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Analysing Factors Influencing Women Unemployment Using a Random Forest Model

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Abstract:

The unemployment crisis has been a persistent issue for both developed and developing countries, resulting in an economic indicator deficit. Women are at a disadvantage and continue to encounter significant obstacles to gaining employment. Nigeria, like many other developing countries with high unemployment rates, has a 33% unemployment rate. Consequently, there has been minimal research on the factors that affect women's unemployment. As a result, the purpose of this study investigates the factors that influence women's unemployment in Nigeria. Although the Random Forest model has been widely applied to classification issues, there is a gap in the literature's use of the random forest as a predictor for analyzing factors influencing women's unemployment. The random forest model was employed in this study because of its characteristics such as strong learning ability, robustness, and feasibility of the hypothesis space. As a result, the Random forest prediction model was benchmarked with seven different cutting-edge classical machine learning prediction models, which include the J48 pruned tree, Support Vector Machine, AdaBoost, Logistic Regression, Naive Bayes, Logistic Model Tree, Bagging, and Random Forest. The experimental results demonstrate that Random Forest outperformed the other seven machine learning classifier models using ten commonly used performance evaluation metrics. According to the study's findings, age groups, ethnicity, marital status, and religion were the essential factors affecting women's unemployment in Nigeria.

Keywords: machine learning, National Demographic and Health Survey, random forest, influencing factors, women unemployment.

使用随机森林模型分析影响女性失业的因素

摘要:

机器学习, 国家人口与健康调查, 随机森林, 影响因素, 女性失业危机一直是发达国家和发展中国家

的一个长期问题，导致经济指标赤字。妇女处于不利地位，在获得就业方面继续遇到重大障碍。与许多其他高失业率的发展中国家一样，尼日利亚的失业率为 33%。因此，对影响妇女失业的因素的研究很少。因此，本研究的目的是调查影响尼日利亚妇女失业的因素。尽管随机森林模型已广泛应用于分类问题，但文献中使用随机森林作为分析影响女性失业因素的预测因子存在差距。由于随机森林模型具有学习能力强、鲁棒性强、假设空间可行等特点，因此本研究采用了随机森林模型。因此，随机森林预测模型以七种不同的前沿经典机器学习预测模型为基准，包括杰 48 剪枝树、支持向量机、适应性提升、逻辑回归、朴素贝叶斯、逻辑模型树、装袋和随机森林。实验结果表明，使用十种常用的性能评估指标，随机森林优于其他七种机器学习分类器模型。根据研究结果，年龄组、种族、婚姻状况和宗教是影响尼日利亚妇女失业的重要因素。

关键词：机器学习，全国人口与健康调查，随机森林，影响因素，女性失业。

1. Introduction

Unemployment is an intrinsic global issue with a never-ending economic ripple effect on the population. According to the International Labor Organization (ILO), unemployment includes people who are unemployed, underemployed, have actively looked for work in the last four weeks and are ready to start work within the next two weeks, or are unemployed and have accepted a job that will start within the two next weeks (Matandare, 2018). In the literature, unemployment is hypothesized to be a stifling catalyst for many large-scale developments and growth (Ajamobe, 2021). The unemployment crisis has been a persistent issue for both developed and developing countries, resulting in the waste of many resources. Recently, Africa has experienced an economic downturn characterized by high inflation and unemployment, which has affected African countries to varying degrees (Yaya et al., 2019). Nigeria, like many other developing countries, has high unemployment because of an economic indicator deficit (Ene, 2018). Nigeria is the most populous country in Sub-Saharan Africa and the tenth most populous country in the world, with an estimated population of 200 million people spread across 250 ethnic groups. an oil-rich country, with oil being one of the world's major natural resources and a major source of income. Men must lead the labor market in many countries around the world.

In Nigeria, there have been instances of women outperforming their male counterparts. Nigeria is a country where men are perceived to be superior to their female counterparts, owing to factors such as disparate cultural beliefs and gender inequality (Olonade et al., 2021). This is evident in the expectation of a woman's position being dedicated to housework, specifically the kitchen, and caring for her husband and children (Ciciolla & Luthar, 2019). These realities are more visible in northern Nigeria, where women are expected not to express themselves when men are present (Sinai et al., 2017). This has led to and promoted the belief among the average Nigerian man that it is unacceptable for the wife to be wealthier or more successful than the husband (Gibby et al., 2021). Modernization has introduced a new dimension to gender inequality, defining it as the unequal treatment of individuals based on their gender (Ewubare & Ogbuagu, 2017).

