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Predictive Model for Financial Availability and Usability: Rural Population Segmentation

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ABSTRACT

Financial inclusion remains a critical challenge in global economic development, with approximately 1.7 billion adults' worldwide still lacking access to basic financial services. Despite significant progress over the past decade, disparities in financial access persist across regions, income levels, and demographic groups. Recent years have seen significant advancements in "financial availability and usability" of banking and financial services prediction accuracy, thanks to AI-driven methods, especially those utilizing "Machine Learning" (ML) techniques. This study addresses the critical issue of financial inclusion by analyzing the impact of demographic variables (age, gender, education, income, occupation, and source of income) on financial availability and usability among rural populations & developing and validating predictive models for financial availability and usability, incorporating rural population segmentation. The most affected areas are categorized into two types through three different cluster analyses like K-means, "Hierarchical Clustering" (HC) and "Partitioning Around Medoids" (PAM) using all the 6 demographic variables. For highly affected areas, it is needed to predict "financial availability and usability". The dat, aset of 102 data points pertaining to 70% of data set is utilized for training while that of 30% is utilized for testing. The collected data was analyzed using descriptive techniques and advanced statistical methods to identify trends and correlations. Efficiency of the models is tested by cluster analysis, decision tree, regression model, and two "Artificial Neural Network" (ANN) models having hidden layer of one and two. All the models are using "Root Mean Squared Error (RMSE)" and "Mean Absolute Errors (MAE)" for performance evaluation. It is investigated that regression models show the lower RMSE and MAE results. Overall, this research highlights the potential advantages of implementing AI-driven methods in various regions and adds to the expanding body of work on using machine learning to accurately predict financial inclusion, a task that is both complex and vitally important.

Keywords: Financial inclusion, AI-driven models, Western Odisha, Sambalpur, RMSE, MAE, Cluster analysis

1. Introduction:

Financial inclusion, a critical factor in economic development and social progress, remains a complex challenge influenced by various demographic variables (Omar & Inaba, 2020). This study employs advanced analytical techniques, including cluster analysis, decision trees, artificial neural networks, and regression models, to examine the intricate relationships between financial availability and usability as dependent variables and demographic factors such as age, gender, education, income, occupation, and source of income as independent variables. By leveraging these sophisticated methodologies, we aim to uncover nuanced insights into the determinants of financial inclusion, potentially informing targeted policy interventions and innovative financial service designs.

The research on financial availability and usability as dependent variables influenced by demographic factors drew upon several key theories. The Life Cycle Hypothesis (Modigliani & Brumberg, 1954) provided a framework for understanding how age impacts financial decisions and inclusion. Social Identity Theory (Tajfel & Turner, 1979) offered insights into how gender and occupation shape financial behaviors. Human Capital Theory (Becker, 1964) underpinned the examination of education's role in financial inclusion. The Permanent Income Hypothesis (Friedman, 1957) informed the analysis of income's impact on financial access and usage. Network Theory (Granovetter, 1973) helped explain how social connections, often tied to occupation and income source, influence financial inclusion. Diffusion of Innovations Theory (Rogers, 1962) provided a lens through which to view the adoption of financial services across different demographic groups. These theories, combined with advanced analytical techniques like decision trees, artificial neural networks, regression models and cluster analysis, enabled a comprehensive exploration of the complex interplay between demographic variables and financial inclusion.

Recent studies demonstrated a growing interest in using machine learning techniques to evaluate financial inclusion by demographic segments, with the integration of Artificial Neural Networks, decision trees, and regression models improving prediction and classification of financial behavior, especially in underbanked populations (Wang et al., 2023; Smith et al., 2021). There was an increasing focus on user-centric financial service design, informed by deep learning insights from demographic data (Brown & Garcia, 2022), and researchers explored granular data to better understand financial usability, shifting away from merely assessing availability (Johnson & Lee, 2022). The digitalization of financial services and the rise of fintech solutions shaped new forms of inclusion, requiring more advanced analytic tools (Zins & Weill, 2016). However, issues such as lack of standardized datasets (Demirgüç-Kunt et al., 2018), algorithmic bias (Barocas et al., 2019), and model interpretability (Lipton, 2018) challenges persisted. Challenges included data privacy and ethical use concerns (Taylor, Floridi, & van der Sloot, 2017), demographic shifts affecting model stability (World Bank, 2022), technological inequality limiting access to fintech solutions (GSMA, 2021), and difficulties in model generalizability (Nguyen et al., 2020) across different contexts.

This study addresses the critical issue of financial inclusion by analyzing the impact of demographic variables (age, gender, education, income, occupation, and source of income) on financial availability and

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usability among rural populations & developing and validating predictive models for financial availability and usability, incorporating rural population segmentation, to enhance targeted interventions and improve access to financial services in underserved areas. Despite global efforts to improve financial access, significant disparities persist across different demographic groups, hindering economic growth and social equity (Mishra et al., 2024). By employing advanced analytical techniques such as Cluster Analysis, Decision Trees, Artificial Neural Networks, and Regression Models, this research aims to uncover nuanced patterns and predictive factors influencing financial inclusion. The findings will contribute to a more comprehensive understanding of the barriers to financial access and usage, enabling policymakers, financial institutions, and stakeholders to develop targeted strategies for enhancing financial inclusion across diverse populations.

The rest of this paper is systematized as follows: In Section 2, there is a summary of important literature. Section 3 discusses the techniques used, including datasets, metrics for performance evaluation, and a detailed look at techniques such as "Decision tree," "ANN," and "Regression" models. Section 4 presents the experimental results and the outputs for all models. Finally, Section 5 offers a detailed analysis of the results, their practical effects, and final thoughts.

2. Related work

Financial inclusion, which encompasses the availability and usability of financial services to all individuals and businesses regardless of income or social status, has gained significant attention as a crucial factor in promoting economic growth, reducing poverty, and fostering social development (Ratnawati, 2020). Examining financial availability and usability is essential for identifying barriers, tailoring solutions, measuring progress, and enhancing economic participation (Jejeniwa et al., 2024; Park & Mercado, 2015). Demographic variables such as age, gender, income level, education, occupation and source of income play a crucial role in understanding financial inclusion patterns and developing effective strategies. To analyze financial inclusion data and predict outcomes, various statistical and machine learning techniques can be employed, including decision trees, artificial neural networks (ANNs), regression models and cluster analysis. These techniques can help identify vulnerable groups, tailor financial products, and design targeted policies to improve financial inclusion.

Demographic characteristics play a crucial role in financial inclusion across various contexts. Income, education, and age consistently emerge as significant factors influencing access to financial services (Raza et al., 2023; Lotto, 2018; Hasan et al., 2021). Higher income and education levels generally correlate with increased financial inclusion (Khushboo & Pradhan, 2024; Kumar & Pradhan, 2024; Susilowati et al., 2024). Age shows a complex relationship, with some studies indicating a non-linear (inverted U-shaped) correlation (Kumar & Pradhan, 2024), while others suggest older age may reduce the likelihood of account ownership (Susilowati et al., 2024). Gender's impact varies across studies, with some finding no significant effect (Susilowati et al., 2024; Nguyễn, 2019) and others highlighting vulnerabilities for female households, particularly in South Asian countries (Khushboo & Pradhan, 2024). Marital status, occupation, and number of dependents also influence financial awareness and inclusion (Kaviyarasu V & Siddiq, 2024; Compaore & Maiga, 2024). Digital engagement and employment status further affect access to financial services (Shamim et al., 2024; Nandru et al., 2021). These demographic factors are crucial for policymakers to consider when developing strategies to enhance financial inclusion, particularly among disadvantaged groups (Nguyễn, 2019).

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Recent studies have explored the influence of demographic factors on financial inclusion, focusing on availability and usability aspects. Behera (2024) indicates that education, income, property ownership, and financial literacy positively impact financial inclusion, while factors like gender, lower socio-economic status, and illiteracy have negative effects. Similarly, Wibisono & Anastasia (2024) and Kumar & Pradhan (2024) emphasize the significance of age, education, income, and gender in shaping saving decisions and access to financial services. Widyastuti et al. (2024) and Ali & Ghildiyal (2023) highlight the importance of digital financial literacy and the positive influence of higher education and income on digital financial inclusion. The Determinants of Financial Inclusion in Asia—A Bayesian Approach (2022) identifies education as the strongest determinant of financial inclusion, with income and employment status also playing crucial roles. Compaore & Maiga (2024) and Issac & Seranmadevi (2024) further emphasize the significance of education and access to resources in moderating financial literacy and resilience. Mawad et al. (2022) note that financial literacy impacts both genders and generations, while Jha et al. (2022) concludes that demographic characteristics contribute to financial exclusion, affecting access to banking services and effective utilization of savings.

Researchers have employed various machine learning techniques to analyze these relationships. For instance, decision trees have been used to identify key demographic predictors of financial service adoption (Smith et al., 2021). Regression models have helped quantify the impact of variables like age, gender, and income on financial access (Johnson & Lee, 2022). Artificial Neural Networks (ANNs) have demonstrated success in predicting financial behavior patterns across different demographic groups (Wang et al., 2023). Additionally, cluster analysis has revealed distinct segments of the population with similar financial inclusion characteristics based on demographic profiles (Brown & Garcia, 2022). These advanced analytical approaches have provided valuable insights into the complex interplay between demographic variables and financial inclusion, informing targeted strategies to enhance financial availability and usability across diverse populations. This literature review highlights the need for continued research utilizing these advanced analytical techniques to inform policy-making and financial service design. Future studies should focus on longitudinal analyses to capture evolving trends and the impact of technological advancements on financial inclusion across diverse demographic groups.

3. Research Methodology

This study employed a four-stage methodology to examine the determinants of financial inclusion and associated factors. An extensive literature review was conducted, analyzing studies, articles, and reports on the influence of socio-economic characteristics on financial inclusion. Databases such as Google Scholar, ProQuest, ResearchGate, and ScienceDirect were utilized as primary sources. Subsequently, a survey instrument was developed and validated by experts. Upon approval, it was distributed to collect the perspectives and experiences of rural inhabitants. The data collected underwent analysis through the application of descriptive techniques and advanced statistical methods to identify trends and correlations. Various AI-driven machine learning models, including "Cluster Analysis," "Decision Tree," "ANN," and "Regression Model," were employed for financial inclusion datasets. The findings suggest that both the ANN and Regression models for financial availability and financial usability outperform all other models, respectively.

