ingegneria sismica
International Journal of Earthquake Engineering
Anno XLIII - Num. 2 - 2026

An Empirical Study on the Impact of Perception of Pension Service Quality on the Choice of Pension Models

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SUMMARY: *Artificial intelligence and intelligent algorithms provide data-driven methods for research on pension scheme selection. To address the issue of unclear mechanisms underlying the influence of perceived service quality, this study proposes a hybrid analysis model combining logistic regression and random forest. Using Python, the researchers performed data cleaning, standardization, variable encoding, and the division of training and testing sets. Building upon the traditional logistic regression model's identification of the direction of influence of explanatory variables, the study introduced random forest to identify nonlinear relationships and key factors.The experimental results show that the Random Forest model achieved an accuracy of 0.859 and an AUC of 0.901, both higher than the 0.813 and 0.846 recorded by the Logistic Regression model, indicating that intelligent algorithms possess superior predictive performance. Service convenience, the level of intelligent services, and service reliability were identified as the primary influencing factors.*

KEYWORDS: *intelligent algorithms; pension plan selection; perceived service quality; logistic regression; Random Forest*

1 Introduction

Pension research has benefited from the reliability of intelligent algorithms and computerized empirical analysis of data. Research now has the capability to identify variables, predict behaviors, and rank factors. Advances in intelligent algorithms and computerized empirical analysis of data have shifted the focus of research on unchangeable factors to changeable factors, describing the possibility to predict behavior, identify variables, and rank factors. The choice of pension models depends on levels of income, policy understanding and awareness, and the willingness to accept some level of risk. Perhaps even more, they depend on the level of reliability, information security, and the convenience of the trusted service. Multiple pension models may employ service design to build trust among consumers, while multiple models explain the level of risk through user behavior. The design of trusted service models can be combined to build trust among consumers. The introduction of computational approaches in the form of random forests and logistic regressions has the ability to answer the question of whether, how, and to what degree the perception of the quality of pension service affects the choice of behavior of the residents.

Using structural equation modeling, Shao and Li studied the relationship between factors in the pension system, the well-being of the elderly, and the choices of elderly care systems of the pension system. Model factors influence the elderly's choice in planning their subsequent

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https://doi.org/10.65102/is2026869 Published: 30 April, 2026

retirement [1]. Mai and Zhang claimed that developmental needs, cognitive ability, and personal traits affect the choice of economic pension plans by urban flexible employment workers [2]. Xu et al. showed that the state of pension systems affects the security of one's income, as well as influences personal conduct in the capital of health [3]. Parawansa and Mustafa argued that the degree of satisfaction and the continued service choice in the pension savings banking services depend on the quality of the services [4]. Pak opines that the social pension systems of security beds are directly related to the elderly's mental health [5].

There has been few studies focused on the perception of service and how it affects the choice of pension models; however, empirical studies on service quality drawing on computer models to examine selection quality are also limited. Filling in the gaps, the system of variables was formed around the constructs of service reliability, service responsiveness, service quality, convenience, security, and level of intelligence. Data manipulation was done using a Python-based model that facilitated data cleansing and gap filling. Through the integration of logistic regression and random forest classification, the direction and criteria of services are prepared to aid in creating and optimizing options of services and fulfillment of the needs of the residents of various pension models.

2 Theoretical Framework and Research Hypotheses

2.1 Theory of Perceived Pension Service Quality

Perceptions of the quality of pension services include everything from the initial entry into the system, the completed service transactions, the distribution of benefits, and the service's ability to engender a sense of trust. The accuracy and timeliness of pension payments, the thoroughness of policy advice, the efficiency of eligibility verification, the ease of account access, and the ease of benefit estimation influence public perceptions. The selection of pension service delivery models, in the era of advanced digitalization, is determined by the stability of systems, the protection of data, intelligent self-service, and the consolidation of cross-departmental data[1].

2.2 Theoretical Framework for Pension Scheme Selection Behavior

Choosing a pension plan requires a careful evaluation of a number of variables such as retirement risk, affordability of pension contributions, expected returns from pension plans, and experience with available pension plans. When choosing between basic pension insurance, individual pension plans, corporate pension plans, or commercial pension insurance, residents evaluate several components that include system stability, fund safety, benefit payment ease, and long-term coverage. Technological services lower information costs and build a better understanding and control through such functions as account inquiry, contribution verification, benefit projection, online enrollment, and risk alerts[2].

2.3 Computer-Assisted Empirical Analysis Methods

The entire process involves the application of computer - assisted empirical analysis, covering data processing, variable construction, model training, and result interpretation. By means of Python and relying on pandas, numpy, and scikit - learn, we conduct data - related tasks including data reading, outlier detection, missing value imputation, variable encoding, standardization, and dataset splitting[3].We then use logistic regression and random forests to analyze the influencing factors, predictive performance, and feature importance of the pension model selection. The workflow details are shown in Figure 1:

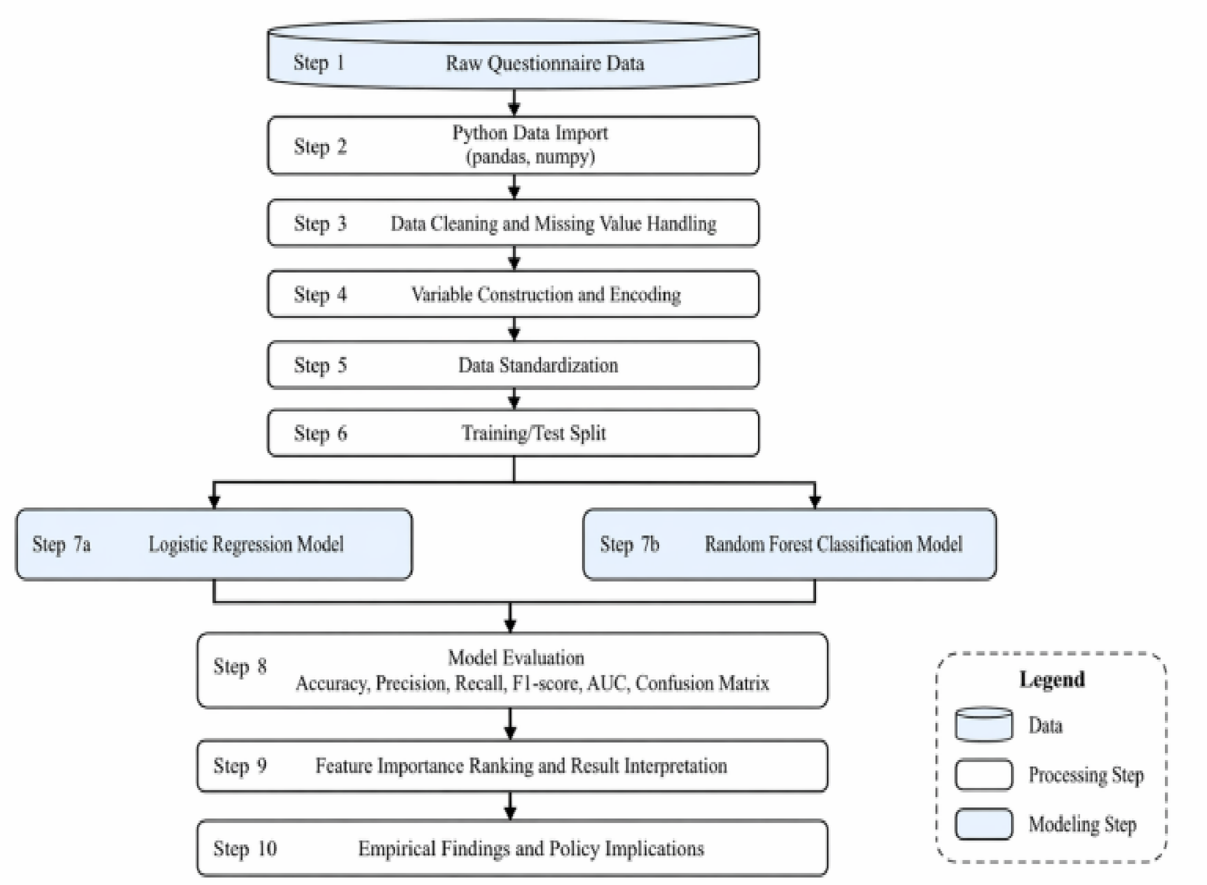

Figure 1: Computer-Assisted Analysis Flowchart

2.4 Research Model and Hypothesis Formulation

The framework of this study was developed on perceived service quality and pension plan choices as building blocks. The service plan choices include service reliability, convenience, and service intelligence, as well as service responsiveness and security. Pension plan choice is treated as a dependent variable[4]. Influencing factors include age, income, education, policy awareness, and risk preference. A combination of logistic regression and variable matrix was developed using Python to examine the nature and significance of the impact. A random forest algorithm was also employed to assess the impact of the principal determinants.

3 Data Collection and Computational Preprocessing

3.1 Data Sources and Sample Characteristics

This data originates from a survey regarding residents' views on the quality of pension services and the options of pension models available. The survey captures responses on service reliability, service responsiveness, service convenience, service security, service intelligence, and demographic data like age, income, educational attainment, and pension model preferences[5]. Following survey data collection, unique identifiers were applied to the questionnaires using Python. I used Python to identify and remove missing values. Outlier data were also removed, and the focus shifted to valid samples for further analysis using the logistic regression and random forest models. Before the time-series analysis, to confirm the valid sample fully met the empirical analysis requirements and to better assess the survey quality, I calculated the valid sample rate, defined as:

$$R = \frac{n}{N} \times 100\% \tag{1}$$

where R represents the response rate, n represents the number of valid questionnaires, and N represents the total number of questionnaires collected. To analyze the distribution of different demographic groups, the formula for calculating the proportion of sample categories is:

$$P_i = \frac{n_i}{n} \times 100\% \tag{2}$$

where P_i represents the proportion of samples in category i among the valid samples, n_i represents the number of samples in category i , n represents the total number of valid samples, and i represents the sample classification codes for gender, age, income, or educational level[6]. This proportion can be used to determine whether the sample distribution is relatively balanced and provides a basis for subsequent variable coding and group analysis.

3.2 Data Cleaning and Missing Value Handling

Once the data from our questionnaires is imported into Python, we check for duplicate records, missing values in relevant variables, and outliers where samples do not make logical sense. All records with excessive rates of missing data in core fields such as pension scheme choice, age and income are dropped. To check the missing values rate for variables, we use below expression:

$$M_i = \frac{m_j}{n} \times 100\% \tag{3}$$

where M_j represents the missing rate of the j th variable, m_j represents the number of missing samples in the j th variable, n represents the total number of valid samples, and j represents the variable ID[7]. As shown in Figure 2, the missing rates for all variables are generally low, with core variables such as pension scheme selection, age, and income exhibiting particularly low missing rates, indicating that the sample data possesses good completeness.For the few missing values in continuous variables, this study employs mean imputation to ensure that subsequent logistic regression and random forest models can run properly[8]. As shown in Figure 2:

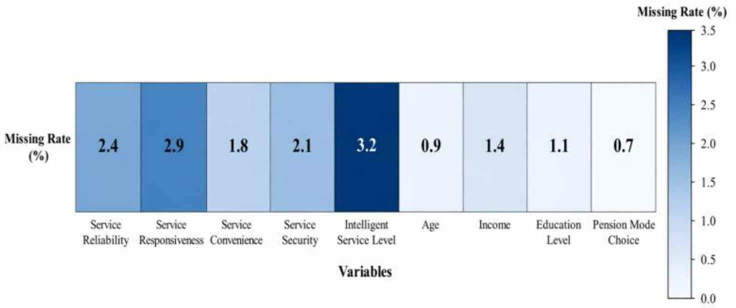

Figure 2: Distribution of Missing Values Across Different Variables

When the missing rate of a variable is low, continuous variables are subjected to mean imputation to guarantee the normal operation of subsequent logistic regression and random forest models. The formula for mean imputation is:

$$\bar{X}_j = \frac{i}{n_j}\sum_{i=1}^{n_j} X_{ij} \tag{4}$$

where $\bar{X}_j$ represents the mean of the j th variable, X_{ij} represents the observation of the i th sample for the j th variable, n_j represents the number of non-missing samples in the j th variable, and i represents the sample ID. After imputation, variable coding and model analysis are performed[9].