Despite these problems, the need for equal treatment of workers remains a large gap that must be filled by all stakeholders. Women make up 49% of the Nigerian population, which is more than one-third of the total national population. However, there is a 6.3% difference in unemployment rates between men and women (Ewing-Nelson, 2021). This disparity demonstrates that most women rely entirely on their male counterparts for a living and, as a result, are helplessly taken for granted or mistreated. Ewing-Nelson (2021) said that factors like education level, family background, maternal commitment, cultural beliefs, and household responsibilities may have contributed to the subliminal marginalization of men and women in the labor market.

Globally, female unemployment is estimated to be higher than male unemployment, and this is especially true in Sub-Saharan Africa, where males are thought to be more dominant than females. Men are expected to get more lucrative and better jobs, forcing women to accept low-wage jobs (Mihret, 2019). Furthermore, most studies on the factors causing women's unemployment in Nigeria have made no mention of other emerging ones that may be relevant to this problem. As a result, the dawn of modernization added a new dimension to gender inequality, defining it as the unequal treatment of individuals based on their gender. Despite this highlighting the need for equal treatment among workers, the unemployment gap remains a large gap that must be filled by all stakeholders. As a result, this paper delves deeper into other possible causes of this bias or inequality toward women in Nigeria. This paper investigates the factors that contribute to women's unemployment in Nigeria, with the main research question being what are the factors that contribute to women's unemployment in Nigeria?

The concise structure of this work is as follows. The relevant literature on women's unemployment in Nigeria is summarized in Section 2. The study's materials and methods are addressed in Section 3. The experimental findings and discussion are presented in Section 4. The paper's Section 5 contains the concluding statements.

2. Related Works

The International Labour Organization defines

unemployment as "the proportion of the economically active population who are unemployed but available and seeking work within the previous five weeks" (Ewing-Nelson, 2021; Ewubare & Ogbuagu, 2017). Many studies show that unemployment is more common among women, and this has been proven to be due to various factors (Matandare, 2018). According to some studies, women are usually exceptional in most businesses and have the same level of productivity as men, but they are not in a better position (Berman, 2018; Zulqaram et al., 2021). However, there is a report in the literature on the high unemployment rate in women, as a cursory glance at gender astute reveals the unemployment rate to be higher for females than their male counterparts due to the predominantly stout challenges they face when attempting to enter the labor force due to early motherhood and a lack of education (Okolie & Igbini, 2020). According to Mihret (2019), women's unemployment is higher than men's unemployment on a global scale.

Existing literature holds unemployment primarily responsible for various societal ills, including crime, suicide, poverty, alcoholism, the spread of HIV/AIDS, gender violence, and prostitution (Biancone & Radwan, 2018; Fakih et al., 2020; Okonko & Okoli, 2020). Furthermore, unemployment has had a significant impact on household income, health, government revenue, GDP, and overall development. Despite women's critical role in the economic development of their families and communities, unemployment, among other factors, impedes their effective performance (Ene, 2018). According to National Bureau statistics from 2010, approximately 68% of 164 million Nigerians are in relative poverty, with the highest rate of 77.7% in the North-West and 76.3% in the North-East geographical zones. Their survey also revealed a trend among women to enter the labor force in pursuit of careers and financial independence, owing to improvements in female education and living standards (Okolie & Igbini, 2020).

Despite ongoing reforms and consolidation in many corporations in certain sectors facilitate women's employment. Additionally, a cost of women's unemployment is an increase in gender-based violence. According to the authors, unemployed women are more vulnerable to violence and abuse because they rely on their spouses for financial support (Tadesse et al., 2022). As a result, Okonko and Okoli (2020) reported a high prevalence of HIV among unemployed pregnant women. Existing literature details the global woes of unemployment, with varying impacts and severity (Hammell, 2019). These consequences are felt globally, with more than 200 million people out of work in 2011 (Ewing-Nelson, 2021).

