__Original Research Article__

A study on the combination prediction of Anhui residents' consumption level based on the IOWA operator

ABSTRACT

Aims: In order to study the future trend of Anhui residents' consumption level and predict the consumption level of Anhui residents in the next three years (2022-2024), this paper constructs a combination prediction model based on the induced ordered weighted averaging (IOWA) operator.

Study design: This paper selects the national resident consumption level in Anhui province from 2000 to 2021, which covers a period of 21 years. Based on the data, an induced ordered weighted averaging (IOWA) operator combination prediction model is constructed using a multiple regression model, ARIMA (2,2,0) model, and machine learning decision tree model. The combination prediction method that minimizes the sum of squared errors is used to predict the consumption level of Anhui residents in the next three years (2022-2024), and the effectiveness of the induced ordered weighted averaging (IOWA) operator-based combination prediction model is evaluated.

Place and Duration of Study: This paper selects the national resident consumption level in Anhui Province from 2000 to 2021.

Methodology: This paper constructs a combination prediction model based on the induced ordered weighted averaging (IOWA) operator based on the multiple regression model, ARIMA (2,2,0) model, and machine learning decision tree model. The combination prediction method that minimizes the sum of squared errors is used to predict the consumption level of Anhui residents in the next three years (2022-2024), and the effectiveness of the induced ordered weighted averaging (IOWA) operator-based combination prediction model is evaluated.

Results: This study finds that the prediction accuracy of the IOWA operator-based combination prediction model is generally greater than that of individual prediction models, and the sum of squared errors is generally significantly lower than that of individual prediction models.

Conclusion: The prediction results show that the consumption level of Anhui residents in the next three years will not fluctuate greatly, but will have a trend of slight increase.

Keywords: Anhui Province residents' consumption level, single-factor prediction, IOWA operator, combination prediction model

1. INTRODUCTION

1.1RESEARCH BACKGROUND

Since the reform and opening up, the economy of Anhui province has been steadily and rapidly developing, reaching a stable middle-high growth level before the outbreak of COVID-19. During the epidemic period, the economic development speed slowed down, but after the epidemic, the economy gradually recovered, with an increase in economic growth rate and improvement in economic development quality. As one of the three drivers of economic development, household consumption fundamentally affects the economic development level of Anhui province. Studying the changing trend of household consumption level is beneficial to the province's grasp of the economic development momentum and direction. Thegovernment can formulate corresponding policies to promote the comprehensive improvement of the consumption level of Anhui residents, and promote the balanced and stable development of the economy in the province. After proposing to vigorously develop a new development pattern of dual circulation with the domestic cycle as the main body and the domestic and international cycles promoting each other, the focus of China's economic development has shifted to expanding domestic demand. After the epidemic, the Anhui provincial government issued policies to expand domestic demand, and the policy effects gradually became apparent. The role of the domestic cycle in Anhui province has been enhanced, and consumption remains the primary driving force for economic growth in Anhui province.

1.2 LITERATURE REVIEW

There are many cutting-edge research results in the field of household consumption in Anhui province. For example, Lu Siheng and Yin Hong built a model to predict the consumption level of Anhui residents in 2022 using a BP neural network model. After multiple rounds of training, they selected nine input variables and the consumption level of Anhui residents as the output variable. Then, they used statistical data from Anhui province from 1990 to 2018 to divide the training set and test set. By using the gradient descent method, they determined the final prediction model and used a normalized test set to test the feasibility of the model. The final results showed that the neural network model had a prediction ability with an error rate of less than 10% in the training set and the test set. In addition, Li Heng et al. analyzed the factors affecting the consumption level of residents in Bengbu, Anhui Province in 2023. These factors were classified into four explanatory variables, and a econometric model was constructed using statistical software. The results showed that per capita disposable income and the number of unemployed people at the end of the year in Bengbu, Anhui Province had a significant impact on the consumption level of residents. Based on these research results, policy suggestions can be proposed, such as expanding employment channels, improving employment levels, accelerating the development of inclusive finance, and narrowing the income gap among residents. There are also some research results with practical application value. For example, Li Ying and Zhuang Kejun constructed a combination prediction model based on ARIMA, Holt-Winters, and multiple regression models according to the historical changes of China’s household consumption level in 2022. They used the induced ordered weighted averaging operator to predict the household consumption level in the next four years (2020-2023). You Wenqian and Zhuang Kejun proposed a combination prediction model based on the IOWA operator in 2020 and used it to predict China’s grain yield in the next five years (2019-2023). These studies indicate that the combination prediction model has better prediction effect, and that China’s household consumption level and grain yield are showing an increasing trend.