3.3 Data Standardization Using Python

After handling the issue of missing values, this investigation uses Python to standardize continuous variables including age, income, policy awareness, and perceived service quality scores. This stops differences in measurement scales from having an impact on the comparison of logistic regression coefficients and makes sure that the data formats for the Random Forest model are uniform. First, Z - score standardization is carried out using the following formula:

$$Z_{ij} = \frac{X_{ij} - \mu_j}{\sigma_j} \tag{5}$$

where Z_{ij} represents the standardized value of the i th sample for the j th variable, X_{ij} represents the original observed value, μ_j represents the mean of the j th variable, σ_j represents the standard deviation of the j th variable, i represents the sample ID, and j represents the variable ID. To normalize certain indicators to a fixed range, Min-Max standardization can also be used, with the formula:

$$X_{ij}^{'} = \frac{X_{ij} - X_{j,\min}}{X_{j,\max} - X_{j,\min}} \tag{6}$$

4 Empirical Models and Algorithm Design

4.1 Methods for Reliability and Validity Testing

Before building the model, this chapter tested the reliability and validity of the Pension Service Quality Perception Scale by using Python. The scale items included tested the dimensions of reliability, responsiveness, convenience, safety, and intelligence in order to ensure the questionnaire data could support subsequent logistic and random forest regression analyses[10]. First, the internal scale reliability was assessed by using the Cronbach’s Alpha coefficient, which was calculated by the following equation:

$$\alpha = \frac{k}{k-1}\left(1 - \frac{\sum_{i=1}^{k}\sigma_i^2}{\sigma_T^2}\right) \tag{7}$$

Here, `$\alpha$` represents the reliability coefficient, `$k$` represents the number of scale items, `$\sigma_i^2$` represents the variance of the `$i$`th item, `$\sigma_T^2$` represents the variance of the total score of all items, and `$i$` represents the item number. To determine whether the variables are suitable for further factor analysis, this study calculates the KMO value, whose formula is:

$$KMO = \frac{\sum r_{ij}^2}{\sum r_{ij}^2 + \sum q_{ij}^2} \tag{8}$$

where KMO denotes the validity test statistic, r_{ij} denotes the correlation coefficient between the i th variable and the j th variable, q_{ij} denotes the partial correlation coefficient between the i th variable and the j th variable, and i and j denote the variable numbers. Based on these calculations, it can be determined whether the scale data is suitable for inclusion in subsequent empirical models[11].

4.2 Construction of the Logistic Regression Model

This study views the choice of pension plan as a binary dependent variable. For instance, if an employee selects a pension plan, the employee variable equals 1; if an employee does not select a pension plan, the employee variable equals 0. The independent variables for the model are service reliability, service responsiveness, convenience and safety of a service, personal characteristics, and employee service intelligence. The logistic regression method in Python is applied to estimate the effect of each variable on the choice probability to verify if the perceived service quality significantly influences the respondents' choice of pension plan. The model becomes:

$$\ln\left(\frac{P_i}{1-P_i}\right) = \beta_0 + \beta_1 X_{i1} + \beta_2 X_{i2} + \ldots + \beta_k X_{ik} \tag{9}$$

where P_i represents the probability that the i th sample selects a specific pension plan, $1-P_i$ represents the probability that the i th sample does not select that plan, β_0 represents the constant term, β_1, β_2,...,β_k represents the regression coefficients of each explanatory variable, $X_{i1}, X_{i2} \ldots X_{ik}$ represents the service quality perception variables and control variables corresponding to the i th sample, and k represents the total number of variables included in the model.The impact of each factor can be analyzed based on the direction and significance of the coefficients.To demonstrate the specific analytical pathway for understanding how the perceived quality of pension services impacts the choice of pension model, the design of a logistic regression model reflects this empirically. This diagram outlines the journey of the explanatory and control variables that ultimately leads to model estimation and results output[12]. This serves as a basis for further regression analysis and impact effect testing, as shown in Figure 3:

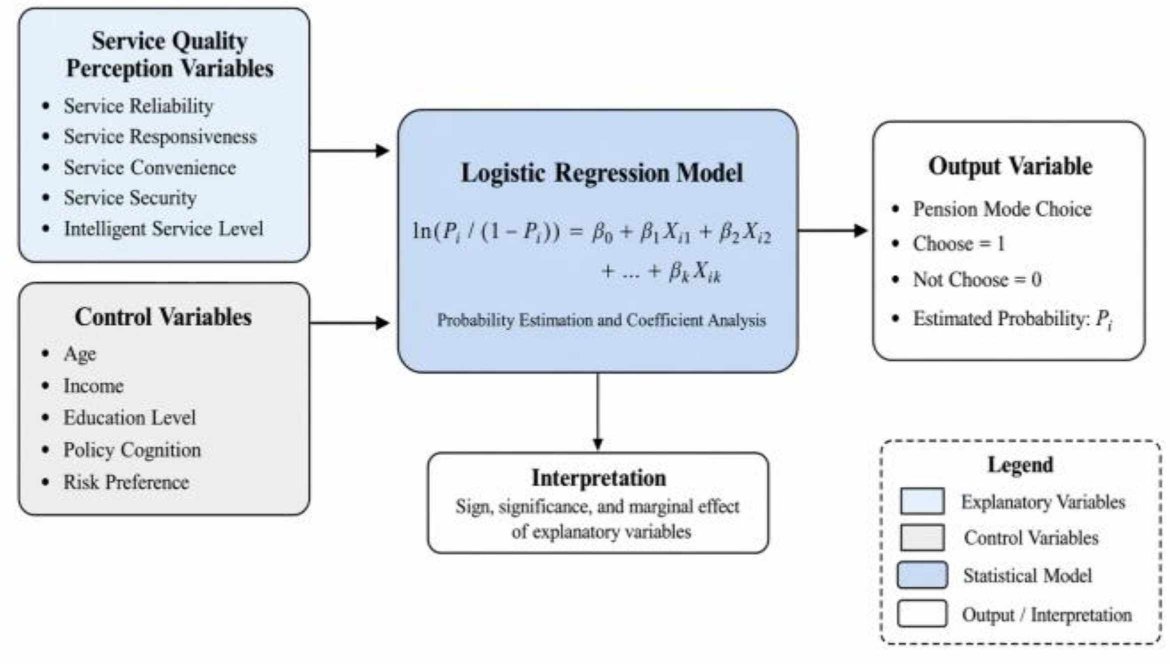

Figure 3: Framework Diagram of the Logistic Regression Model

4.3 Construction of the Random Forest Classification Model

This study adds predictive analysis of pension scheme selection via the Random Forest classification algorithm in Python, building on a previous analysis of linear variable impacts using a logistic regression framework. With a model based on the variables of service reliability, responsiveness, convenience, security, intelligence, and personal characteristics, multiple decision trees collaboratively ascertain whether residents opt for a pension scheme in order to bolster the reliability of classification outcomes[13]. In Random Forest, the classification outcome is computed via majority rule, employing the following formula:

$$\hat{Y} = \operatorname{mod} e\{h_1(X_i), h_2(X_i), \ldots h_T(X_i)\} \tag{10}$$

where $\hat{Y}_i$ represents the predicted pension plan selection result for the i th sample, X_i denotes the set of input variables for the i th sample, $h_t(X_i)$ indicates the classification result of the t th decision tree for sample X_i , T denotes the total number of decision trees in the Random Forest, $\operatorname{mod} e\{\cdot\}$ represents the category with the highest occurrence frequency, and t denotes the decision tree number.This method produces predictive outcomes from the model and further offers a ranking of the importance of variables. To enhance understanding of the steps involved in constructing the Random Forest classification model, a diagram of a model framework is presented. This framework illustrates the basic steps of the process where input variables are subjected to the Bootstrap sampling method, several decision trees are created, and the results are output as the selected pension plan through majority voting, as shown in Figure 4:

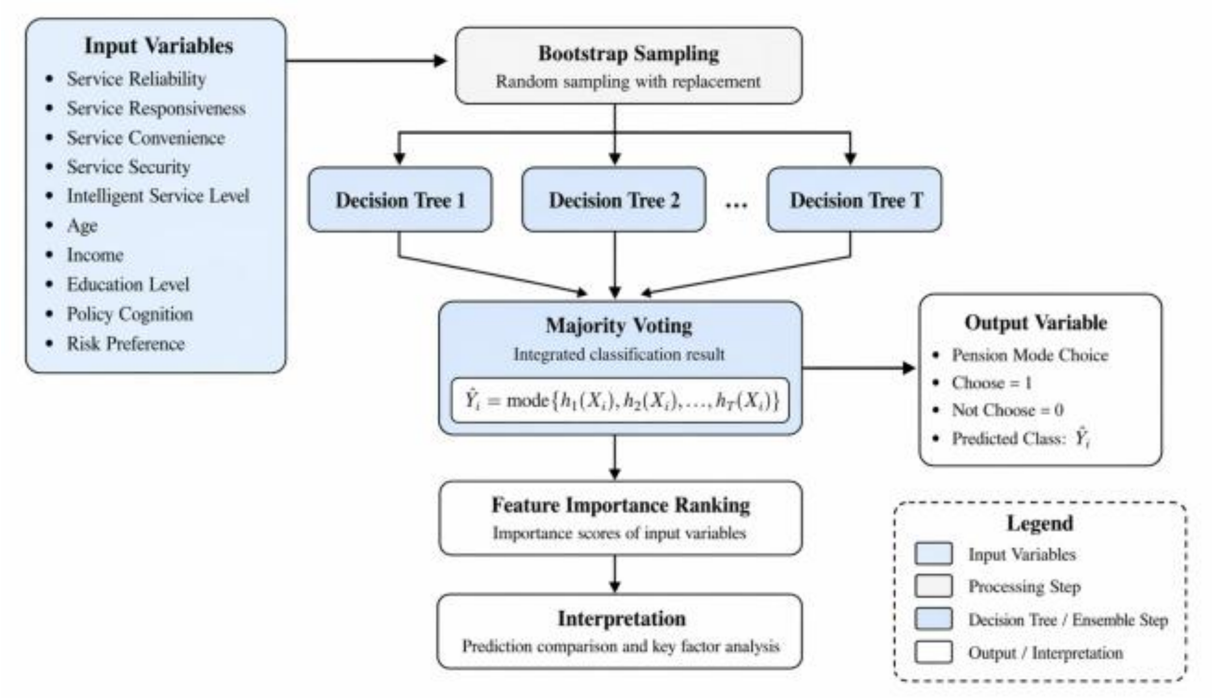

Figure 4: Framework Diagram of the Random Forest Classification Model

4.4 Design of Model Evaluation Metrics

This paper offers a comparison of predictive performance of random forest and logistic regression models in the context of pension scheme selection, calculating classification judgement scores for each test set using Python[14]. To measure selected classifications, model output results are compared with selection results and the accuracy score, which is the first measure of overall classification accuracy, is determined using the following formula:

$$A_{ccuracy} = \frac{TP + TN}{TP + TN + FP + FN} \tag{11}$$

where $Accuracy$ represents the accuracy rate, TP represents the number of samples that were actually selected and predicted to be selected, TN represents the number of samples that were actually not selected and predicted to be not selected, FP represents the number of samples that were actually not selected but predicted to be selected, and FN represents the number of samples that were actually selected but predicted to be not selected. Considering that the samples for pension scheme selection may exhibit category differences, the F1 score is further calculated using the following formula:

$$F1 = \frac{2 \times \mathrm{Pr}ecision \times \mathrm{Re}call}{\mathrm{Pr}ecision + \mathrm{Re}call} \tag{12}$$

where $F1$ represents the combined evaluation metric of precision and recall, $\mathrm{Pr}ecision$ denotes the proportion of samples predicted as selected that were actually selected, and $\mathrm{Re}call$ denotes the proportion of samples actually selected that were correctly predicted. Using these metrics, the classification performance of the two types of computer models can be objectively compared[15].To systematically illustrate the composition of model evaluation metrics and their interrelationships, a model evaluation metric framework diagram has been created to visually demonstrate the corresponding pathways between classification results, confusion matrices, and various evaluation metrics, as shown in Figure 5:

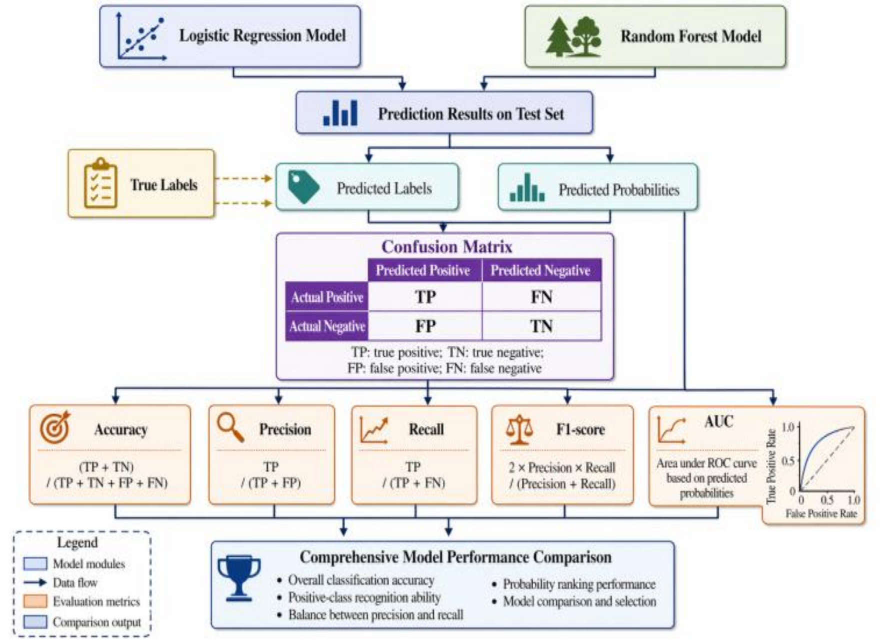

Figure 5: Model Evaluation Metric System Diagram

5 Empirical Results and Computational Analysis

5.1 Descriptive Statistics and Correlation Analysis

This paper examines the mean, standard deviations, and sample range for several variables. Descriptive statistics are used to analyze the data quality and general distribution of sample variables based on perceptions of pension service quality and pension plan selection. Analyzed variables include reliability, service, responsiveness, convenience, security, level of digitalization, age, income, education, policy awareness, and risk preference. The results are reported and summarized in Table 1:

Table 1: Descriptive Statistics for Key Variables

<table>
<tr><th>Variable Name</th><th>Variable Symbol</th><th>Sample Size N</th><th>Mean</th><th>Standard Deviation Std. Dev.</th><th>Minimum</th><th>Max</th></tr>
<tr><td>Service Reliability</td><td>SR</td><td rowspan="11">426</td><td>3.89</td><td>0.71</td><td rowspan="5">1.00</td><td rowspan="5">5.00</td></tr>
<tr><td>Service Responsiveness</td><td>SS</td><td>3.74</td><td>0.76</td></tr>
<tr><td>Convenience of Service</td><td>SC</td><td>4.02</td><td>0.68</td></tr>
<tr><td>Service Safety</td><td>SE</td><td>3.81</td><td>0.73</td></tr>
<tr><td>Level of Smart Services</td><td>ISL</td><td>3.57</td><td>0.84</td></tr>
<tr><td>Age</td><td>AGE</td><td>43.62</td><td>10.94</td><td>22.00</td><td>67.00</td></tr>
<tr><td>Income Level (1–5)</td><td>INC</td><td>2.96</td><td>1.07</td><td rowspan="4">1.00</td><td rowspan="4">5.00</td></tr>
<tr><td>Educational Attainment (Levels 1–5)</td><td>EDU</td><td>3.11</td><td>0.93</td></tr>
<tr><td>Level of Policy Awareness</td><td>PC</td><td>3.28</td><td>0.81</td></tr>
<tr><td>Risk Appetite</td><td>RP</td><td>2.84</td><td>0.88</td></tr>
<tr><td>Pension Plan Choice (0/1)</td><td>PMC</td><td>0.47</td><td>0.50</td><td>0.00</td><td>1.00</td></tr>
</table>

As can be seen from Table 1, among the 426 valid samples, the mean score for service convenience was the highest, standing at 4.02, which implies that respondents rated the convenience of pension service processing highly. The mean score for the intelligent service level was 3.57, lower compared to other service quality dimensions, indicating that there is still room to improve the digital service experience. The mean of the pension model selection variable was 0.47, showing that the proportions of selected and unselected samples were relatively near, making it appropriate for carrying out logistic regression and random forest classification analyses[16].

Starting from the descriptive statistics, we further used Pearson correlation analysis to study the linear relationships among the key variables. The purpose was to figure out the direction and strength of the correlations between service reliability, responsiveness, convenience, security, and the level of intelligence, and the decision on the pension model. At the same time, we examined for excessive correlations among the explanatory variables to establish a basis for subsequent regression and machine - learning modeling. The results are shown in Table 2

Table 2: Results of Pearson Correlation Analysis for Key Variables

Variable	SR	SS	SC	SE	ISL	AGE	NC	EDU	PC	RP	PMC
SR	1										
SS	0.583**	1									
SC	0.516**	0.548**	1								
SE	0.601**	0.492**	0.537**	1							
ISL	0.447**	0.471**	0.529**	0.438**	1						
AGE	-0.086	-0.072	-0.118*	-0.064	-0.192**	1					
INC	0.154**	0.129**	0.168**	0.141**	0.206**	-0.057	1				
EDU	0.173**	0.148**	0.182**	0.133**	0.251**	-0.214**	0.336**	1			
PC	0.322**	0.287**	0.341**	0.295**	0.318**	-0.091	0.224**	0.268**	1		
RP	0.107*	0.094	0.121*	0.086	0.169**	-0.176**	0.281**	0.245**	0.198**	1	
PMC	0.286**	0.241**	0.334**	0.258**	0.307**	-0.149**	0.231**	0.204**	0.276**	0.187**	1

Note: ** indicates a strong correlation at the 0.01 level; * indicates a strong correlation at the 0.05 level[17].

