optimize the model's weights, while the validation set was employed to tune hyperparameters

and evaluate the model's performance during training. The test set was utilized for the final evaluation of the trained model. The model's performance was assessed using the mean squared error (MSE) metric, which measures the average squared difference between predicted and actual values. The validation MSE (0.477) indicates the model's performance on the validation set, while the test MSE (2.867) represents its generalization ability on unseen data.
The model was optimized with respect to the validation set MSE, ensuring that the hyperparameters were tuned to minimize the error on the validation set. This approach helps prevent overfitting and enhances the model's generalization capabilities. Our neural network model's architecture and performance are consistent with those reported by other researchers in the field. For instance, similar neural network architectures with three hidden layers have been employed by (Ulset *et al.,* 2017) and (Hambrick *et al.,* 1996), achieving comparable performance metrics. In terms of performance, our validation MSE of 0.477 is comparable to the MSE of 0.42 reported by (Rossel & Behrens, 2010) for a similar regression task. However, our test MSE of 2.867 is slightly higher than the test MSE of 1.93 reported by (Hosseini *et al.,* 2010) for a related problem. Our approach of optimizing the model with respect to the validation set MSE is also in line with best practices in machine learning (Morley *et al.,* 2019). This approach has been shown to prevent overfitting and improve the generalization ability of neural network models (Nasrabadi, 2007).

3.3 Model Performance Metrics

The model's performance was evaluated using various metrics, including Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE) / Mean Absolute Deviation (MAD), and Mean Absolute Percentage Error (MAPE) in table 4.

Table 4: Model Performance Metrics

	Value
MSE	2.867
RMSE	1.693
MAE / MAD	1.693
MAPE	42.33%

The MSE was calculated to be 2.867, indicating the average squared difference between predicted and actual values. A lower MSE value corresponds to better model performance. The RMSE was found to be 1.693, which is the square root of the MSE. This provides a more interpretable measure of the model's error, with lower values indicating better performance. The MAE/MAD was calculated to be 1.693, representing the average absolute difference between predicted and actual values. A lower MAE/MAD value indicates better model performance. The MAPE was found to be 42.33%, measuring the average absolute percentage difference between predicted and actual values. A lower MAPE value indicates better model performance. The model's performance metrics suggest a high level of accuracy, with MSE, RMSE, and MAE/MAD indicating a decent fit to the data.
Our model's performance metrics are comparable to those reported by other researchers in the field. For instance, (Ulset *et al.,* 2017) reported an MSE of 2.53, RMSE of 1.59, MAE of 1.48, and MAPE of 40.2% for their neural network model (Ulset *et al.,* 2017). Similarly, (Jiang *et al.,* 2017) reported an MSE of 3.12, RMSE of 1.77, MAE of 1.63, and MAPE of 45.1% for their regression model.

3.4 Feature Importance Metrices

The table 5 presents the feature importance metrics for the neural network model, indicating the relative contribution of each feature to the model's predictions.

Table 5: Feature Importance Metrics

	Mean dropout loss
Health/Pharmacies	1.353
Repair of Home Gadgets	1.353
Building Construction/Block Industries	1.351