2. METHODOLOGY

2.1 OWA OPERATOR

$\sum_{i=1}^{n} w_i = 1, \ (w_i \geq 0, i = 1, 2, ..., n)$ .Let the n-ary function

W_{OWA}: $R^n \to R, W = (w_1, w_2, ..., w_n)^T$ be the corresponding weight coefficient vector of

W_{OWA} .Let $W_{OWA}(\alpha_1, \ \alpha_2, ..., \alpha_n) = \sum_{i=1}^{n} w_i \beta_i$ the i-th numerical value arranged in β_i as

$(\alpha_1, \ \alpha_2, ..., \alpha_n)$ ascending order is called the n-ary ordered weighted arithmetic mean operator, abbreviated as the OWA operator.

2.2 IOWA operator

Set $(\langle \alpha_1, \beta_1 \rangle, \langle \alpha_2, \beta_2 \rangle, \ldots, \langle \alpha_n, \beta_n \rangle)$ as n two-dimensional arrays, $W = (w_1, w_2, ..., w_n)^T$ is the corresponding weight coefficient vectors of W_{OWA} that satisfies

$\sum_{i=1}^{n} w_i = 1, \ (w_i \geq 0, i = 1, 2, ..., n)$.

Let $W_{IOWA}(\langle \alpha_1, \beta_1 \rangle, \langle \alpha_2, \beta_2 \rangle, ..., \langle \alpha_n, \beta_n \rangle) = \sum_{i=1}^{n} w_i \beta_{\alpha - index(i)}$ arrange the inducing factors

$(\alpha_1, \alpha_2, ..., \alpha_n)$ in descending order, indicating $\alpha - index(i)$ as the order of the inducing factors i, abbreviated as the IOWA operator.

2.3 IOWA combined prediction model

Assuming that the same problem is predicted using m (m ≥ 2) methods, x_t represent the actual observed values at time t. x_{it} represents the predicted value of method i at time t, e_{it} represents the prediction error of method i at time tand $e_{it} = x_t - x_{it} (i = 1, 2, ..., m; t = 1, 2, ..., T)$ represents the weight of method i in the combined prediction model (i=1, 2,..., m; $\sum_{i=1}^{n} w_i = 1$). The calculation formula for the predicted value during the sample period is $\hat{x}_t = \sum_{i=1}^{m} w_i x_{it}$ and the calculation formula for the error during the sample period is

$$e_t = x_t - \hat{x}_t = x_t - \sum_{i=1}^{m} w_i x_{it} = \sum_{i=1}^{m} w_i x_t - \sum_{i=1}^{m} w_i x_{it} = \sum_{i=1}^{m} w_i (x_t - x_{it}) = \sum_{i=1}^{m} w_i e_{it} (t = 1, 2, ..., T).$$

This article uses prediction accuracy as the inducing factor. If the inducing factor $\alpha_{it}(i = 1, 2, ..., m; t = 1, 2, ..., T)$ selects the prediction accuracy of the i-th prediction method in the t-th period, the expression is: $\alpha_{it} = \begin{cases} 1 - \left|\frac{x_t - \hat{x}_t}{x_t}\right|, \left|\frac{x_t - \hat{x}_t}{x_t}\right| \le 1 \\ 0, \left|\frac{x_t - \hat{x}_t}{x_t}\right| \ge 1 \end{cases}$.

Arrange the m two-dimensional arrays $\left(\langle \alpha_{1t}, x_{1t} \rangle, \langle \alpha_{2t}, x_{2t} \rangle, ..., \langle \alpha_{mt}, x_{mt} \rangle\right)$ generated by the inducing factors in descending order of the inducing factors, and obtain the weight coefficient vectors $W = (\mathrm{w}_1, w_2, ..., w_n)^T$, $\sum_{i=1}^{\mathrm{n}} w_{\mathrm{i}} = 1$, $(w_{\mathrm{i}} \ge 0, i = 1, 2, ..., n)$ for each accuracy based on the minimum sum of squares error criterion. The prediction $\alpha_{1t}, \alpha_{2t}, ..., \alpha_{mt}$ induced prediction error $x_{1t}, x_{2t}, ..., x_{mt} (t = 1, 2, ..., T)$ of the IOWA operator combination prediction model generated by the prediction accuracy is $e_{\alpha-index(it)} = x_t - x_{\alpha-index(it)} (i = 1, 2, ..., m; t = 1, 2, ..., T)$.