3.1. Data and Preliminary Analysis

Our research is concentrated in the Sambalpur District of Western Odisha, a developing region within the state. A significant portion of the population in Sambalpur remains underdeveloped and requires

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integration into inclusive financial systems. Numerous studies have endeavored to assess and quantify financial inclusion in India. This study aims to evaluate the influence of socio-economic characteristics on variables related to "financial inclusion" and to identify causal factors. Data were collected through in-person surveys conducted in the rural areas of Sambalpur District. The survey comprised two sections: demographic and general information, and participants' understanding and experiences with financial inclusion. The rural population was the primary focus, identified through visits to the District Rural Development Agency, Odisha Rural Development and Marketing Society, and Mission Shakti Office in Sambalpur. Employing a multistage sampling technique, 102 respondents were selected from the district, specifically from the Jamankira and Dhankauda blocks, as well as the Kulundi and Jamadarpali villages. The dataset is partitioned such that 70% is utilized for training, while the remaining 30% is reserved for testing all models. Figure 1 illustrates the current study area within the Sambalpur District, and Figure 2 depicts the studied blocks and villages within the district.

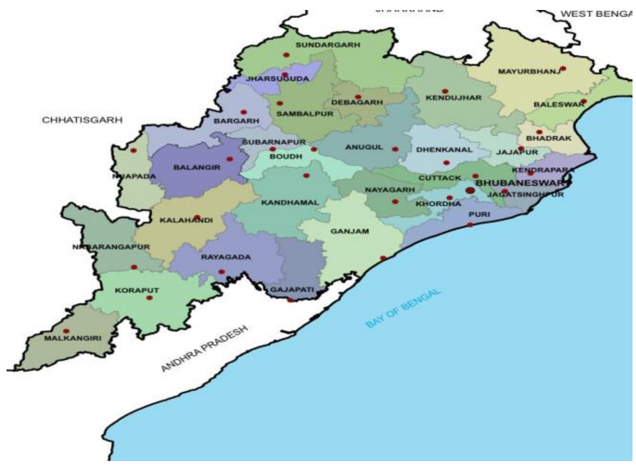

Figure 1: Sambalpur District in Odisha

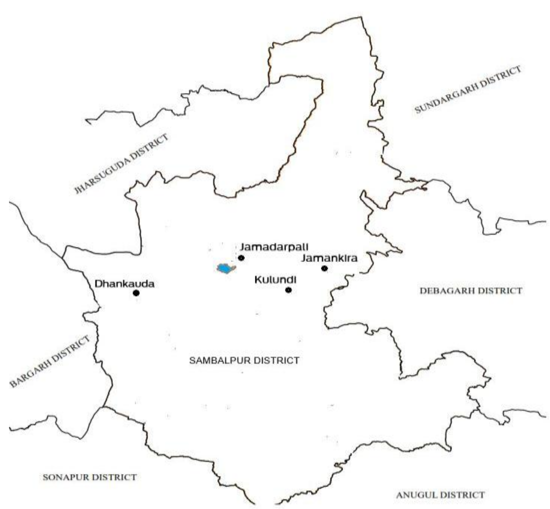

Figure 2: Studied Villages in Sambalpur

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Table 1: Descriptive Statistics of the Demographic Variables and Two Financial Inclusion Variables of Sambalpur District

Sl. No.	Variables	Variable types	Minimum	Q1	Median	Mean	Q3	Standard Deviation	Maximum	Skewness	Kurtosis
1	Gender	Int	1.000	1.000	2.000	1.529	2.000	0.5015991	2.000	-0.1178511	1.013889
2	Age	Int	18.00	29.00	35.00	38.99	47.00	13.3783445	73.00	0.6167612	2.622677
3	Education	Int	1.000	1.000	2.000	1.775	2.000	0.6118769	3.000	0.1628468	2.466901
4	Occupation	Int	1.000	3.000	5.000	4.853	7.000	2.1452091	7.000	-0.3342328	1.567332
5	Income	Int	1.000	1.000	1.000	1.569	2.000	0.8618401	5.000	1.6051652	5.308544
6	Source of income	Int	1.000	2.000	2.000	3.461	4.000	2.0376242	7.000	0.8789504	2.255638
7	Financial availability	num	1.420	2.000	2.210	2.176	2.370	0.3083189	2.740	-0.7063998	3.451384
8	Financial usability	num	1.110	1.670	1.805	2.132	2.720	0.6725721	3.670	0.6276240	2.332755

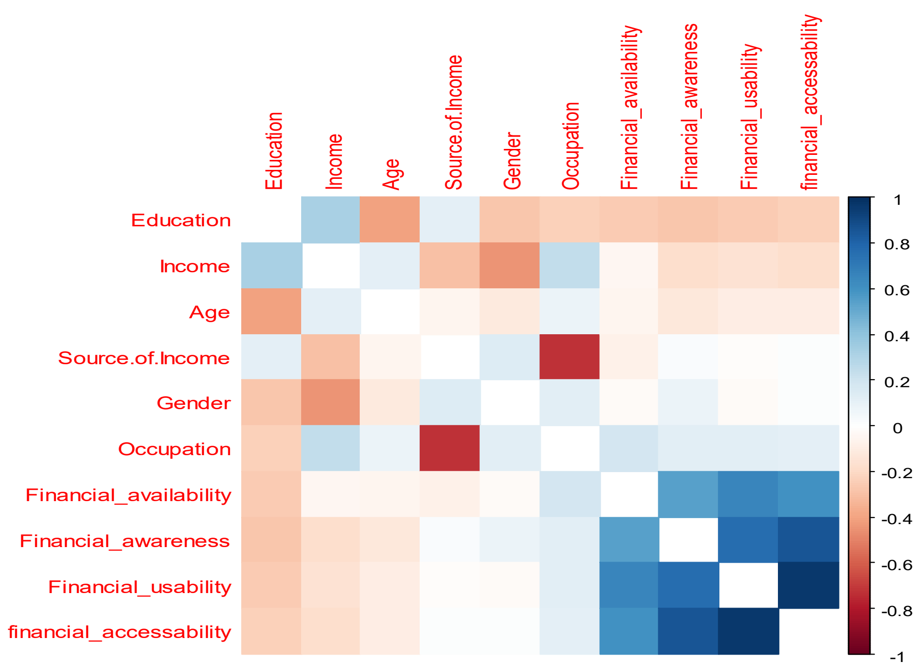

Figure 3: Correlation Plot of Six Demographic Variables and Four Financial Inclusion Variables

3.2. Performance Measurement Metrics

The "Root Mean Square Error (RMSE)" and the "Mean Absolute Error (MAE)" are utilized to assess effectiveness of diverse predicting models on financial inclusion datasets (Chakraborty et al., 2020). The equations for these two performance assessment metrics are delineated as follows:

$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_i - \hat{x}_i)^2}$ and $MAE = \frac{\sum_{i=1}^{n}|x_i - \hat{x}_i|}{\mathrm{n}}$

The quantity of data points within the time series is represented by n, with x_i denoting the true value and $\hat{x}_i$ indicating the estimated value. A lower value of the performance metrics indicates a more effective model.

3.3. Cluster Analysis

Cluster analysis is a statistical technique used to group similar objects or data points into clusters based on their characteristics or attributes (Jain et al., 1999). This method aims to maximize intra-cluster similarity while minimizing inter-cluster similarity, allowing researchers to identify patterns and structures within complex datasets (Xu and Wunsch, 2005). Various clustering algorithms exist, including hierarchical clustering, which creates a tree-like structure of clusters, and partitional clustering, such as k-means, which divides data into a predetermined number of groups (MacQueen, 1967). Cluster analysis has wide-ranging applications across multiple disciplines, including market segmentation, image processing, and bioinformatics, where it helps uncover hidden patterns and relationships in large datasets (Berkhin, 2006).

3.4. Decision tree

Decision trees are powerful machine learning algorithms widely used for classification and regression tasks in various domains, including finance, healthcare, and marketing. These hierarchical models make decisions by recursively splitting data based on feature values, creating a tree-like structure of nodes and branches (Quinlan, 1986). Decision trees offer several advantages, such as interpretability, handling both numerical and categorical data, and capturing non-linear relationships (Breiman et al., 1984). However, they are prone to overfitting, especially when dealing with complex datasets (Hastie et al., 2009). To address this limitation, ensemble methods like Random Forests and Gradient Boosting have been developed, combining multiple decision trees to improve predictive performance and generalization (Breiman, 2001; Friedman, 2001). Recent advancements in decision tree algorithms focus on optimizing computational efficiency and handling high-dimensional data, making them valuable tools in the era of big data and machine learning (Chen & Guestrin, 2016).

3.5. Artificial Neural Networks

Artificial Neural Networks (ANNs) are computational models inspired by the structure and function of biological neural networks in the human brain (Kruse et al., 2016). These networks consist of interconnected nodes, or "neurons," organized in layers that process and transmit information. ANNs learn from data by adjusting the strengths of connections between neurons, allowing them to recognize patterns and make predictions. The architecture of ANNs typically includes an input layer, one or more hidden layers, and an output layer, with each layer performing specific computations. Through training algorithms such as back propagation, ANNs can optimize their parameters to minimize errors and improve performance (Zhou et al., 2020). This adaptability makes ANNs powerful tools for various tasks, including image and speech recognition, natural language processing, and complex decision-making processes (Jia et al., 2023).

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3.6. Regression Model

Regression models are statistical techniques used to analyze the relationship between a dependent variable and one or more independent variables. These models aim to estimate the impact of predictor variables on the outcome variable, allowing for prediction and inference (Bender, 2009; Nick & Campbell, 2007). Linear regression, a common type, assumes a linear relationship between variables and uses the method of least squares to fit a line that minimizes the sum of squared residuals. More complex regression models, such as polynomial or multiple regression, can capture non-linear relationships or incorporate multiple predictors (Marill, 2004). Regression analysis is widely applied in various fields, including economics, social sciences, and natural sciences, to understand patterns, make predictions, and inform decision-making processes (Mack et al., 1981; Peterson et al., 1999).

4. Experimental Evaluation and Results of AI-Driven Financial Availability and Financial Usability Models

Determining the traits and attributes of financial inclusion datasets presents an important challenge. For the data sets of financial availability and usability of the two villages such as Kulundi and Jamadarpali studied. The present research focuses on evolving data-driven forecast of availability and usability of financial and banking services at Sambalpur district with respect to the demographic variables namely age, gender, education, occupation, income & source of income using Cluster Analysis, Decision Tree, ANN, & Regression model. Table 1 shows the description of the different components related to financial inclusion of the Sambalpur district. Figure 3 shows the correlation plot of all the six variables.