As represented in Table 2, the selection of a pension plan is strongly correlated with service reliability, responsiveness, ease of use, safety, and level of smart services. The most significant of these is the ease of use of the service, with a correlation coefficient of 0.334, followed by the level of smart services with a coefficient of 0.307, and service reliability with a coefficient of 0.286. From this, we can say that the better the service, the more the residents choose the pension plan of greater concern. In addition, the older the people surveyed, the lower the selection of the pension plan, with a coefficient of -0.149. This means that in these older groups, the choices made are somewhat conservative.

5.2 Analysis of the Impact of Perceived Service Quality on Pension Plan Selection

To assess the effect that perceived pension service quality has on pension plan choice, respondent's choice of pension plan was treated as a binary dependant variable, assigning a value of 1 to those who chose a plan and a value of 0 to those who did not. Five core service quality variables were chosen to be the reliability of service, responsiveness, convenience, security, and the level of service intelligence. Age, income, education, policy awareness, and risk preference were considered as control variables[18]. A logistic regression model was developed using Python, and the results are given in Table 3:

Table 3: Logistic Regression Results of Perceived Service Quality on Pension Scheme Selection

Variable Name	Variable Symbol	Regression Coefficient β	Standard Error S.E.	Wald Statistic	p-value	Odds Ratio (OR)	95% confidence interval for OR
Service reliability	SR	0.318	0.122	6.80	0.009	1.374	1.082–1.745
Service responsiveness	SS	0.184	0.118	2.43	0.119	1.202	0.954–1.515
Service Convenience	SC	0.467	0.129	13.12	0.000	1.595	1.239–2.053
Service Security	SE	0.276	0.116	5.67	0.017	1.318	1.050–1.653
Intelligent Service Level	ISL	0.392	0.124	9.99	0.002	1.480	1.160–1.888
Age	AGE	-0.221	0.093	5.65	0.017	0.802	0.668–0.963
Income level	INC	0.286	0.101	8.02	0.005	1.331	1.092–1.622
Educational Attainment	EDU	0.169	0.097	3.04	0.081	1.184	0.979–1.432
Level of Policy Awareness	PC	0.343	0.109	9.90	0.002	1.409	1.138–1.744
Risk appetite	RP	0.205	0.094	4.76	0.029	1.228	1.021–1.476
Constant term	Constant	-0.426	0.174	5.99	0.014	0.653	—
Sample size	N	426					
-2 Log-likelihood	-2LL	429.36					
Nagelkerke R²		0.246					
Hosmer-Lemeshow Test		0.412					

Table 3 shows the results of the impact of service convenience, level of intelligent service, service reliability, and service security. Service convenience has the greatest impact among them, with the highest regression coefficient of 0.467, and an OR of 1.595[19].Service convenience will increase the likelihood of a resident choosing the target pension model by 59.5% for every one-unit increase in perceived service convenience. For the other factors, the regression coefficient for level of intelligent services is 0.392 with an OR of 1.480, meaning that residents' willingness to choose a pension model is impacted by their experiences with services of online inquiry, intelligent customer services, and data verification. The p-value for service responsiveness is 0.119, which shows that the service responsiveness has a limited impact. As for the control variables, the level of income, policy awareness, and preference for risk all had a significant positive impact. Age, on the other hand, had a negative impact, where the regression coefficient for age is -0.221, meaning pension model preference was more cautious in choosing older age cohorts. Overall, the perceived quality of pension services is an excellent rationale for the differences in residents' choices with respect to pension schemes. A heatmap was drawn for the variables to describe the strength and direction of the correlation among the perceived quality of the pension services and the individual variables/characteristics to describe the census scheme choice as shown in Figure 6:

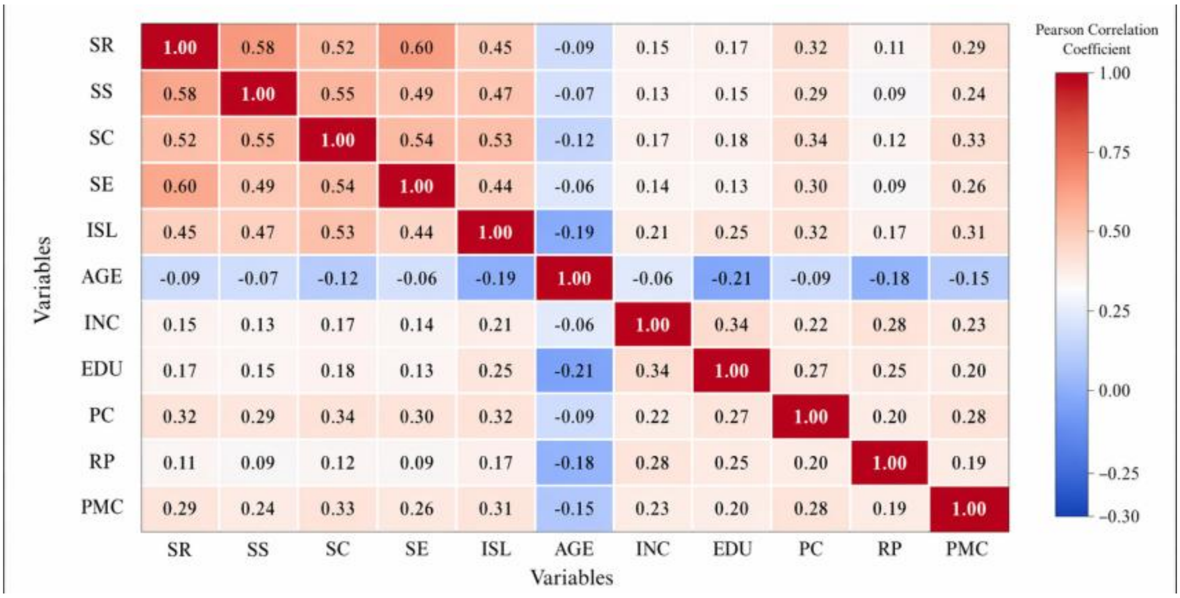

Figure 6: Correlation Heatmap of Main Variables

5.3 Analysis of Machine Learning Prediction Results

This study aimed to assess whether machine learning methods could be applied to predict the selection of pension schemes. Using the service dimension variables (reliability, responsiveness, convenience, security, the level of intelligent service and individual characteristic variables), a Random Forest classification model was performed in the Python environment. Considering the number of decision trees, the depth of the trees, and the minimum number of samples per leaf, it was designed with several parameter combinations for comparison. Random Forest parameters (e.g. accuracy, precision, recall, F1 score, AUC, and the confusion matrix) were performed on the same test set to predict and classify the predictive stability of the model. The results are displayed in Table 4:

Table 4: Results of Random Forest Model Parameter Tuning and Prediction Performance

Model ID	Number of Decision Trees n_estimators	Maximum Depth max_depth	Minimum Samples per Leaf Node min_samples_leaf	Accuracy	Precision	Recall	F1 score	AUC	OOB Score	True Negative	FP	FN	TP
RF-1	100	None	1	0.836	0.810	0.850	0.829	0.878	0.812	56	12	9	51
RF-2	200	8	3	0.844	0.833	0.833	0.833	0.889	0.827	58	10	10	50
RF-3	300	10	3	0.859	0.839	0.867	0.852	0.901	0.841	58	10	8	52
RF-4	500	12	5	0.852	0.847	0.833	0.840	0.895	0.838	59	9	10	50
RF-5	300	6	5	0.820	0.814	0.800	0.807	0.867	0.806	57	11	12	48

RF-3 Model performed the best overall of the 5 models and obtained a score of 0.859 for accuracy, 0.852 for the F1 score, and 0.901 for the AUC. Note, these scores of the RF-3 model are all better than the results of the other models. As seen in the confusion matrix, this model classified 58 unselected samples and 52 selected samples, and as a result of only 10 misclassifications and 8 omissions. Overview of the confusion matrix, shows that this model possesses the AI model possesses the good classification and the Good generalization performance[20]. For an intuitive assessment of predictive power of Random Forest models, this paper provides performance metrics for the Random Forest models that are plotted as lines and trends are evaluated for the accuracy, precision, recall, F1 score and AUC with the performance metrics obtained from the models listed in Table 4. Performance for the Random

Forest models RF-1 and RF-5 is evaluated and plotted as shown in Figure 7:

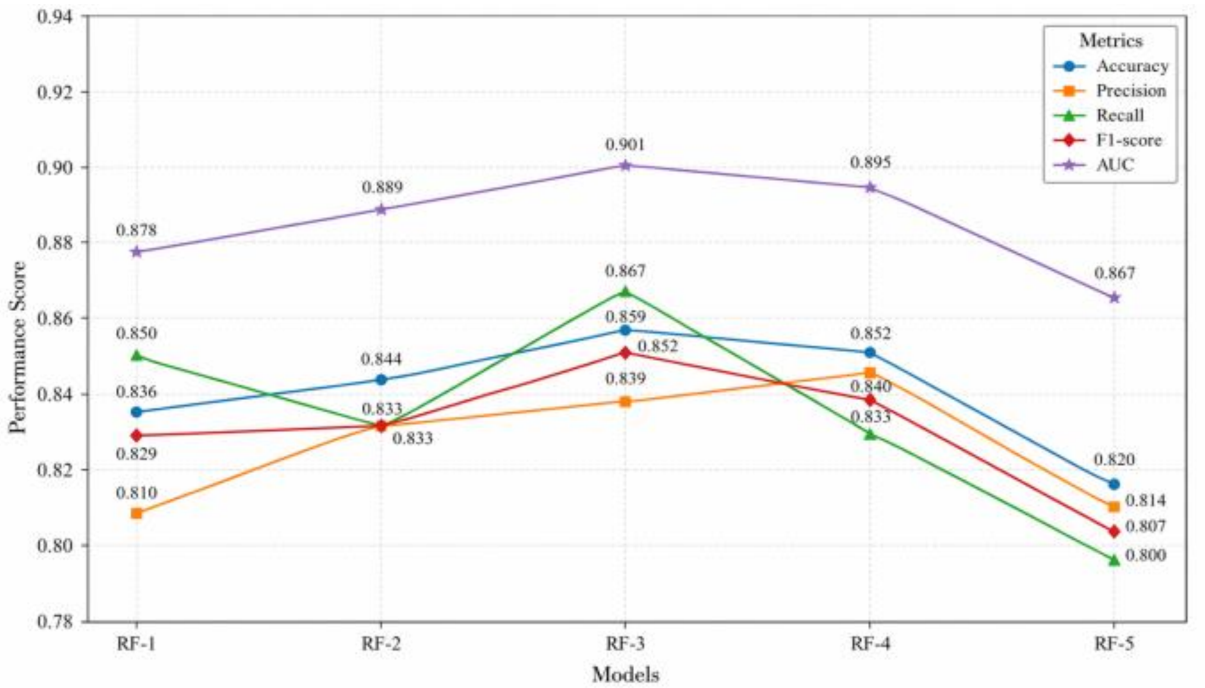

Figure 7: Comparison of Predictive Performance for Random Forest Models

5.4 Comparison of Model Performance and Ranking of Influencing Factors

In order to understand how traditional statistical models and machine learning models predict pension plan selection differently, Logistic Regression and the best Random Forest model (RF-3) are selected for this analysis. Logistic Regression will aim to understand the significance and direction of the effect that service quality perception variables have on selection behavior, while the Random Forest model will focus on predicting the class and determining variable importance. Both models will be assessed using the same test set comprising of 128 samples. In Table 5, these results are displayed:

Table 5: Comparison of Model Performance and Ranking of Influencing Factors

Model Name	Accuracy	Precision	Recall	F1 Score	AUC	True Negative	FP	FN	TP	Rank 1	Rank 2	Rank 3	Rank 4	Rank 5
Logistic Regression Model	0.813	0.790	0.817	0.803	0.846	55	13	11	49	Service Convenience	Level of Smart Services	Level of Policy Awareness	Service Reliability	Income Level
Random Forest Model RF-3	0.859	0.839	0.867	0.852	0.901	58	10	8	52	Convenience of Service	Level of Smart Services	Service Reliability	Level of Policy Awareness	Service Safety
Difference RF-3−Logistic	0.046	0.049	0.050	0.049	0.055	3	-3	-3	3	—	—	—	—	—

As shown in Table 5, out of all of the predictive metrics, Random Forest model RF-3 has the highest performance compared to the Logistic Regression model. RF-3 has an accuracy of 0.859, which is 0.046 higher than Logistic Regression, and [its] AUC value is 0.901 which is 0.055 higher than [that](the) of Logistic Regression. Thus, the Random Forest Classifier model RF-3 has better classifying ability to identify pension plan schemes. The confusion matrix states that RF-3 has 8 misclassifications, which is fewer than the 11 of the Logistic Regression model, and has correctly classified 52 of the selected [patients] and 58 of the unselected [patients]. Regarding the ranking of the framework's variables, both models show that the top [factors] are the automated [services] and the [services] features, which means that processing convenience is influenced by (1) the pension services (including the online retirement services), (2) the computerized services of support, and (3) the automated [services] and service processing. In order to provide a graphical representation of the predictive performance gap of the Random Forest model RF-3 compared to Logistic Regression, a model performance curve was created to show the distribution of the value of each metric, as shown in Figure 8:

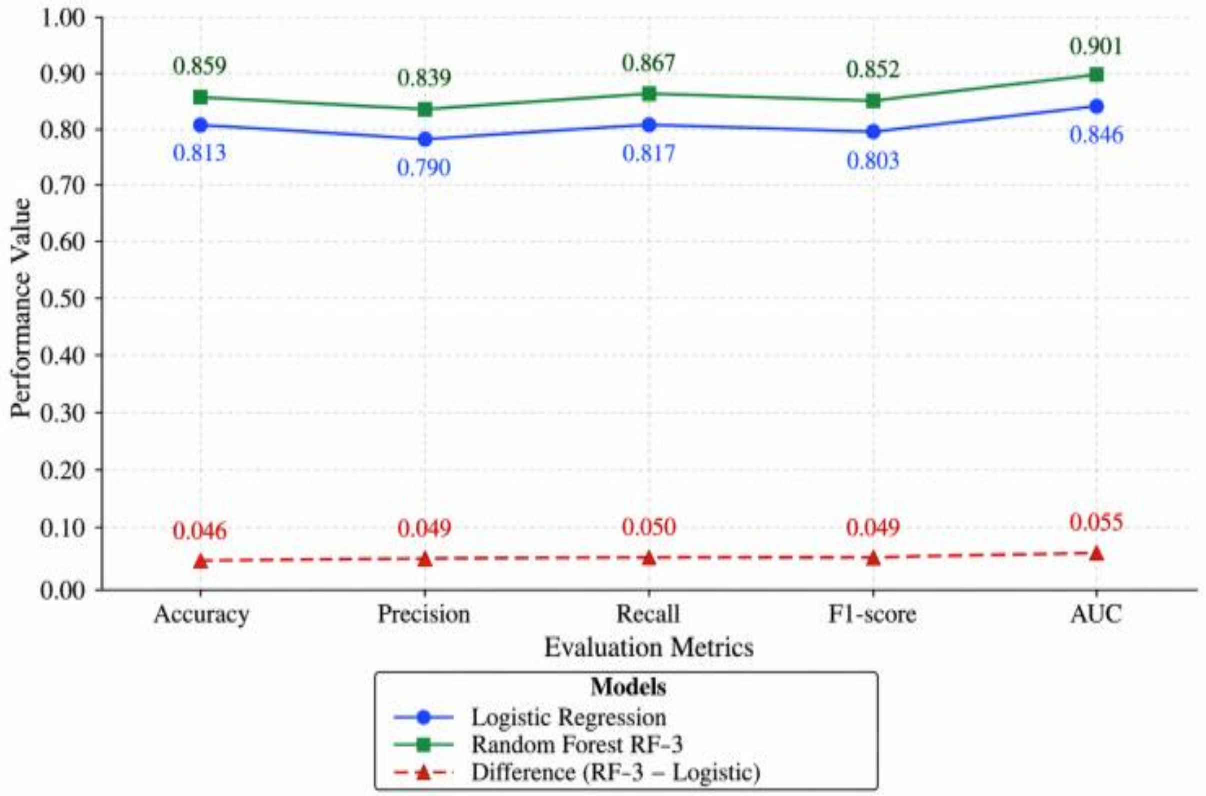

Figure 8: Performance Comparison of Logistic Regression and Random Forest RF-3

6 Conclusions

The perceived quality of the pension services influences the choice of pension plan. Among the four criteria (service convenience, reliability, intelligent services, and secure services), service quality is the most dominant. Residents perceive the trade-off between the services they received and the benefits they get from institutional trust from the services they received. This paper empirically analyzes the pension plan choice of the residential communities using predictive analytics and machine learning. This paper highlights the influence the quality of service renders. Service quality variables influence the choice of the pension plan offered by the community. This indicates that the quality of services offered in the communities helps to shape the residential communities. The predictive analytics and machine learning model will help improve the quality of pension planning offered to the communities in the future. The author hopes that the inequalities in his sample size and the design of both the geographical and the socio economic variables of the survey will be solved by his contemporaries. The author encourages his contemporaries to carry out research in the future that combines the various socio-economic variables taken geospatially, and combines XGBoost and Support Vector

Machine prediction plans, along with improving the pension plan's pricing in the communities.

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