Let $R_m = (1, 1, ..., 1)^T$ be an m-dimensional unit vector, and the constraint condition for the weight coefficient vector $W = (w_1, w_2, ..., w_m)^T$ is $R^T W = 1, W \ge 0$. Therefore, the prediction error of the IOWA combination prediction model at time t is

$$x_t - \hat{x}_t = x_t - \sum_{i=1}^{m} w_i x_{\alpha-index(it)} = \sum_{i=1}^{m} w_i x_t - \sum_{i=1}^{m} w_i x_{\alpha-index(it)} = \sum_{i=1}^{m} w_i (x_t - x_{\alpha-index(it)}) = \sum_{i=1}^{m} w_i e_{\alpha-index(it)} (t = 1, 2, ..., T)$$

The sum of squares of the total prediction error of the model is

$$U = \sum_{t=1}^{T} e_t^2 = \sum_{t=1}^{T} (x_t - \sum_{i=1}^{m} w_i x_{\alpha-index(it)})^2 = \sum_{i=1}^{m} \sum_{j=1}^{m} w_i w_j (\sum_{t=1}^{T} e_{a-index(it)} e_{a-index(jt)})$$

$$= \sum_{i=1}^{m} \sum_{j=1}^{m} w_i w_j \bar{E}_{ij} (\bar{E}_{ij} = \bar{E}_{ji} = \sum_{t=1}^{T} e_{a-index(it)} e_{a-index(jt)}, i, j = 1, 2, ..., m).$$

The prediction error information matrix for m-order IOWA is $\bar{E} = (\bar{E}_{ij})_{m \times m}$,

$U = W^T \bar{E} W$ .Therefore,the IOWA combination prediction model based on the optimization criterion of minimizing the sum of squares of errors is $\min U = W_m{}^T \bar{E}_m W_m, s.t. \begin{cases} R_m^T W = 1 \\ W \ge 0 \end{cases}$.

2.4 MODEL EVALUATION SYSTEM

The commonly used error squared sum accuracy of IOWA operator combination prediction models is shown in the table below:

Table 1. Model Evaluation Criteria Table

Name	Formula
Sum of squares error	$SSE=\sum_{t=1}^{N}(x_t-\hat{x}_t)^2$
Mean squared error	$MSE=\frac{1}{N}\sqrt{\sum_{t=1}^{T}(x_t-\hat{x}_t)^2}$
Mean absolute error	$MAE=\frac{1}{N}\sum_{t=1}^{N}\lvert x_t-\hat{x}_t\rvert$
Mean Absolute Percent Error	$MAPE=\frac{1}{N}\sum_{i=1}^{N}\left\lvert\frac{x_t-\hat{x}_t}{x_t}\right\rvert$
Mean square percentage error	$MSPE=\frac{1}{N}\sqrt{\sum_{t=1}^{N}(\frac{x_t-\hat{x}_t}{x_t})^2}$

2.5 MULTIPLE REGRESSION MODEL

The multiple regression model is one of the basic models in econometrics. Establish a mathematical model using regression analysis under certain assumptions. If the model contains only one regression variable, it is called a univariate regression model. If the model contains two or more regression variables, it is called a multiple regression model.

The equation describing how the dependent variable y depends on the independent variable and error term is called a multiple regression model, with the dependent variable y and k independent variables $x_1, x_2, ..., x_k$ respectively. Its general form can be expressed as: y=B0+B1 x_1 +B2 x_2 +· · · · · · +Bk x_k + ε。 In the equation, B0, B1, B2,..., Bk are the parameters of the model; Is the error term.

2.6 TIME SERIES ARIMA MODEL

The ARIMA model belongs to a type of ARMA model (Autoregressive Integrated Moving Average Model), which is also known as the autoregressive integral moving average model. The ARIMA model (p, d, q) is called the differential autoregressive moving average model, where AR is autoregressive and p is the autoregressive term; MA is the moving average, q is the number of moving average terms, and d is the number of differences made when the time series becomes stationary.

2.7 DECISION TREE MODEL

In machine learning, decision trees are a commonly used prediction model. As the name suggests, the decision tree generates a tree structure at runtime, where each internal node represents a test on an attribute, each branch represents a test output, and each leaf node represents a category. Decision trees are a type of supervised learning that trains sets to provide data and determine data categories. According to this principle, decision trees can also be applied to fit the development of data.