4.1. Rural Population Segmentation through Cluster Analysis: Financial Availability and Usability

Various cluster analysis techniques, including K-means, Hierarchical Clustering (HC), and Partitioning Around Medoids (PAM), have been employed on a dataset consisting of 102 data points to segment items related to Financial Inclusion. The analysis revealed that the data points were divided into two clusters, with sizes [67, 35] for K-means and [80, 22] for HC and PAM. These methods identified two primary components of financial inclusion: financial availability and financial usability. The study aims to predict financial availability and usability within the context of financial inclusion in Odisha, India. Figure 4 illustrates the distance matrix plot, while Figure 6 depicts the optimal number of clusters for the six variables under consideration. Figures 7, 10 and 11 present the K-means, hierarchical dendrogram, and PAM cluster plots, respectively, all of which yield two clusters for Financial Inclusion. Figure 9 provides a visual representation of the dataset, displaying the numerical values of variables in the cluster analysis, indicative of length or height. The analysis revealed two distinct groups within banking and financial services: one with well-developed infrastructure and another with less developed infrastructure. K-means analysis identified significant population characteristics, including individuals aged 45 or older, with incomes below 1 lakh (100,000), and occupations such as self-employed, farmers, and homemakers. Hierarchical Clustering (HC) results highlighted population characteristics including education levels of matriculation and graduation, occupations such as students and homemakers, and incomes less than 50,000. These findings provide insights into the demographic and socioeconomic factors associated with banking and financial services usage in the studied population, revealing distinct segments with varying levels of access and engagement in the financial sector.

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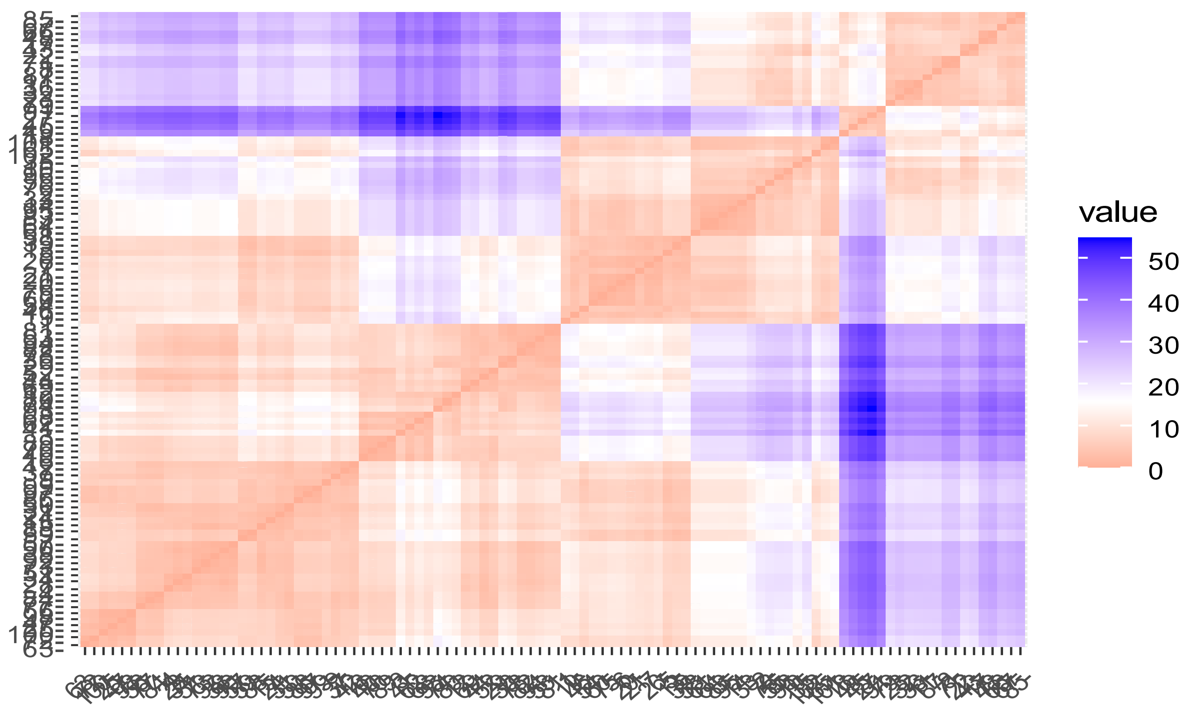

Figure 4: Plotting of Distance Matrix

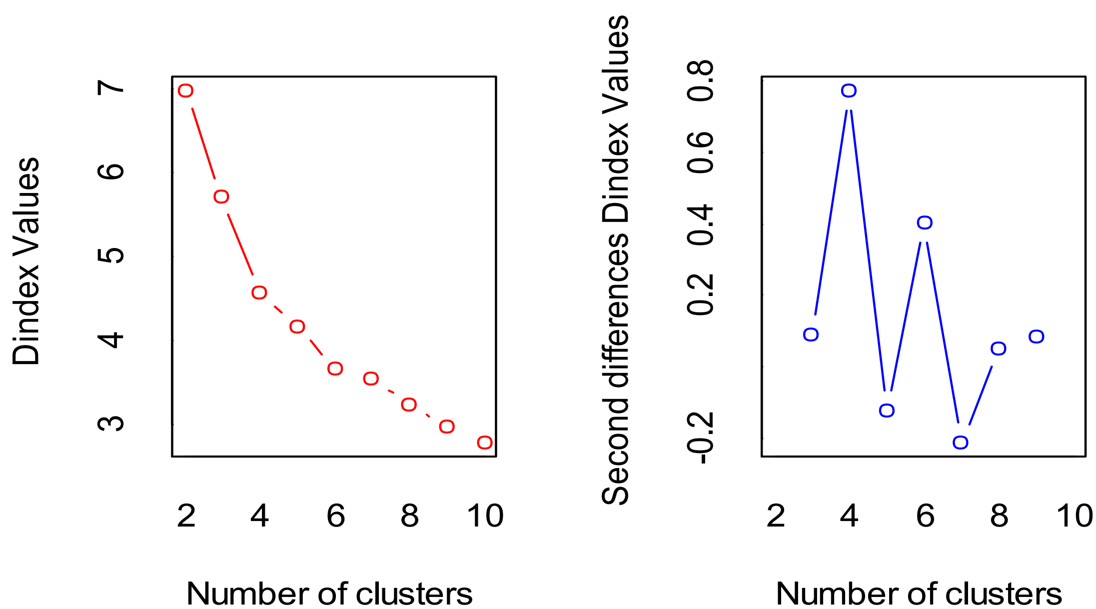

Figure 5: Optimal number of clusters

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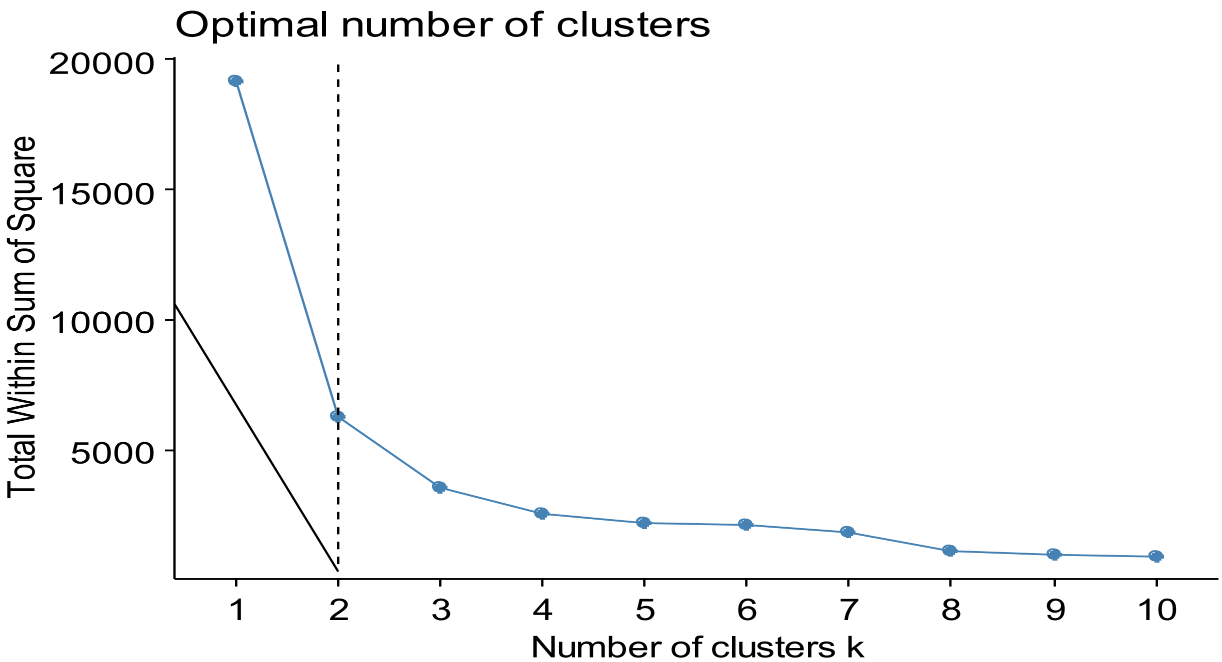
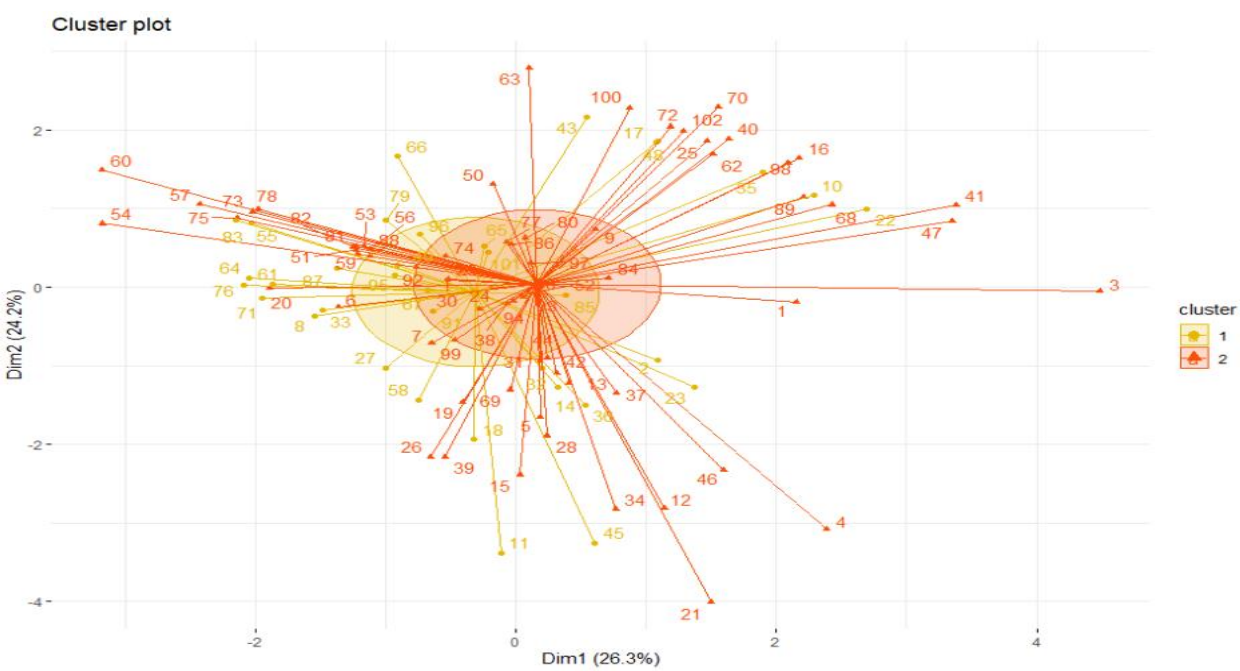