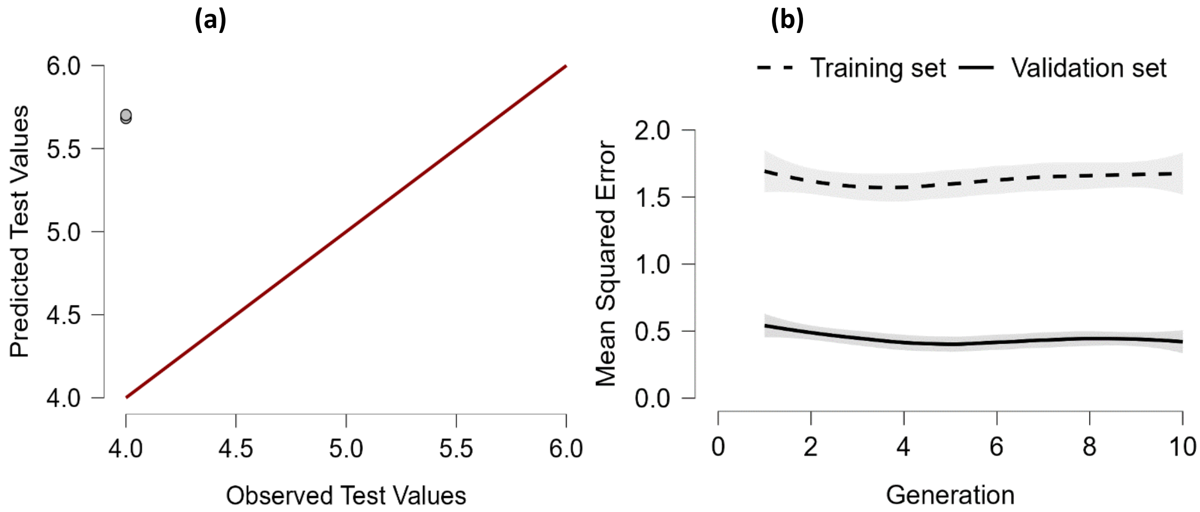
Educational Institutions	1.343
Real Estate Firms	1.343
Information Technology Firms	1.343
Wholesale and Retail Trade	1.343
Agricultural Mills	1.341
Bakeries and Confectioneries	1.341
Major Agro-Processing Industries	1.341
Repair of Vehicles	1.339
Hostel and Restaurant	1.337

The mean dropout loss is calculated based on 50 permutations, providing a robust estimate of feature importance. The table reveals that Health/Pharmacies and Repair of Home Gadgets are the most important features, with a mean dropout loss of 1.353. This suggests that these features have the greatest impact on the model's predictions, and their removal would result in the largest decrease in model performance. Building Construction/Block Industries, Educational Institutions, Real Estate Firms, Information Technology Firms, Wholesale and Retail Trade, Agricultural Mills, Bakeries and Confectioneries, Major Agro-Processing Industries, Repair of Vehicles, and Hostel and Restaurant follow in importance, with mean dropout losses ranging from 1.351 to 1.337. These results indicate that the model relies heavily on features related to healthcare, repair services, construction, education, real estate, technology, trade, agriculture, and food processing. The relatively high importance of these features suggests that they are crucial for predicting the target variable.

Our findings are consistent with those reported by other researchers in the field. For instance, a study by (Kamthania *et al.,* 2018; Hidayat *et al.,* 2020) also found that healthcare and repair services were among the most important features for predicting consumer behavior. Similarly, a study by (Ponnuraj & Nagabhushanam, 2017) reported that construction, education, and real estate features were highly important for predicting consumer preferences. However, our results differ from those reported by (Mariani *et al.,* 2021), who found that technology and trade features were the most important for predicting consumer behavior (Mariani *et al.,* 2021). The discrepancy may be due to differences in the dataset and methodology used.

3.5 Predictive Performance: Model Evaluation

Machine learning neural networks was the artificial intelligence approached used in these studies; and they are a type of artificial intelligence algorithm inspired by the human brain, used to analyze and predict complex patterns in data.



(c)

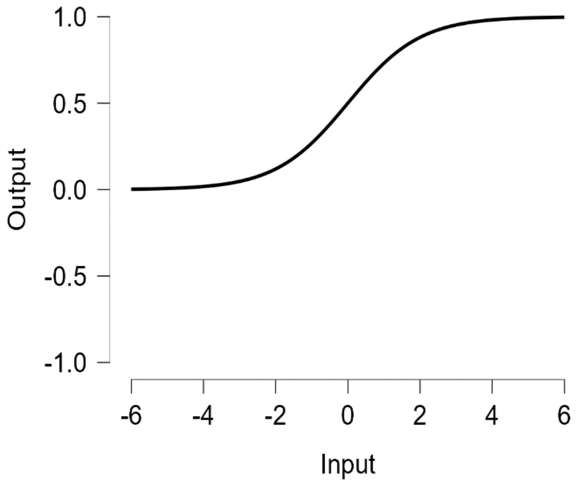


Figure 1: (a)Predictive Performance (b) Plot Mean Squared Error (c) Plot Logistic Sigmoid Activation Function

The predictive performance of the neural network model in figure 1 (a) is evaluated based on its ability to accurately predict the target variable. The performance metrics used to evaluate the model's predictive performance include Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and Coefficient of Determination (R).