Unemployment in Nigeria is a consistent and persistent uprising phenomenon. Even though Nigeria is known as one of the world's oil giants, brought significant economic and financial reforms, there are reports of an alarming increase in unemployment (Osioibe & Oseghe, 2020). Consequently,

unemployment is a developmental issue that affects every developing economy, including Nigeria. The literature also emphasizes Nigeria's governments' and policymakers' failure to deal with the unemployment phenomenon, attributing this to a lack of adequate job creation provision (Shimfe & Wajim, 2020; Tukur & Aguiyi, 2022). According to the literature, the inadequacies of the fundamental structural changes presenting a structural shift in Nigeria have failed to provide significant sustainable economic growth and development that addresses unemployment.

According to (Olorunfemi, 2021), most of the unemployed youth are females in general, and he could also reveal that approximately 50% of females in Nigeria were unemployed between 2008 and 2012. Considering at the Nigerian system critically, some employers do not want to hire women because they require more leave days than their male counterparts, and this is due to pregnancy, during which most women are not as productive as they may suffer from many pregnancy-related medical conditions throughout most of their pregnancies. It does not end there; they will also need maternity leave once the baby arrives. Employers, particularly those in small businesses, face a low productivity level, which may have a significant impact on the sustainability of such businesses, particularly in areas where most employees are women.

Furthermore, there is a cultural value, which is an important factor to consider regarding unemployment in Nigeria. Cultural practices in Nigeria do not favor women in terms of employment compared to their western counterparts (Enfield, 2019). Furthermore, it is widely believed and supported in many parts of the country that women cannot inherit their parents' properties because they are expected to marry into another family and receive whatever they require from that new family. Regardless, they have no right to inherit in whatever family they are married to; their husbands are the only ones eligible for any inheritance that may be available.

Prior research has revealed an alarming rate of unemployment in Nigeria, which can be attributed to various factors such as a lack of proper training and essential employable skills, the state economy and economic activities, the political agenda, security reasons, cultural factors, skewed budget allocation, and an inadequate intervention program (Ewubare & Ogbuagu, 2017).

Despite all these consequences, there have been numerous attempts to reduce unemployment in Nigeria, including educational curriculum changes that include vocational courses; the Programme Life for Rural Women; the Family Support Programme; and the National Directorate of Employment (NDE), which was established on November 22, 1986. Furthermore, numerous studies have been conducted to investigate youth unemployment in Nigeria (Adebimpe et al., 2021; Uju & Racheal, 2018). This creates a gap and emphasizes the need for studies that take a different approach and include women because of their critical

role in the economy and society. As a result, investigating unemployment as it relates to women is critical. It is expected that researching the factors influencing women's unemployment will make a significant contribution to efforts to address the issues raised.

3. Materials and Methods

The dataset came from the National Demographic and Health Survey (NDHS) (National Population Commission, 2019), a cross-sectional descriptive survey of the total population that focused primarily on the empowerment of women. The 2018 Nigeria Demographic and Health Survey was conducted by the National Population Commission (NPC), which supported data collected from 14 August to December 29, 2018. The data include 41821 study participants, who were women between the ages of 15 and 49. No pre-processing of the data was required. The selection of features is important for machine learning classifier models. Finding the right features for a classification model to employ helps it function more effectively (Mqadi et al., 2021). The dataset in this instance had 13 features; however, 12 of the features were chosen, as shown in Table 1. (1) highest education level, (2) Wealth index, (3) type of place of residence, (4) currently pregnant, (5) currently breastfeeding, (6) currently marital, (7) households age, (8) woman age at the first birth, (9) occupational status, (10) region, (11) ethnicity and (12) age.

Table 1. Description of the NDHS data (n = 41821)

Features	Categories	Frequency	Percentage (%)
Region	Northcentral	7772	18.6
	Northeast	7639	18.3
	Northwest	10129	24.2
	Southeast	5571	13.0
	South-south	5080	12.1
	Southwest	5630	13.5
The type of place of residence	Urban	24837	59.4
	Rural	16984	40.6
Age	15–19	8423	20.2
	20–24	6844	16.4
	25–29	7203	17.2
	30–34	5997	14.3
	35–39	5406	12.9
	40–44	4057	9.7
	45–49	3891	9.3
Educational level	Higher	4342	10.4
	No education	14398	34.4
	Primary	6383	15.3
	Secondary	16698	39.9
Ethnicity	Ekoi	275	0.7
	Fulani	2953	7.1
	Hausa	10765	25.7
	Ibibio	801	1.9
	Igala	457	1.1
	Igbo	5714	13.7
	Ijaw	1201	2.9
	Kanuri	873	2.1
	Tiv	976	2.3
Yoruba	5372	12.8	