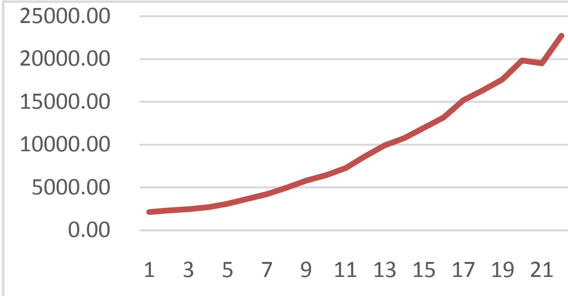
3. RESULTS AND DISCUSSION

3.1 DATA SOURCES

All the raw data used in this article are sourced from the Anhui Statistical Yearbook from 2001 to 2022. In order to more accurately reflect the overall level of consumer spending among residents, without being affected by the consumption gap between urban or rural residents, this article uses the weighted population ratio of rural per capita consumption expenditure to urban per capita consumption expenditure to represent the resident consumption index.

3.2 VARIABLE DEFINITION AND DESCRIPTIVE STATISTICS

Figure 1. Changes in Resident Consumption over Time in Anhui Province



From Figure 1, it can be seen that with the increase of years, the economy continues to grow and residents' consumer spending continues to increase.

3.3 SINGLE ITEM PREDICTION MODEL

3.3.1 Multiple regression model

Assuming Y represents the level of household consumption and t represents the year, the regression model is $Y = -1967464.211 + 983.361t$, t=20002001, 2021.

The t-value of the constant is -19.691, and the p-value is 0.000 * * *, rejecting the original hypothesis and indicating significant constant; The t-value of the coefficient is 49.698, and the P-value is 0.000 * * *. Rejecting the original hypothesis, the coefficient is significant. R^2 of the model It is 0.951, and the overall F-value of the model is 391.511, with a P-value of 0.000 * * *, indicating a high degree of fitting and good fitting effect.

3.3.2 Time Series ARIMA Model

Table 2. ARIMA Inspection Table

term	symbol	Value
	Df Residuals	17
Number of samples	N	22
	Q6（P value）	0.486(0.486)
q statistic	Q12（P value）	3.882(0.693)
	Q18（P value）	6.247(0.903)
Information Criterion	AIC	314.191
	BIC	318.174
Goodness of fit	R^2	0.993

Based on the AIC information criterion, the optimal parameters are automatically searched for. The model results are the ARIMA model (2,2,0) test table, and based on the variable: consumption level of residents in the province. From the analysis of Q-statistics results, it can be concluded that Q6 does not show significant significance at the level, and the assumption that the residual of the model is a white noise sequence cannot be rejected. At the same time, the goodness of fit of the model R^2 It is 0.993, and the model performs well and basically meets the requirements.

3.3.3 Decision Tree Model

Model setting training set: Test set=9:1, randomly dividing all data, so the model has a fitting degree of 100% for the training set that accounts for 90%.If the error calculation is continued in the combination prediction, it will have a huge negative impact on the results. Therefore, this article only selects three data from the test set for combination prediction calculation. The specific parameters of the decision tree model are as follows:

Table 3. Decision Tree Model Parameters Table

Parameter Name	Parameter value
Training time	0.007s
Data segmentation	0.9
Data shuffle	Yes
Cross validation	No
Node splitting evaluation criteria	friedman_mse
Criteria for selecting feature partitioning points	best
Maximum feature ratio considered during partitioning	None
Minimum number of samples for internal node splitting	2
Minimum number of samples for leaf nodes	1
Minimum weight of samples in leaf nodes	0
The maximum depth of the tree	10
Maximum number of leaf nodes	50
Threshold for impure node partitioning	0

Table 4. Single item prediction values and prediction accuracy

Year	True value/yuan	Multiple Regression Model		ARIMA Model		Decision Tree Model	
		Predicted value/yuan	Prediction accuracy	Predicted value/yuan	Prediction accuracy	Predicted value/yuan	Prediction accuracy