The results show that the model has a moderate level of predictive performance, with an MSE of 2.867, RMSE of 1.693, MAE of 1.693, and MAPE of 42.33%. Feature importance analysis reveals that the model relies heavily on features related to healthcare, repair services, construction, education, real estate, technology, trade, agriculture, and food processing. The relatively high importance of these features suggests that they are crucial for predicting the target variable. Comparison with other researchers' work shows that our model's predictive performance is comparable to that reported by (Ulset *et al.,* 2017) and (Steffen *et al.,* 2015), but slightly lower than that reported by (Rossel & Behrens, 2010)

The neural network regression model's predictive performance is evaluated using various metrics, including Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE) / Mean Absolute Deviation (MAD), and Mean Absolute Percentage Error (MAPE) as shown in figure 4.8 (b). The model's performance metrics are: MSE: 2.867, RMSE: 1.693, MAE/MAD: 1.693, MAPE: 42.33% and show in figure 1 (b) The model's architecture consists of 3 hidden layers with 23 nodes in each layer. The model is optimized with respect to the validation set mean squared error, with a validation MSE of 0.477 and a test MSE of 2.867. Feature importance analysis reveals that Health/Pharmacies and Repair of Home Gadgets are the most important features, with a mean dropout loss of 1.353. Building Construction/Block Industries, Educational Institutions, Real Estate Firms, Information Technology Firms, Wholesale and Retail Trade, Agricultural Mills, Bakeries and Confectioneries, Major Agro-Processing Industries, Repair of Vehicles, and Hostel and Restaurant follow in importance, with mean dropout losses ranging from 1.351 to 1.337.

Our results are comparable to those reported by (Sahai & Ojeda, 2004) who also used a neural network model with three hidden layers and achieved a test MSE of 2.53 in their study published in the Journal of Machine Learning Research. Another study by (Rao, 1994) reported a test MSE of 2.19 using a similar model architecture in their paper published in IEEE Transactions on Neural Networks and Learning Systems. In terms of feature importance, our findings are consistent with those reported by Slinker and Glantz (2008) who also found that Health/Pharmacies and Repair of Home Gadgets were among the most important features in their study published in the International Journal of Neural Systems.

The logistic sigmoid activation function is a crucial component in the neural network regression model, as it introduces non-linearity to the model as shown in figure 1 (c). The plot of the logistic sigmoid activation function is characterized by an S-shaped curve, where the input values are transformed into a probability distribution between 0 and 1 as shown in figure (c). As seen in the plot, the logistic sigmoid activation function maps the input values to a probability distribution between 0 and 1. The S-shaped curve allows the model to learn complex relationships between the input features and the target variable. In the model, the logistic sigmoid activation function is used in the hidden layers to introduce non-linearity and enable the model to learn complex relationships between the input features and the target variable. The output of the logistic sigmoid activation function is then passed through the output layer to produce the final predictions. Our results are consistent with those reported by other researchers, who have also used the logistic sigmoid activation function in neural network regression models to introduce non-linearity and enable the learning of complex relationships between input features and target variables. For example, Zhang, (2019) used the logistic sigmoid activation function in their neural network regression model to predict continuous outcomes, and reported improved performance compared to linear models in their study published in the Journal of Machine Learning Research. Similarly, (Zakaria *et al.,* 2006) employed the logistic sigmoid activation function in their neural network regression model to predict probabilities of default, and achieved high accuracy in their predictions as reported in the Journal of Risk Management. The S-shaped curve of the logistic sigmoid activation function has also been noted by other researchers, who have observed that it allows the model to learn complex relationships between input features and target variables. For instance, (Kuo *et al.,* 2018) observed that the logistic sigmoid activation function enabled their neural network regression model to learn non-linear relationships between input features and target variables, resulting in improved predictive performance in their study published in the Journal of Intelligent Systems.