Figure 6: Optimal Number of Clusters

Figure 7: K-means cluster plot dividing two clusters using 6 variables



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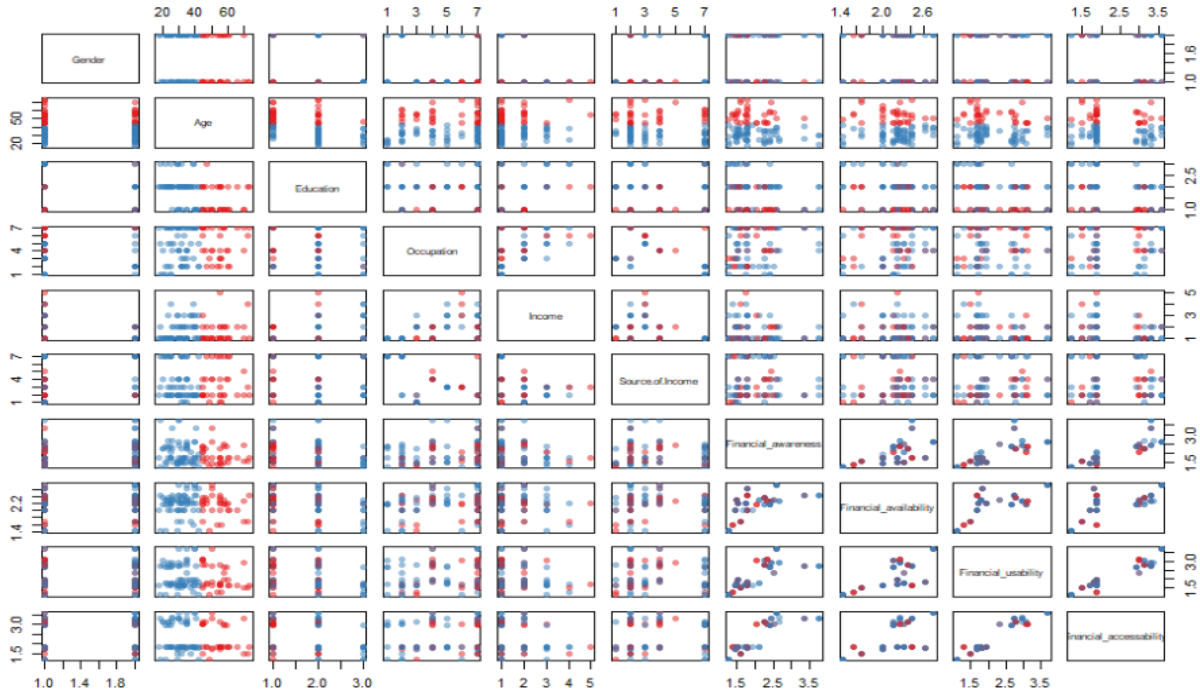

Figure 8: Scatter plot

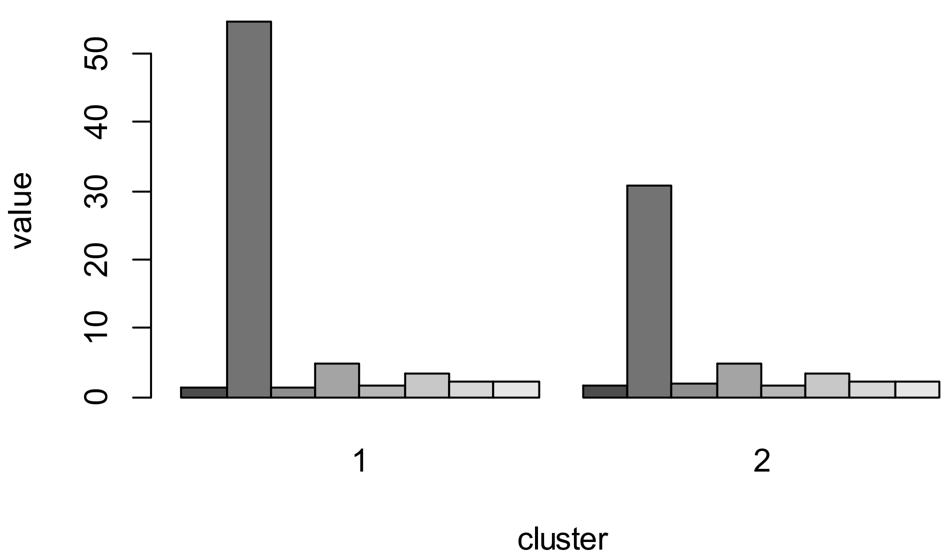

Figure 9: Pictorial Representation of the Dataset Contain the Numerical Values of Variables in Cluster Analysis that Represent the Length or Height

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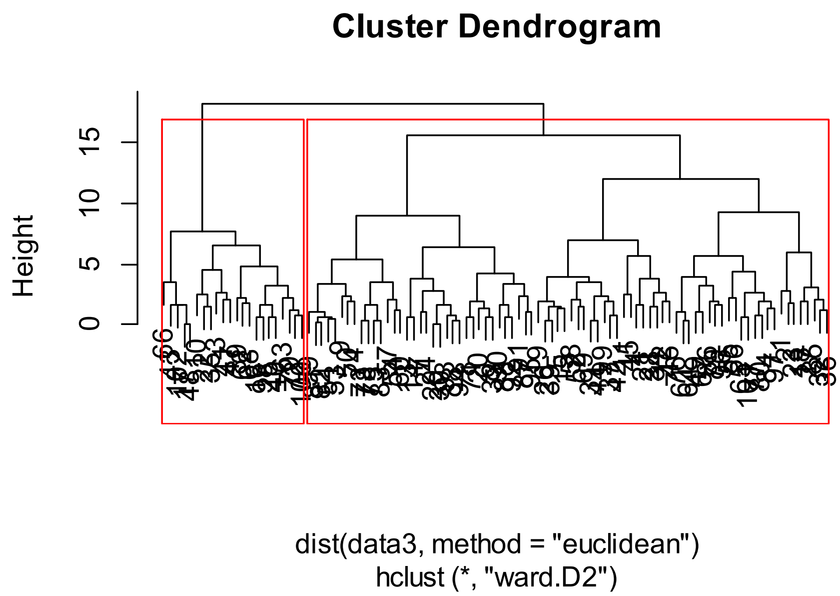

Figure 10: Hierarchical cluster plot dividing two clusters using 6 variables

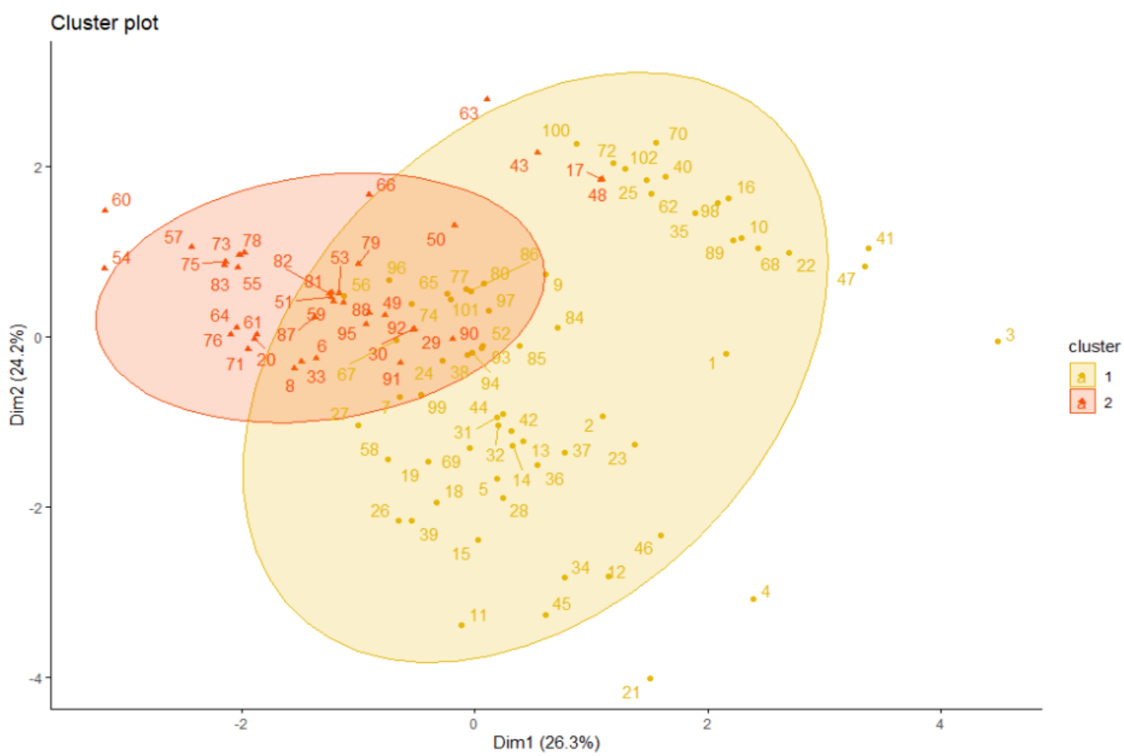

Figure 11: PAM Cluster plot dividing two clusters using 6 variables

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4.2. Predictive Modeling of Financial Availability and Usability

4.2.1. Decision Tree Model for Financial Availability

Decision Tree (DT) models function as effective classifiers by utilizing a tree-like structure to delineate the relationships between features and potential outcomes. Upon reaching a final decision, the tree culminates in leaf nodes, also referred to as terminal nodes, which indicate the action based on the decision path followed. In predictive models, these leaf nodes represent the anticipated outcome resulting from the sequence of events traversing the tree. The decision to employ a decision tree model for identifying key input variables from six demographic factors, alongside a financial inclusion variable, specifically financial availability (FAV), aims to forecast the level of banking and financial services availability in the rural area of the Sambalpur district. This model was selected due to its simplicity, interpretability, and high accuracy. An optimal decision tree model was applied to a dataset comprising 102 daily records to identify potential causal variables that could predict availability levels in Sambalpur. The decision tree analysis was executed using the "rpart" package in R software, with the control parameter "minsplit" set at 10 percent of the total data. The model's predictive accuracy was evaluated using RMSE. The most effective decision tree was developed using six input variables with a "minsplit" of 5, assigning equal costs to each variable. Figure 13 presents the list of variable importance, while Figure 12 illustrates the fitted tree. The analysis using the decision tree identified three of the six potential input variables as highly significant.