		Continuation of Table 1		
Religion	Others	11404	27.3	
	Don't know	30	0.1	
	Catholic	4436	10.6	
	Islam	20959	50.1	
	Other	200	0.5	
	Other	16070	38.4	
	Christian			
	Traditionalist	156	0.4	
	Household Head	Female	7207	17.2
	Gender	Male	34614	82.8
	Wealth index	Middle	8859	21.2
		poorer	8346	20.0
poorest		7747	18.5	
Richer		8840	21.1	
Richest		8029	19.2	
Current marital Status	Divorced	543	1.3	
	Partnership	1047	2.5	
	Married	27841	66.6	
	Never in union	10669	25.5	
	Separated	604	1.4	
	Widowed	1117	2.7	
	Age of respondents at 1st birth	0–20	19524	46.7
21–40		10453	25.0	
40–41		15	0.0	
Undisclosed		11829	28.3	
Currently pregnant	No and Unsure	37630	90.0	
	Yes	4191	10.0	
Pregnancy Term	0-3 Months	1149	2.7	
	4-6 Months	1596	3.8	
	7-10 Months	1446	3.5	
	Undisclosed	37630	90.0	

In the literature, there are various cross-validation techniques for choosing a sample to use as training data. Actual samples were separated into k equal-sized subsamples using the k-fold cross-validation approach. The classification model is tested using each subsample as the validation data, and the process is repeated k times. This method has an advantage over repeated random subsampling because training and validation are performed for each at least once (Raju et al., 2018). Because it helps reduce the variability of accuracy estimations for statistical comparison, 10-fold cross-validation was performed in this study (Berrar, 2019). To determine the relevant elements that impact women's employment in Nigeria, a machine learning approach was used. All eight machine learning classifier models had their classification rules adopted during the training stage; as a result, the testing stage is used to evaluate the classification rules' accuracy. To execute algorithms and acquire statistical findings, WEKA, a data mining tool, was employed. The design of the NDHS women unemployment in Nigeria used in this study is depicted in Figure 1.

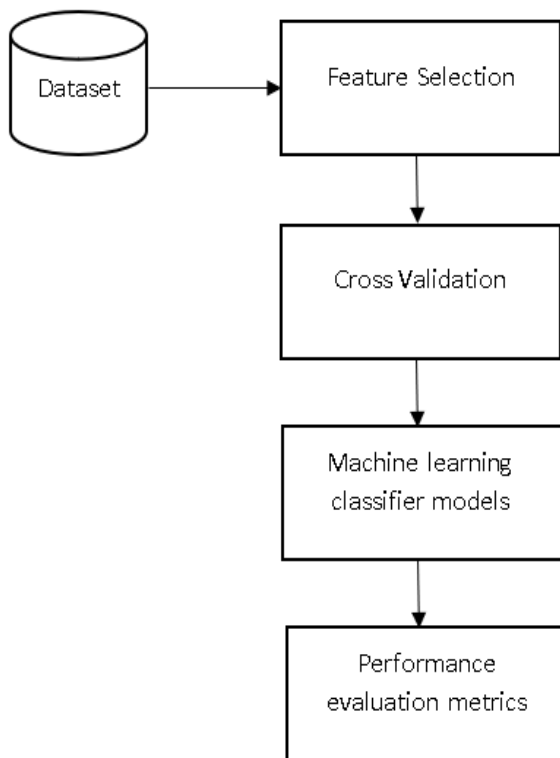


Figure 1. The study design of women unemployment in Nigeria using machine learning classifier models

3.1. J48 Pruned Tree

Using information gain, J48 pruned tree constructs the decision tree from the training data set and evaluates the same after selecting an attribute for data splitting. The algorithm then iterates over smaller selections. If every instance in a subset belongs to the same class, the splitting process comes to an end. The decision tree's leaf node, which presents the outcomes, is then formed. Considering that decisions are made using the Depth-first technique, J48 is marginally improved from C4.5 (Ratra et al., 2021).