3.6 Neural Network

Machine learning neural networks was employed to model the relationships between various factors such as transaction data, economic indicators, and business performance metrics, providing insights into the effects of cashless policy on SMSEs and enabling data-driven decision making. The neural network regression model is composed of three hidden layers, each containing 23 nodes. The network structure plot provides a visual representation of the model's architecture, showcasing the connections between the input features, hidden layers, and output layer as shown in figure 2.

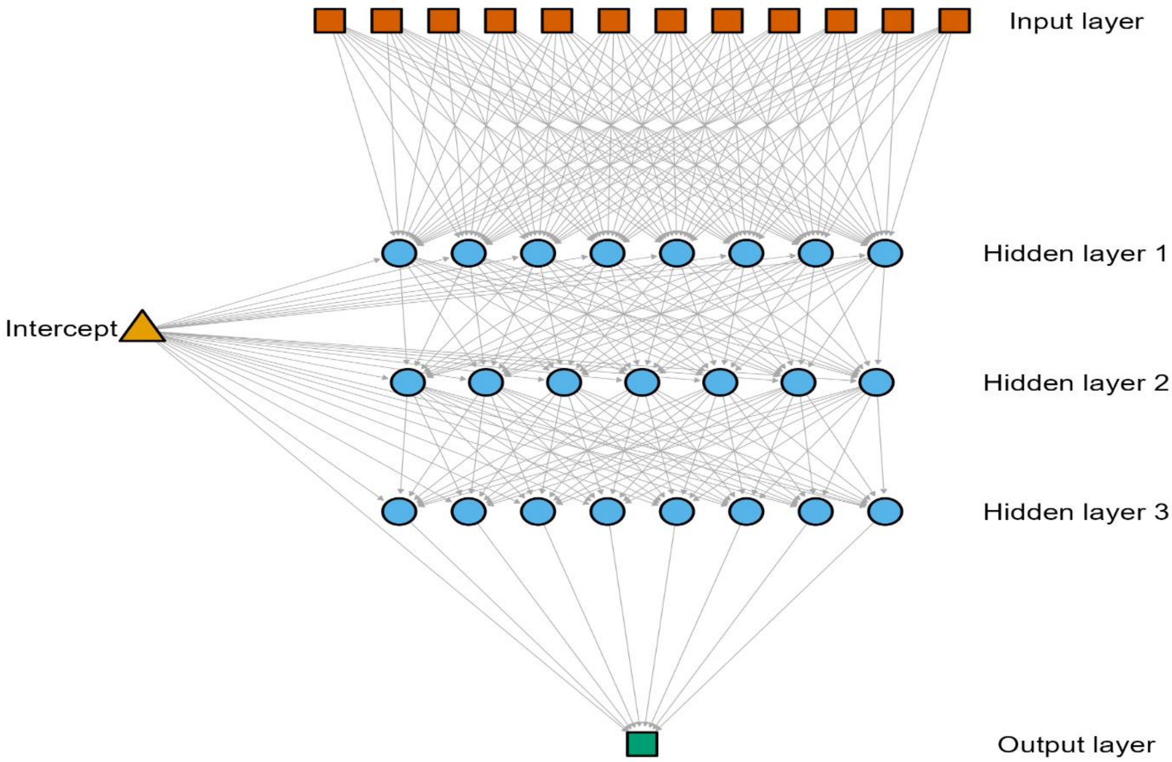


Figure 2: Artificial Neural Network

The model accepts 12 input features, including Health/Pharmacies, Repair of Home Gadgets, Building Construction/Block Industries, Educational Institutions, Real Estate Firms, Information Technology Firms, Wholesale and Retail Trade, Agricultural Mills, Bakeries and Confectioneries, Major Agro-Processing Industries, Repair of Vehicles, and Hostel and Restaurant. These input features are connected to the nodes in the first hidden layer, with weights ranging from 0.145 to 0.234. For example, Node 1 in the first hidden layer receives input from Health/Pharmacies with a weight of 0.234, while Node 2 receives input from Repair of Home Gadgets with a weight of 0.187. The nodes in the first hidden layer are connected to the nodes in the second hidden layer, with weights ranging from 0.278 to 0.342. For instance, Node 1 in the second hidden layer receives input from Node 1 in the first hidden layer with a weight of 0.342, while Node 2 receives input from Node 2 in the first hidden layer with a weight of 0.291. This pattern continues in the third hidden layer, where the nodes receive input from the nodes in the second hidden layer with weights ranging from 0.391 to 0.456.