Utilizing the "rpart" package facilitates the examination of various levels of cost complexity. To evaluate the errors associated with each level, "rpart" conducts a ten-fold cross-validation by calculating errors on the validation data. The optimal decision tree is depicted in Figure 12, comprising 15 internal nodes and 16 terminal nodes, constructed using six variables for its model. By setting cp to zero, this tree can be expanded into a complete tree with 16 terminal nodes, as shown in Figure 14. In Figure 14, the y-axis represents the error from cross-validation, while the lower x-axis displays values related to cost complexity, and the upper x-axis indicates the number of terminal nodes. As the tree extends beyond 16 terminal nodes, the reduction in errors becomes less pronounced due to increased depth. In predicting financial availability in the Sambalpur District, the decision tree identified six significant variables from the total available. Each of the 102 daily data points from the six demographic factors is analyzed using the decision tree illustrated in Figure 12. In this tree, each data point is evaluated at a node, proceeding left for a "Yes" response or right for a "No" response. For individuals whose occupations are students, homemakers, or farmers and are under the age of 23, the financial availability (FAV) is 1.8, with a probability of chance at 4%. For those in the same occupational categories aged 37 or older, with farming as their source of income, the FAV is 1.7, and the probability of chance is 3%. For individuals aged between 24 and 54, with income sources such as salary, daily wages, government subsidies/benefits, livestock, or others, and who are either illiterate or have completed matriculation, the FAV is 1.8, and the probability of chance is 4%. If these individuals have attained graduation or post-graduation, the FAV increases to 2.1, with a probability of chance of 2%. For those aged over 55, the FAV is 2.2, with a probability of chance of 4%. For individuals aged between 24 and 36, the FAV is 2.2, with a probability of chance of 14%. For those whose occupations are daily wage workers, private employees, government employees, self-employed, or others, and who have completed graduation or post-graduation, the FAV is 1.9, with a probability of chance of 5%. If these individuals are illiterate or have completed matriculation and are aged 63 or older, the FAV is 2, with a probability of chance of 5%. For self-employed individuals and others with matriculation education, aged between 43 and 62, the FAV is 2, with a probability of chance of 3%. If they are younger than 43, the FAV is 2.2, with a probability of chance of 17%. For self-employed individuals and others with no education, aged under 36, the FAV is 2.1, with a probability of chance of 5%. If they are aged 41 or older, the FAV is 2.3, with a probability of chance

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of 12%. For those aged between 36 and 41, the FAV is 2.7, with a probability of chance of 3%. For daily wage workers and private employees who are illiterate or have completed matriculation and are aged between 57 and 62, the FAV is 2.2, with a probability of chance of 2%. If they are younger than 48, the FAV is 2.4, with a probability of chance of 16%. For those aged between 48 and 62, the FAV is 2.6, with a probability of chance of 3%.

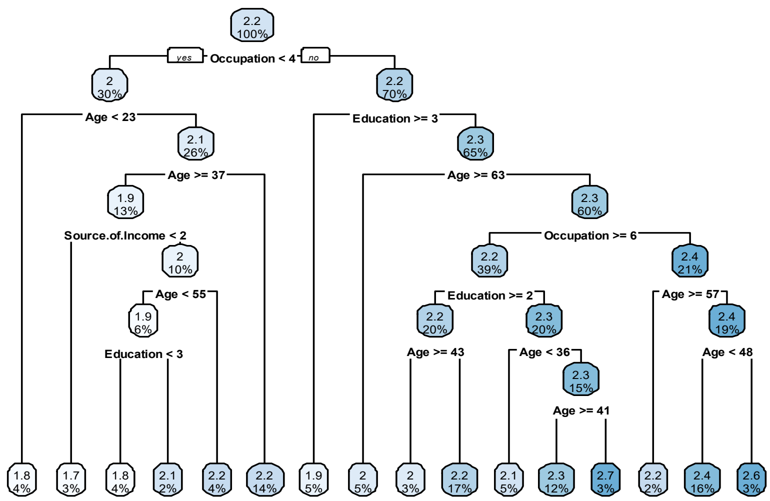

Figure 12: Decision tree for prediction of Financial Availability at Sambalpur District

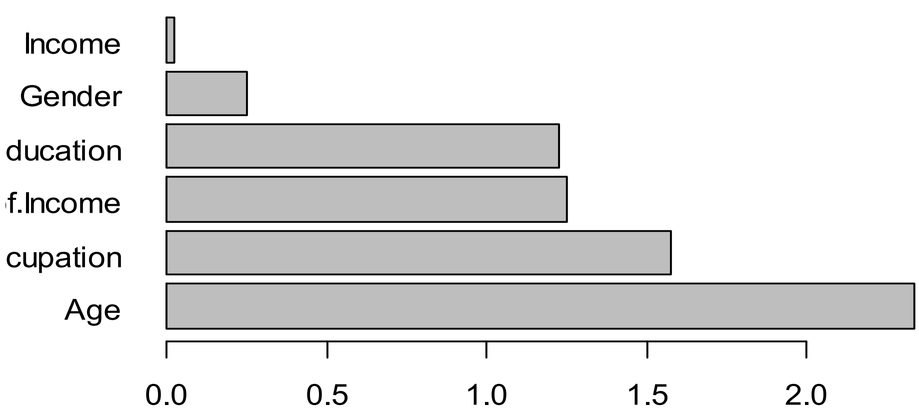

Figure 13: Variable Importance for Prediction of Financial Availability

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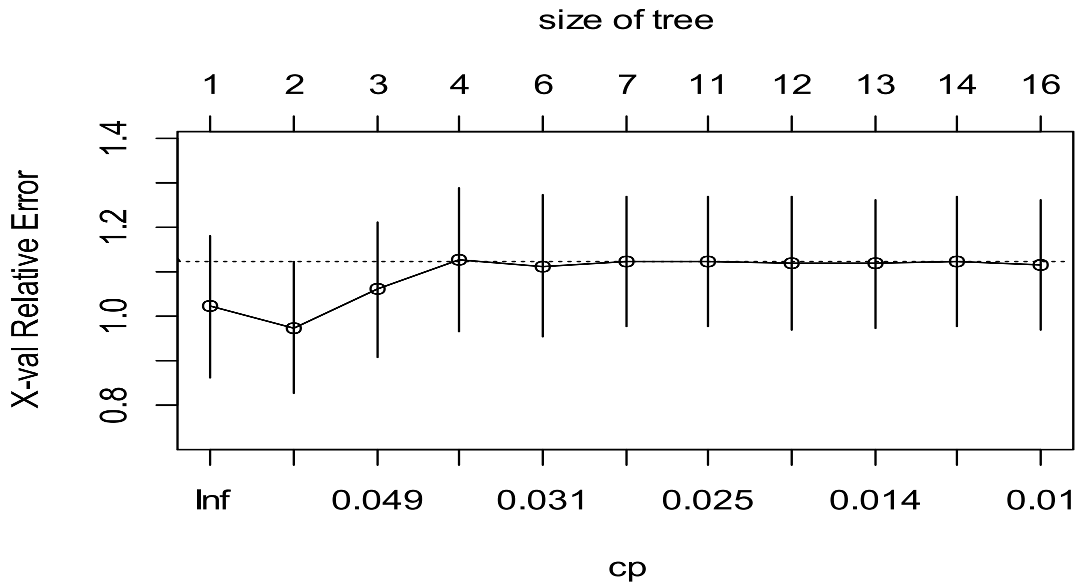

Figure 14: Complex Parameter for Prediction of Financial Availability

4.2.2. Artificial Neural Network and Regression Models for Financial Availability Prediction

The study utilizes Artificial Neural Networks (ANN) and regression models to examine the impact of demographic variables, including age, gender, education, occupation, income, and source of income, on financial availability in the Sambalpur district. The analysis is conducted to predict financial availability for the population of the Sambalpur district. The first ANN model integrates six demographic input variables into a three-layer feed-forward neural network, featuring eight neurons in the hidden layer and a single neuron for output. Similarly, the second ANN model employs six input variables and is configured as a four-layer feed-forward neural network. This configuration includes two hidden layers, comprising eight and four neurons, respectively, in addition to a single output neuron. A regression model is also developed to predict financial availability in the Sambalpur district, incorporating all six demographic variables. Table 2 presents the notations used in the various AI-driven models. This study focuses on predicting financial availability for the Sambalpur district of Western Odisha. Equations 1 and 2 present the ANN models.

Table 2: Notations used in Different Prediction Models

Terms		Description
Age	:	Age of the participants
Gen	:	Gender of the participants
Edu	:	Educational qualification of the participants
Occup	:	Occupation of the participants
Inc	:	Annual income of the participants
Sourcinc	:	Number of Sources of income of the participants household

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Terms		Description
Finavail	:	Availability of financial and banking services of the participants (Financial Availability)
Finusab	:	Usability of the financial and banking services of the participants (Financial Usability)
α	:	Constant in regression model
β_i	:	Coefficients in regression model (i=1, 2......k)
ε	:	Random error
$Finavail_{(ANN,8)}$	:	A three-layer feedforward neural network comprising an input layer and a hidden layer with 8 neurons, and a single target of $Financial\ availability$
$Finavail_{(ANN,8-4)}$	:	A four-layer feedforward neural network comprises an input layer, two hidden layers with 8 and 4 neurons respectively, and a single output target of $Financial\ availability$
$Finusab_{(ANN,4)}$	:	A three-layer feedforward neural network comprising an input layer and a hidden layer with 8 neurons, and a single target of $Financial\ usability$
$Finusab_{(ANN,8-4)}$	:	A four-layer feedforward neural network comprises an input layer, two hidden layers with 8 and 4 neurons respectively, and a single output target of $Financial\ usability$