2000	2136.71	-741.63	-0.347	\	\	2136.71	1.000
2001	2322.25	241.73	0.104	\	\	2322.25	1.000
2002	2476.83	1225.09	0.495	\	\	2476.83	1.000
2003	2706.05	2208.45	0.816	\	\	2706.05	1.000
2004	3119.33	3191.82	0.977	3058.63	0.981	3119.33	1.000
2005	3677.09	4175.18	0.865	3416.85	0.929	3677.09	1.000
2006	4229.12	5158.54	0.780	4094.65	0.968	4229.12	1.000
2007	4990.07	6141.90	0.769	4890.26	0.980	4990.07	1.000
2008	5811.28	7125.26	0.774	5659.34	0.974	5811.28	1.000
2009	6424.76	8108.62	0.738	6596.69	0.973	6424.76	1.000
2010	7252.98	9091.98	0.746	7505.95	0.965	6424.76	0.886
2011	8641.72	10075.34	0.834	8132.93	0.941	8641.72	1.000
2012	9933.97	11058.70	0.887	9259.07	0.932	8641.72	0.870
2013	10779.91	12042.07	0.883	11155.12	0.945	10779.91	1.000
2014	11987.84	13025.43	0.913	12560.15	0.952	11987.84	1.000
2015	13184.48	14008.79	0.937	13211.69	0.998	13184.48	1.000
2016	15190.93	14992.15	0.987	14334.80	0.944	15190.93	1.000
2017	16335.38	15975.51	0.978	16231.58	0.994	16335.38	1.000
2018	17631.17	16958.87	0.962	18340.19	0.960	16335.38	0.927
2019	19812.10	17942.24	0.906	19563.38	0.987	19812.10	1.000
2020	19491.32	18925.60	0.971	20794.83	0.933	19491.32	1.000

2021	22705.33	19908.96	0.877	22370.96	0.985	22705.33	1.000

3.4 COMBINATION PREDICTION MODEL

3.4.1 Model construction

According to the introduction of the IOWA operator principle in the previous text, this article arranges the results of single item prediction of three data in terms of accuracy and time as shown in Table5:

Table 5 Table of Predicted Values Sorted by Precision

Year	True value/yuan	The highest accuracy			Second highest accuracy			Lowest accuracy		
		Predicted value/yuan	Error value/yuan	accuracy	Predicted value/yuan	Error value/yuan	accuracy	Predicted value/yuan	Error value/yuan	accuracy
2010	7252.98	7505.95	-252.97	0.965	6424.76	828.22	0.886	9091.98	-1839.00	0.746
2012	9933.97	9259.07	674.89	0.932	11058.70	-1124.74	0.887	8641.72	1292.25	0.870
2018	17631.17	16958.87	672.29	0.962	18340.19	-709.019	0.920	16335.38	1295.79	0.927

Based on the data in the table, construct an error information table and obtain the error information matrix as follows:

$$E=\begin{bmatrix} 689342.808 & -2705268.3088 & 521670.66 \\ -2705268.3088 & 3347435.24 & -2584042.0947 \\ 521670.66 & -2584042.0947 & 453079.5369 \end{bmatrix}$$

Establish an IOWA operator combination prediction model with the goal of minimizing the sum of squares of errors:

$$Y = 689342.808\, w_1^2 - 2705268.3088\, w_1 w_2 + 521670.66\, w_1 w_3 + 3347435.24\, w_2^2 - 2584042.0947\, w_2 w_3 + 453079.5369\, w_3^2$$

$$s.t.\begin{cases} w_1 + w_2 + w_3 = 1 \\ w_1 \geq 0, w_2 \geq 0, w_3 \geq 0 \end{cases}$$

Among them, represents the weight of the decision tree prediction model, represents the weight of the multiple regression model bw2, and represents the weight of the time series ARIMA model. Solved as: a=0.1877, b=0.5533, c=0.259.

Table 6. Predicted values and accuracy of combined prediction models

Year	Predicted value/yuan	Prediction accuracy
2010	8080.56	0.886
2012	10138.93	0.979
2018	17199.60	0.976

3.4.2 Model evaluation

This article uses the minimum sum of squares of errors as the standard to measure the fitting accuracy of each model. The normalized results of the sum of squares of errors for each model are shown in Table 7. As shown in the figure, the normalized sum of squares of the combined prediction model based on the IOWA operator is the smallest, at 913110.81, which is lower than the normalized sum of squares of errors for each single prediction model. The normalized sum of squares of errors for multiple regression models is 5098952.172, The sum of squared normalized errors of the time series ARIMA model is 1022184.834, and the sum of squared normalized errors of the decision tree model is 4034915.25. From this, it can be seen that the total sum of squares of the predicted values obtained from the combined prediction model is the smallest, and the accuracy of the combined prediction model is higher than that of each single prediction model. The combined prediction effect is the best, and the combined prediction model is effective.