3.2. Support Vector Machine

To separate and organize features, a support vector machine built a hyperplane. To determine the best hyperplane, support vectors are produced on either side of the hyperplane, with each vector maximizing the distance between them. A more precise decision boundary between the category features is produced by a larger vector distance around the hyperplane (Hansrajh et al., 2021; Mqadi et al., 2021). Depending on where they are on the hyperplane, the data points are divided into several classes. The primary goal is to increase the gaps between the hyperplane and the data point. Support vector machines, which have been successful in many real-world applications, give conspicuous qualities including margin maximization and nonlinear classification using kernel tricks (Naicker et al., 2020).

3.3. AdaBoost

AdaBoost, an ensemble learning algorithm, is used to improve the precision of decision trees and other weak binary classifiers. Here, weak classifiers add

sequentially in contrast to random forest. A dataset with N feature variables will produce N decision stump. All decision stumps were initially given equally weighted data. Based on the lower value of Entropy, the base model, which is the first stump, will be chosen. Following that, each observation is updated with a new weight adjusted depending on performance and overall inaccuracy (Chhillar, 2021).

3.4. Logistic Regression

In each data set, the Logistic Regression inducer looks for a link between the independent variable and the class label that is based on likelihood. The objective is to develop a probability function that accepts features as inputs and outputs the likelihood that an instance belongs to a particular class. The logistic regression needs significantly fewer computational resources and does not require scaling of the input features (Mutanga et al., 2022).

3.5. Naïve Bayes

A straightforward machine learning technique called Naive Bayes (NB) uses the Bayes theorem to calculate class probabilities while assuming that the features are independent. The class with the highest likelihood then receives the predictions. Their probability distributions must be estimated to derive probabilities from continuous features. Usually, kernel density estimation is used for this. The classifier has demonstrated that it can compete with more sophisticated classifiers even though the independence assumption of NB rarely holds in practice (Ijaz et al., 2021).

3.6. Logistic Model Tree

The C4.5 method and logistic regression (LR) functions are combined in the logistic model tree. The LogitBoost approach is used to fit the logistics regression functions at a tree node after the information gain ratio technique has been used to divide the tree into nodes and leaves. The C4.5 algorithm chooses features using the entropy strategy since it is the quickest way to produce accurate classification results (Nhu et al., 2020).

3.7. Bagging

Bootstrap aggregating, also known as bagging, entails giving each model in the ensemble the same weight when voting (Kabari & Onwuka, 2019). The different iterations of the base predictive model are created by bootstrap replications, which use one of the most widely used methods for data resampling in statistical research. Predictive model bagging is a framework that reduces variance and avoid overfitting (Lin et al., 2022).

3.8. Random Forest

The random forests framework is an ensemble learning method that, during training, integrates a collection of decision trees and creates a class representing the mode of the classes found inside the

various trees (Lin et al., 2022).

In random forests, each tree in the group is constructed using a bootstrap sample, or an example is drawn with substitution, from the training set (Dutta et al., 2018). Similarly, when dividing a node during tree construction, the split that is chosen is no longer the best split across all features. Instead, the split that is chosen is the best split among a selection of traits that were chosen at random. The bias of the forest slightly increases due to this unpredictability, but because of averaging, its volatility also decreases, often more than making up for the increase in propensity, leading to an overall superior model. Overfitting is a general problem in decision trees; hence, random forests help prevent it.

4. Results and Discussion

The random forest learning model outperformed the other seven classical learning models with an accuracy of 86.9% as shown in Table 2. The J48 pruned tree achieved an accuracy of 75.2%, followed by Support Vector Machine (71.1%), AdaBoost (71.0%), Logistic Regression (72.0 %), Naive Bayes (68.0 %), Logistic Model Tree (74.2 %), and Bagging (70.7 %). Because random forest had the advantage of guaranteeing greater levels of accuracy and efficiency, it outperformed the next conventional learning model, Bagging, by 9.6% in terms of accuracy.

Table 2. Performance evaluation metrics of the machine learning classifier models

	Accuracy (%)	Precision	Recall	F-measure	MCC
Random Forest	86.9	0,869	0,869	0,869	0,713
J48 pruned tree	75.2	0,746	0,752	0,744	0,436
Support Vector Machine	71.1	0,700	0,711	0,699	0,335
AdaBoost	71.0	0,700	0,710	0,686	0,320
Logistic Regression	72.0	0,710	0,720	0,709	0,357
Naive Bayes	68.0	0,692	0,680	0,684	0,323
Logistic Model Tree	74.2	0,735	0,742	0,734	0,413
Bagging	77.7	0,773	0,777	0,772	0,498

Furthermore, Table 1 results show that the Random Forest learning model outperforms other traditional learning models. The bagging learning model is the closest to the RF learning model, with precision, recall and F-measure scores of 0.773, 0.777, and 0.772 respectively. RF achieved the greatest average precision, recall and F-measure score of 0.869. Consequently, MCC essentially measures the correlation between the predicted and actual series. The bagging learning model reached second best with a score of 0.498, while the random forest learning model had the best score of 0.713 for MCC.