Advanced analytical techniques, including artificial neural networks (ANN) and regression models, have been employed to examine the impact of demographic variables—namely age, gender, education, occupation, income, and source of income—on financial availability in the Sambalpur district. This analysis aims to predict financial availability for the population of Sambalpur district in Western Odisha. The dataset, consisting of 102 data points, is divided into a 70:30 ratio, with 70% allocated for training the network and the remaining 30% for testing purposes. Two ANN models have been developed: the first model features a hidden layer with eight neurons, while the second model includes two hidden layers with eight and four neurons, respectively. Both models utilize six input variables. In the initial ANN model, the six demographic variables are processed through a three-layer feed-forward neural network, comprising eight neurons in the hidden layer and a single output neuron. Similarly, the second ANN model also employs six input variables but is configured as a four-layer feed-forward neural network, incorporating hidden layers with eight and four neurons, along with one output neuron. A regression model has also been developed to predict financial availability in the Sambalpur district, utilizing all six demographic variables. Figures 15 and 16 illustrate the two distinct ANN models used to predict financial availability in the Sambalpur district. Equations 1 and 2 depict the structure of the two different ANN models, featuring one and two hidden layers, respectively. Table 3 presents the accuracy levels of the training and testing datasets for the two ANN models, evaluated using RMSE and MAE. The data indicates that the second ANN model achieves lower RMSE and MAE values for the training datasets, while the first ANN model achieves lower RMSE and MAE values for the testing datasets. Specifically, the second ANN model demonstrates reduced RMSE and MAE results, with values of [0.2241799, 0.1678536] for the training data, whereas the first ANN

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model demonstrates reduced RMSE and MAE results, with values of [0.2298341, 0.1716948] for the testing data, in predicting financial availability in the Sambalpur district.

$$Finavail_{(ANN,8)} = f(Age, Gen, Edu, Occup, Inc, Sourc\ inc) \quad (1)$$

$$Finavail_{(ANN,8-4)} = f(Age, Gen, Edu, Occup, Inc, Sourc\ inc) \quad (2)$$

The regression model was developed to examine the impact of demographic factors, including age, gender, education, occupation, income, and income source, on financial availability in the Sambalpur district. The dataset was divided in a 70:30 ratio, with 70% allocated for training the network and the remaining 30% for testing purposes. Equation 3 illustrates the structure of the regression model. Figure 17 presents the diagnostic evaluation of the regression model for predicting financial availability in the Sambalpur district. Table 3 displays the accuracy levels of the training and testing data using RMSE and MAE for the regression model. The investigation reveals that the regression model yields RMSE and MAE values of [0.222662, 0.171178] for the training data and [0.198166, 0.156029] for the testing data, respectively, in predicting financial availability in the Sambalpur district. For both training and testing data, the regression model outperforms other financial availability models.

$$\text{Finavail} = \alpha + \beta_1\text{Age} + \beta_2\text{Gen} + \beta_3\text{Edu} + \beta_4\text{Occup} + \beta_5\text{Inc} + \beta_6\text{Sourc inc} + \varepsilon \quad (3)$$

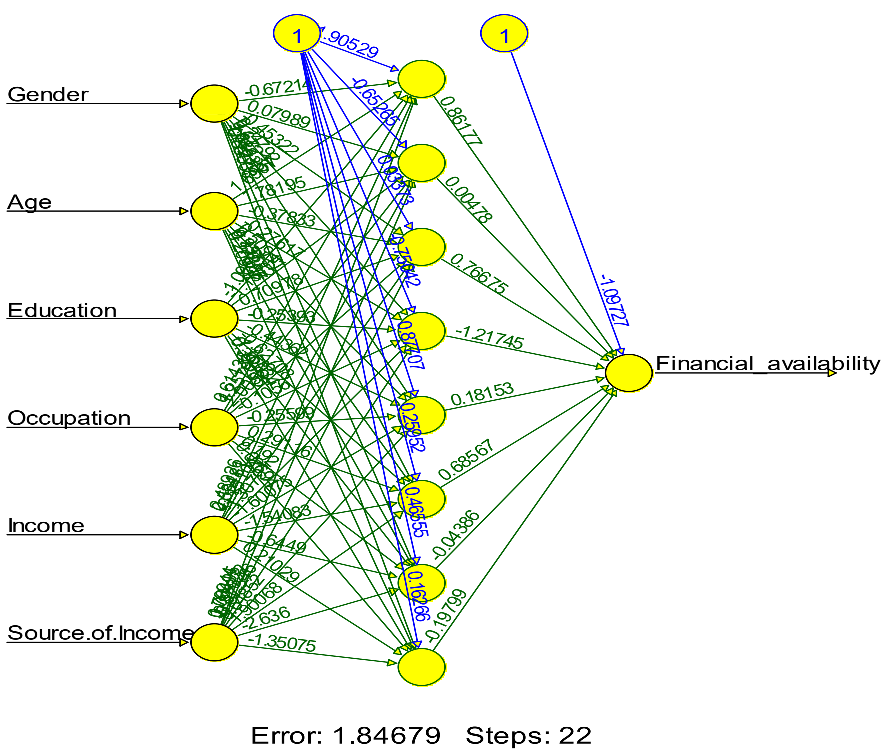

Figure 15: ANN with One Hidden Layer Model to Predict Average Financial Availability of Sambalpur District

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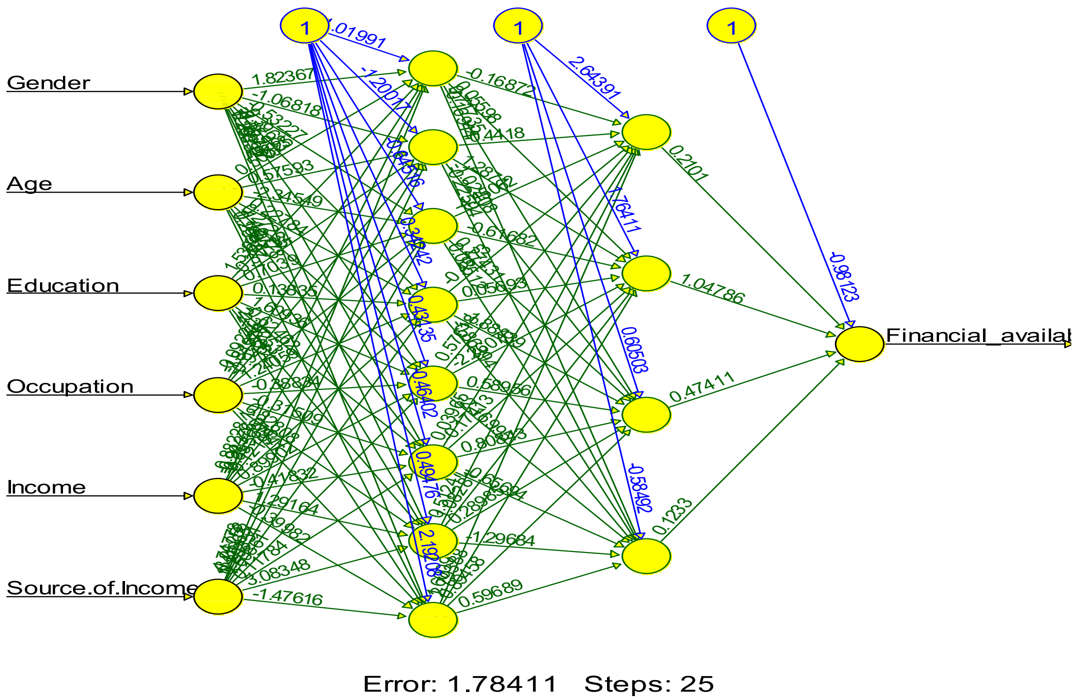

Figure 16: ANN with Two Hidden Layers Model to Predict Average Financial Availability of Sambalpur District

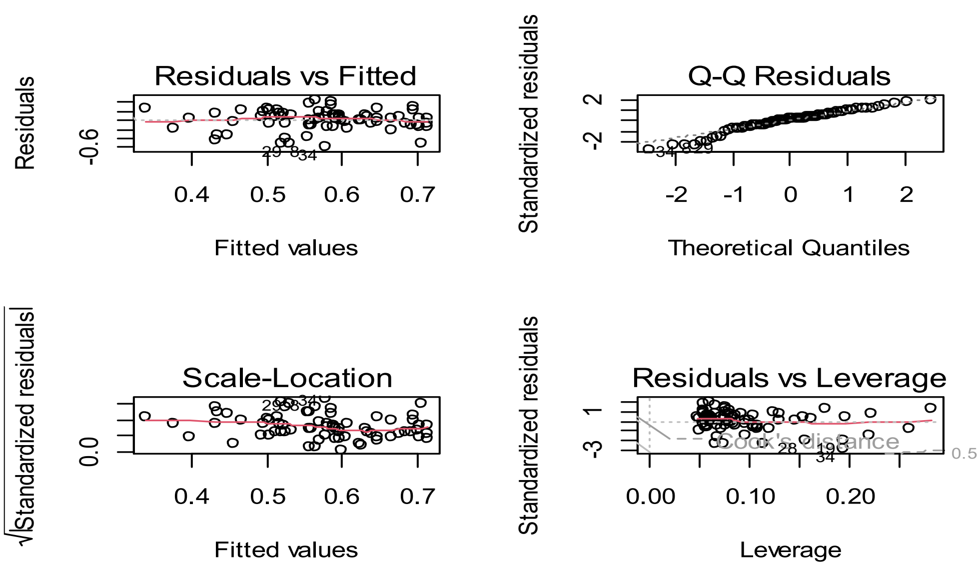

Figure 17: Diagnostic Checking of the Financial Availability Regression model

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4.2.3. Decision Tree Model for Financial Usability

The decision to employ a decision tree model for identifying key input variables from six demographic factors, alongside a financial inclusion variable, specifically financial usability, is aimed at forecasting the level of banking and financial services usability in the rural area of the Sambalpur district. This model was selected due to its simplicity, clarity in interpretation, and high accuracy rate. An optimal decision tree model was applied to a dataset comprising 102 daily records to identify potential causal variables that could predict usability levels in Sambalpur. The decision tree analysis was conducted using the "rpart" package in R software, with the control parameter "minsplit" set at 10 percent of the overall data. The model's predictive accuracy was assessed using RMSE. The most effective decision tree was developed using six input variables with a "minsplit" of 5, assigning equal costs to each variable. Figure 19 presents the list of variable importance, while Figure 18 illustrates the fitted tree. The analysis using the decision tree revealed that, among the six potential input variables, three were identified as highly significant.

Utilizing the "rpart" package facilitates the exploration of various levels of cost complexity. To analyze the errors associated with each level of cost complexity, "rpart" performs a ten-fold cross-validation process by calculating errors on the validation data. The optimal decision tree is depicted in Figure 18, featuring 17 internal nodes and 18 terminal nodes, which were constructed using six variables for its model. Setting cp to zero allows for the expansion of this tree into a complete tree with 18 terminal nodes, as shown in Figure 20. In Figure 20, the y-axis indicates the error from cross-validation, while the lower x-axis presents values related to cost complexity. The upper x-axis shows the number of terminal nodes. When the tree expands beyond 18 terminal nodes, the reduction in errors becomes less pronounced as the tree deepens. In predicting financial usability in the Sambalpur District, the decision tree selected six important variables from the total of six available. Each of the 102 daily data points from the six demographic factors is examined using the decision tree shown in Figure 18. In this tree, each data point is evaluated at a node and proceeds left for a "Yes" answer or right for a "No" answer.