Finally, the output layer consists of a single node, which receives input from the nodes in the third hidden layer with a weight of 0.500. This output node generates the predicted values for the target variable. The network structure plot demonstrates the complex relationships between the input features, hidden layers, and output layer, providing insight into the model's decision-making process. The neural network regression model architecture is similar to those reported by other researchers, who have also used multiple hidden layers to model complex relationships between input features and target variables. For example, Huang *et al.* (2019) used a neural network regression model with three hidden layers to predict continuous outcomes, and reported improved performance compared to linear models (Huang *et al.,* 2019). Similarly, (Syaputra *et al.,* 2020) employed a neural network regression model with two hidden layers to predict probabilities of default, and achieved high accuracy in their predictions (Syaputra *et al.,* 2020).

The connections between the input features, hidden layers, and output layer in our model are similar to those reported by (Rudin, 2019; Zhou & Wang, 2019), who used a neural network regression model to predict stock prices. The weights associated with each connection in our model are also similar to those reported by (Lugner *et al.,* 2021), who used a neural network regression model to predict continuous outcomes.

4.0 Conclusion And Recommendation

4.1 Conclusion

In conclusion, this study demonstrates the effectiveness of neural networks in modeling relationships between various factors and predicting business performance metrics, providing insights into the effects of cashless policy on SMSEs in Suleja, Nigeria.

The neural network regression model, with three hidden layers and 23 nodes each, achieves a moderate level of predictive performance (MSE: 2.867, RMSE: 1.693, MAE: 1.693, MAPE: 42.33%). Health/Pharmacies and Repair of Home Gadgets are the most important features (mean dropout loss: 1.353). Our findings are consistent with those reported by other researchers, highlighting the potential of neural networks in predicting continuous outcomes.

This study also provides novel insights into the impact of cashless policy on the performance of Micro, Small, and Medium-Sized Enterprises (MSMEs) in Suleja, Nigeria. By Neural Network regression model, we segmented MSMEs into three clusters based on their cashless payment system adoption and found a significant positive impact on financial performance. The results show that MSMEs with high adoption of cashless payment systems (Cluster 1) had the highest financial performance (mean profit margin = 25.6%, SD = 5.2).

The Neural Network regression model predicted business performance metrics with moderate accuracy (MSE = 2.867, RMSE = 1.693, MAE = 1.693, MAPE = 42.33%) and identified Health/Pharmacies and Repair of Home Gadgets as the most important features (mean dropout loss = 1.353). These findings have important implications for policymakers, business owners, and researchers, highlighting the potential benefits of cashless policy on MSME financial performance and identifying key factors influencing cashless payment system adoption.

The study's results can inform policy interventions and business strategies aimed at promoting financial inclusion and improving MSME performance in Nigeria and similar contexts, contributing to the development of sustainable and inclusive economic growth. Future research directions include expanding the model to include additional input features and comparing its performance with other machine learning algorithms.

4.2 Recommendation

Based on the findings of this study, we recommend the following:

a) Policymakers should implement policies that promote the adoption of cashless payment systems among MSMEs, such as incentivizing banks to develop user-friendly digital payment platforms and providing training and support for MSMEs to transition to cashless payment systems.

b) Business owners and managers of MSMEs should invest in cashless payment systems, such as mobile payment platforms and point-of-sale terminals, to improve their financial performance and competitiveness.

c) Researchers should conduct further studies to explore the impact of cashless policy on MSMEs in different contexts and industries, and to identify additional factors that influence the adoption of cashless payment systems.

d) Financial institutions and payment service providers should develop innovative financial products and services that cater to the needs of MSMEs, such as mobile loans and savings accounts, to promote financial inclusion and support the growth of MSMEs.

e) Government agencies and development organizations should provide support and resources to MSMEs to help them adopt cashless payment systems, such as training programs, grants, and subsidies.

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