The largest portion of the ROC and PRC areas is covered by RF (0.945) as shown in Table 3. Higher values for kappa statistics, which range from 0 to 1, assume a stronger inter-rate agreement. It is a more

accurate projection of a Percentage treaty than usual. As shown in Table 3, RF continues to perform better than other traditional learning models, recording a kappa statistic score of 0.713.

Additionally, it can be shown that AdaBoost outperforms other learning models in terms of MAE value, having the highest value (0.371), while Random Forest has the lowest value (0.224). Finally, the length of time needed to construct the model differs, with Naive Bayes recording the shortest training time (11.9 seconds) and Random Forest recording the longest training time (18.9 seconds). RF outperformed the other seven classical learning models on all nine performance evaluation parameters, despite having the highest training time.

Table 3. ROC area, PRC area, the Kappa statistics, mean absolute error and training time of the machine learning classifier models

	ROC Area	PRC Area	Kappa Statistics	Mean Absolute Error	Training Time (s)
Random Forest	0,945	0,945	0.713	0.224	18.5
J48 pruned tree	0,775	0,776	0.429	0.352	12.6
Support Vector Machine	0,653	0,653	0.327	0.289	12.8
AdaBoost	0,756	0,750	0.297	0.371	13.2
Logistic Regression	0,768	0,768	0.350	0.367	12.0
Naive Bayes	0,736	0,738	0.322	0.351	11.9
Logistic Model Tree	0,792	0,798	0.407	0.348	12.6
Bagging	0,850	0,851	0.494	0.317	16.1

The confusion matrix for the random forest, which produced the most accurately categorized class for the unemployed women in Nigeria in the NDHS dataset, is shown in Figure 2.

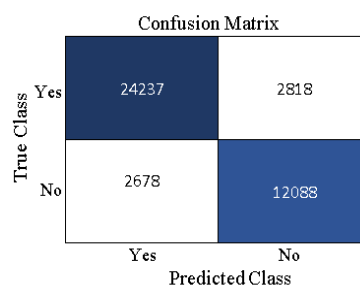


Figure 2. Random forest confusion matrix

5. Conclusion

Ensemble classifiers like Random Forest used in this work outperformed other classical machine learning models because of the inherent problem of significant variation, which makes it difficult for classical machine learning models to correctly categorize the dataset. The factors examined in this study provide significant insights with potential recommendations to reduce women's unemployment and assist the primary drivers of sustainable employment in Nigeria in the investigation of factors influencing women's unemployment in Nigeria. Only secondary data from the Nigeria Demographic and Health Survey were used in this study (NDHS). In this study, the twelve factors identified to be explored and investigated were as follows: highest education level, wealth index, type of place of residence, currently pregnant, currently breastfeeding, currently marital, households ages, woman age at the first birth, occupational status, region, ethnicity and age. In this study, a random forest was used to analyze each of these factors and determine their effects on women unemployed in Nigeria. Because the results were acquired using the NDHS dataset, the variables and models developed can be used to estimate new data produced in the future to analyze factors influencing women's unemployment. Instead of traditional attempts to analyzing the influencing factors associated with women's unemployment, this study applied machine learning, a current statistical, algorithmic approach. The outcome shows that, out of the twelve categories, age groups, ethnicity, marital status, and religion are the four main factors affecting women's unemployment in Nigeria. As a result, the results might not be representative of the unemployment problem in other developing countries. Generalization, on the other hand, was not intended because the goal was to emphasize the significance of the identified factors that influence women's unemployment in Nigeria. This study offers insightful information on the phenomenon of women's unemployment for governmental and non-governmental issues. To strengthen future research on women unemployment, the criteria considered during data collection should be expanded as literature has shown that women are more susceptible to unemployment, which might be caused by gender health inequality (Acevedo et al., 2020).

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