For individuals whose occupations are categorized as students, homemakers, or farmers and who are aged 37 years or older, the FU is 1.5, with a probability of chance at 13%. Conversely, for those whose occupations are homemakers or farmers and who are younger than 34 years, the FU is 1.8, with a probability of chance at 10%. However, if the occupation is that of a student and the individual is under 34 years of age, the FU increases to 2.2, with a probability of chance at 5%. For those whose occupations are students, homemakers, or farmers and who are aged between 34 and 37 years, the FU is 2.7, with a probability of chance at 3%.

For individuals whose occupations include daily wage work, private employment, government employment, self-employment, or other sources of income such as farming, owning a business, or receiving a salary, and whose income ranges from 50,001 to 1,00,000, 1,00,001 to 2,00,000, 2,00,001 to 5,00,000, or above 5,00,000, the following conditions apply: If the individual is aged 25 or older and has attained an education level of matriculation, graduation, or post-graduation, the FU is 1.7, with a probability of chance at 20%. Conversely, if the individual lacks formal education and is aged 41 or older, the FU is 2, with a probability of chance at 4%. For those aged between 25 and 40, the FU is 2.8, with a probability of chance at 2%. For individuals under the age of 25, the FU is 2.7, with a probability of chance at 2%. In cases where the income is less than 50,000 and the individual is aged 53 or older, the FU is 1.6, with a probability of chance at 3%. If the individual is under 53, the FU is 1.7, with a probability of chance at 3%. For those aged between 24 and 52, the FU is 2.2, with a probability of chance at 9%. For individuals aged 41 to 52 with an income less than 50,000, if the gender is female, the FU is 2.4, with a probability of chance at 3%; if male,

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the FU is 3, with a probability of chance at 3%. For those aged between 34 and 40, the FU is 3.5, with a probability of chance at 3%.

If the occupation is categorized as a daily wage worker, private employee, government employee, self-employed, or other, with sources of income such as daily wages, government subsidies/benefits, or livestock, and the income is less than 50,000, then the FU is 2.4, and the probability of chance is 12%. For individuals in the same occupational categories with income ranging from 50,001 to 1,00,000, 1,00,001 to 2,00,000, 2,00,001 to 5,00,000, or above 5,00,000, and aged 55 or older, the FU is 2.8, and the probability of chance is 2%. Conversely, if the age is less than 55, the FU is 3.4, and the probability of chance is 3%.

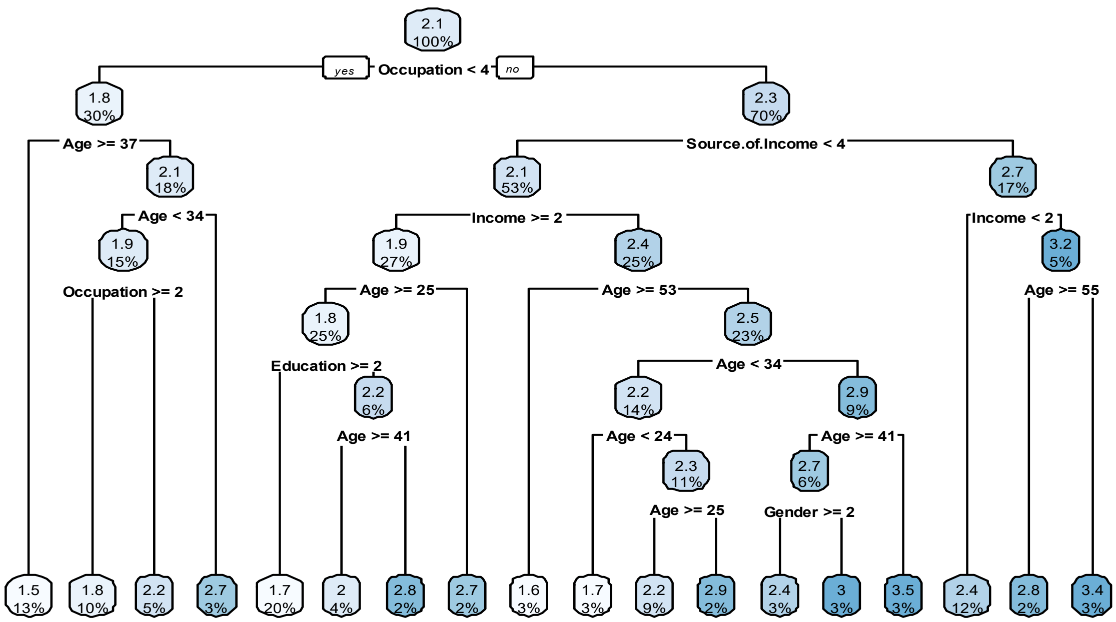

Figure 18: Decision Tree for Prediction of Financial Usability

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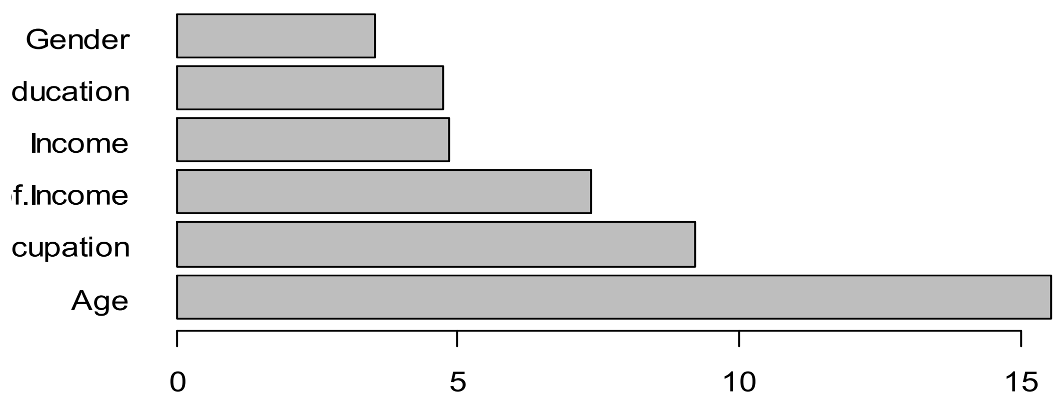

Figure 19: Variable Importance for Prediction of Financial Usability

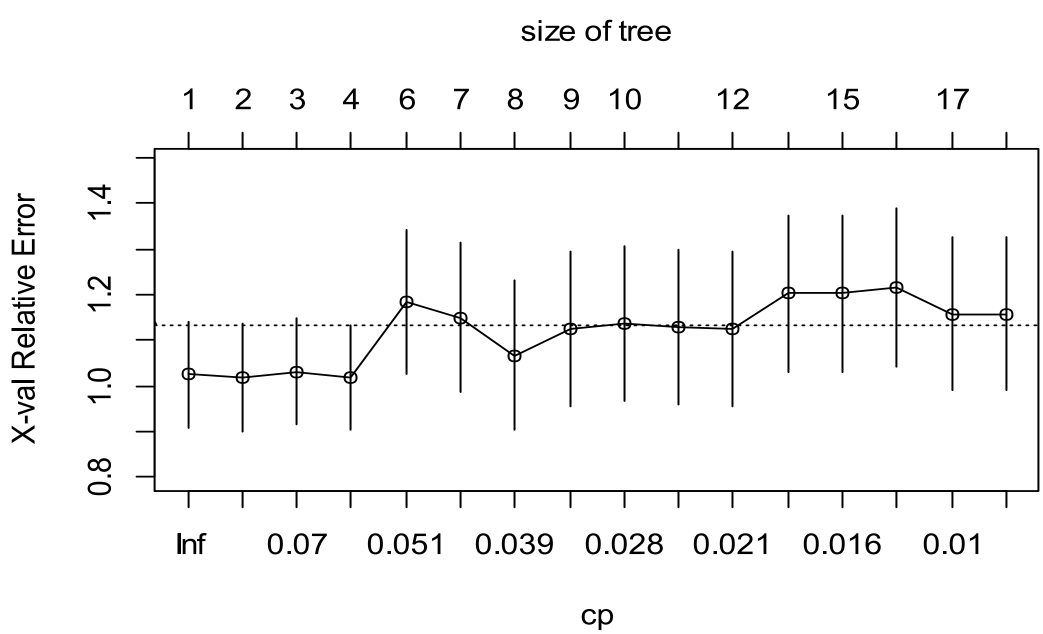

Figure 20: Complex Parameter for Prediction of Financial Usability

4.2.4. Artificial Neural Network and Regression Models for Financial Usability Prediction

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The artificial neural network (ANN) and regression models have been developed to examine the impact of demographic variables—namely age, gender, education, occupation, income, and source of income—on financial usability in the Sambalpur district. This analysis aims to predict financial usability within the population of the Sambalpur district in Western Odisha. The dataset, consisting of 102 data points, is divided in a 70:30 ratio, with 70% allocated for training the network and the remaining 30% for testing. Two ANN models have been constructed. The first model features a single hidden layer with eight neurons, while the second model includes two hidden layers, with eight neurons in the first layer and four in the second, both utilizing six input variables. The first ANN model processes six demographic input variables through a three-layer feed-forward neural network, comprising a single hidden layer with eight neurons and one output neuron. The second ANN model also employs six input variables but is structured as a four-layer feed-forward neural network. This model incorporates two hidden layers, with the first layer containing eight neurons and the second layer four neurons, along with a final output neuron. A regression model has also been developed to predict financial usability in the Sambalpur district, incorporating all six demographic variables. Figures 21 and 22 illustrate the two distinct ANN models used to predict financial usability in the Sambalpur district. Equations 4 and 5 depict the structure of the two different ANN models with one and two hidden layers, respectively. Table 3 presents the accuracy levels of the training and testing datasets using RMSE and MAE for the two ANN models. The results indicate that the first ANN model demonstrates lower RMSE and MAE values for both the training and testing datasets compared to the second model. Specifically, the first ANN model exhibits RMSE and MAE values of [0.2422973, 0.2153188] for the training data and [0.2604167, 0.228181] for the test data, respectively, in predicting financial usability in the Sambalpur district. The ANN model with a single hidden layer has delivered the best performance, achieving RMSE and MAE values of 0.2422973 and 0.2153188, respectively, for the training dataset, thereby surpassing other models focused on financial usability.

$$Finusab_{(ANN,8)} = f(Age, Gen, Edu, Occup, Inc, Sourc\ inc) \quad (4)$$

$$Finusab_{(ANN,8-4)} = f(Age, Gen, Edu, Occup, Inc, Sourc\ inc) \quad (5)$$

A regression model has been developed to investigate the influence of demographic factors, including age, gender, education, occupation, income, and income source, on financial usability in the Sambalpur district. The dataset is partitioned into two segments, with 70% allocated for model training and the remaining 30% reserved for testing. Equation 6 delineates the structure of the regression model. Figure 23 provides a diagnostic evaluation of the regression model's efficacy in predicting financial usability within the Sambalpur district. Table 3 presents the accuracy metrics of the training and testing datasets, utilizing RMSE and MAE as evaluation criteria for the regression model. The analysis indicates that the regression model achieves RMSE and MAE values of [0.237739, 0.201777] for the training data and [0.235127, 0.202381] for the testing data, respectively, in predicting financial usability in the Sambalpur district. The regression model demonstrates superior performance, with RMSE and MAE values of 0.235127 and 0.202381, respectively, for the test dataset, outperforming other financial usability models.

$$\text{Finusab} = \alpha + \beta_1 \text{Age} + \beta_2 \text{Gen} + \beta_3 \text{Edu} + \beta_4 \text{Occup} + \beta_5 \text{Inc} + \beta_6 \text{Sourc inc} + \varepsilon \quad (6)$$

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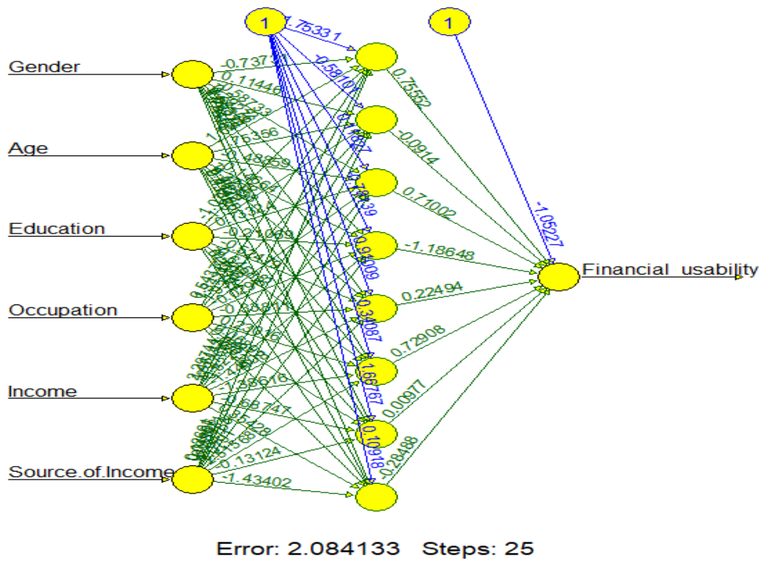

Figure 21: ANN with One Hidden Layer Model to Predict Average Financial Usability

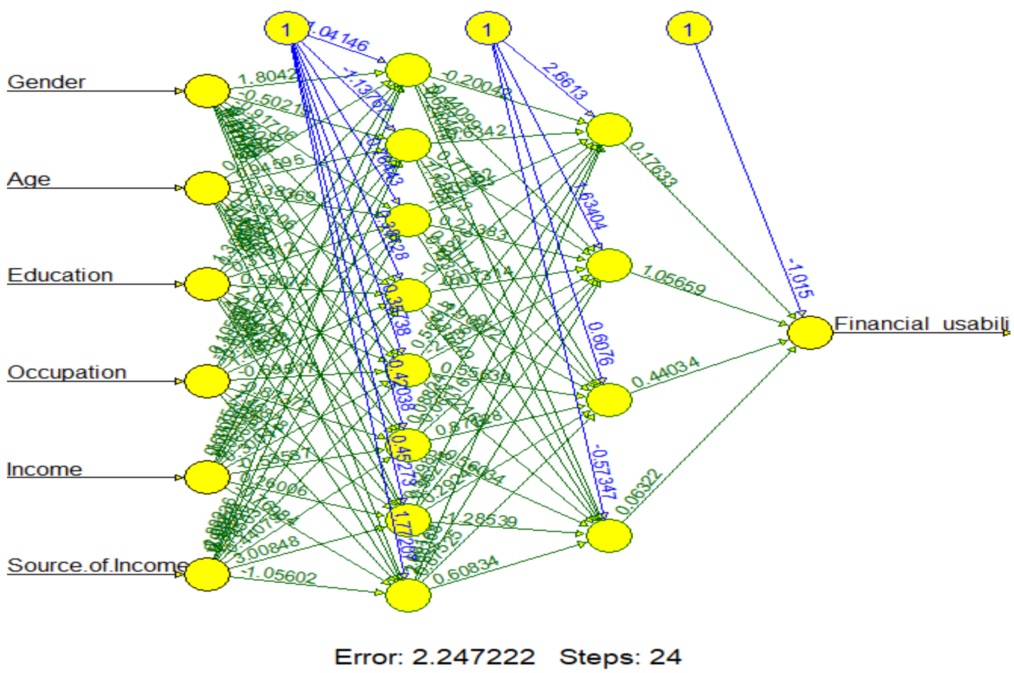

Figure 22: ANN with Two Hidden Layers Model to Predict Average Financial Usability

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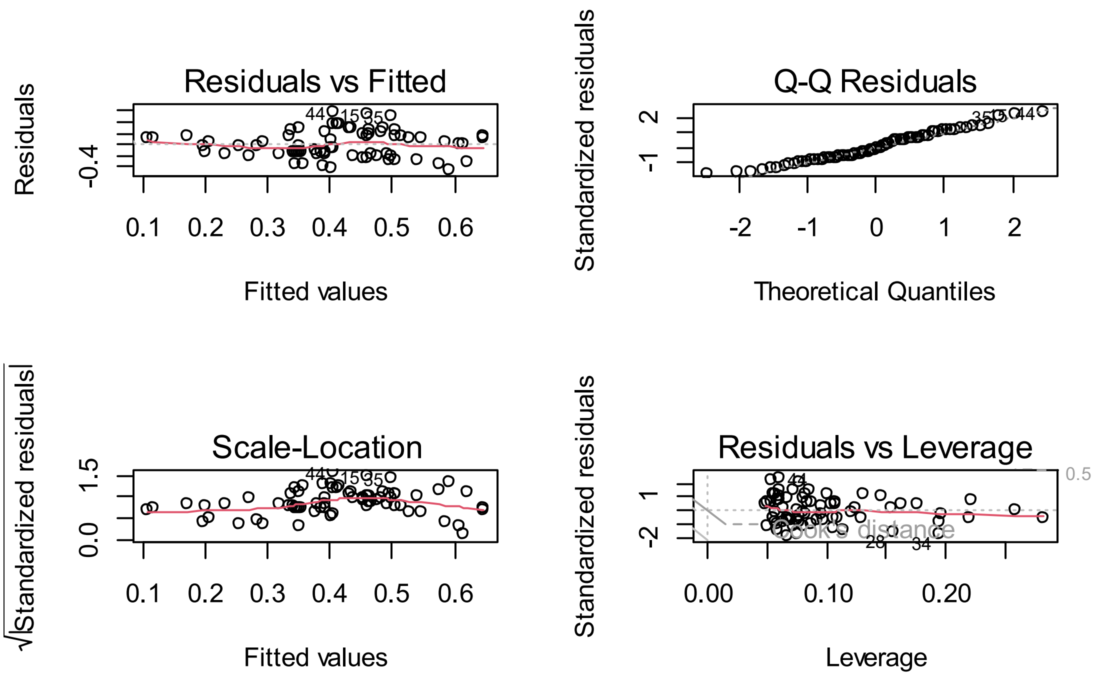

Figure 23: Diagnostic Checking of the Financial Usability Regression Model

Table 3: Performance Measure of Different Financial Inclusion Prediction Models

Target Variable	AI-Driven Model	Neurons in Input, Hidden and Output Layers	RMSE		MAE	
			Training (70%)	Testing (30%)	Training (70%)	Testing (30%)
Financial Availability	ANN	6-8-1	0.2280839	0.2298341	0.1822534	0.1716948
	ANN	6-8-4-1	0.2241799	0.2374552	0.1678536	0.1822553
	Regression	6-1	0.222662	0.198166	0.171178	0.156029
Financial Usability	ANN	6-8-1	0.2422973	0.2604167	0.2153188	0.228181
	ANN	6-8-4-1	0.2515989	0.2657399	0.2207323	0.2399378
	Regression	6-1	0.237739	0.235127	0.201777	0.202381

5. Conclusion

This study addresses the critical issue of financial inclusion by analyzing the impact of demographic variables (age, gender, education, income, occupation, and source of income) on financial availability and

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usability among rural populations & developing and validating predictive models for financial availability and usability, incorporating rural population segmentation. Seventy percent of the dataset is allocated for training purposes, while the remaining 30% is utilized for testing all the models. We have employed a variety of AI-based models, including "cluster analysis", "decision trees", an "artificial neural network (ANN)" with a single hidden layer, an "ANN" with two hidden layers, and regression, to analyze financial inclusion datasets. The most affected areas are categorized into two types through three different cluster analyses like K-means, "Hierarchical Clustering" (HC) and "Partitioning Around Medoids" (PAM) using all the 6 demographic variables. For highly affected areas, it is needed to predict "financial availability and usability". The lowest values of errors evaluation suggests for the best approach which is an efficient solution for the financial inclusion prediction. Within the framework of the financial availability model, the regression model demonstrated superior performance, achieving RMSE and MAE values of 0.222662 and 0.171178 for the training dataset, respectively. Similarly, for the test dataset, the regression model excelled, with RMSE and MAE values of 0.198166 and 0.156029, respectively. In the context of the financial usability model, the regression model also yielded the most favorable results, with RMSE and MAE values of 0.237739 and 0.201777 for the training dataset, respectively. For the test dataset, the regression model maintained optimal performance, with RMSE and MAE values of 0.235127 and 0.202381, respectively. These models are independently outperforms other models to enhance financial inclusion prediction. The predictive model designed to forecast the financial inclusion program offers valuable insights for a variety of stakeholders. It has important ramifications for Sambalpur's local administration, national government, and regional financial institutions. Despite using data from two Sambalpur villages, the findings are applicable to other rural areas. These forecasts also provide a basis for other researchers to enhance methodologies, make cross-regional comparisons, and record worldwide reactions to disruptions, thereby promoting the creation of robust and adaptable strategies for the future.

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