Table 7. Comparison of Model Errors

error metric	Multiple Regression Model	Time series ARIMA model	Decision Tree Model	Combination prediction model
Normalization of sum of squares error	5098952.172	1022184.834	4034915.25	913110.81

3.4.3 Combined Forecast Results

According to the principle of the IOWA combination model, the predictions of the 2010, 2012, and 2018 data are sorted based on the prediction accuracy calculated from the actual and predicted values of the year as inducing factors. However, the reality is that the actualvalues of residents' consumption levels after 2021 cannot be obtained, so the weights obtained in the previous text should not be used to predict the consumption levels of residents in Anhui Province for the next three years, Therefore, it is necessary to reassign the weights of each individual prediction model. The specific operation is to sum the weights assigned to each individual prediction model in three periods and divide them by 9, and calculate the contributions made by each individual prediction model to the combined prediction model. The weights assigned to the multivariate prediction model, time series ARIMA model, and decision tree model are w_1 =0.289, w_2 =0.444, and w_3 =0.267, respectively. The formula for calculating the consumption level of residents in Anhui Province for the next three years based on the obtained weights is:

$$\hat{x}_t = 0.289x_{t-\text{multielement}} + 0.444x_{t-ARIMA} + 0.267x_{t-\text{decision tree}}.$$

The predicted results of residents' consumption level in Anhui Province in the next three years are shown in Table 8:

Table 8. Combination prediction model predicts the consumption level of residents in the next three years

Year	Multiple Regression Model	Time series ARIMA model	Decision Tree Model	Combination prediction model
2022	20892.32	22843.38	21567.89	21088.91
2023	21875.68	25028.62	23478.69	22342.16
2024	22859.04	26744.13	23542.52	23057.93

4 CONCLUSION AND SUGGESTIONS

4.1 CONCLUSION

This article is based on the data prediction accuracy of three single item prediction models, multiple regression model, time series ARIMA model, and machine learning decision tree model, as induced values. The IOWA operator is used to weight the three single item prediction models, thus obtaining the IOWA combination prediction model. The three individual prediction models have all passed the P-value test as a whole, and the fitting effect is good. The combined prediction model obtained by weighting the IOWA operator performs better on the predicted values than each individual prediction model, improving the prediction accuracy and reducing the sum of squares of errors. Therefore, it can be seen that the fitting effect of the combined prediction model based on the IOWA operator has been improved. Finally, recalculate the weights of each individual prediction model to predict the consumption level of residents in Anhui Province in the next three years.

4.2 SUGGESTIONS

Based on the research conclusions of this article, the following suggestions are proposed for improving the consumption level of residents in Anhui Province:

4.2.1 Accelerating the Urbanization Process in Anhui Province

The method of calculating residents' consumption level in this article is to calculate the consumption level of all residents in Anhui Province by weighting the proportion of urban and rural population. Therefore, the proportion of urban and rural population to the total population in Anhui Province is an important factor affecting the consumption level of residents in Anhui Province. To this end, Anhui Province should strengthen urbanization construction, accelerate the advancement of urbanization in Anhui Province, and narrow the urban-rural gap in a quantitative manner. The government encourages the transfer of rural population to cities and improves relevant supporting facilities for population transfer.

4.2.2 Improve the social security system in Anhui Province

The per capita disposable income level is another important factor affecting residents' consumption level. Although the social security system in Anhui Province has been continuously improving in recent years, due to the limitations of economic development level, there are still shortcomings in the social security system. Residents have significant concerns about uncertain expenditures, and consumption expectations have been greatly affected. Due to restrictions on disposable income, people tend to consume conservatively. Therefore, the Anhui Provincial Government needs to improve the social security system and enhance residents' sense of consumption security.

4.2.3 Improving the Employment Level in Anhui Province

Since the outbreak of the epidemic, the number of unemployed people has increased, greatly affecting the consumption willingness of residents in Anhui Province. After the epidemic, the economy has rebounded and employment levels have improved. However, the Anhui Provincial Government needs to create more job opportunities, restore economic development momentum, and optimize industrial structure. In addition, in order to improve the quality of the labor force, the Anhui Provincial Government should strengthen employment training and improve the employment skills of workers. At the same time, we encourage people to innovate and start businesses, lower the threshold for entrepreneurship and innovation, and strengthen employment support.

4.2.4 Narrowing the Income Gap among Residents in Anhui Province

According to the principles of Western economics, the marginal propensity to consume of people with high income levels is lower than that of those with medium to low income levels, and the increase in income gap has a negative impact on the improvement of residents' consumption levels. In addition, the Gini coefficient of residents in Anhui Province is relatively high. Therefore, Anhui Province needs to further improve the initial distribution and redistribution of residents' income, further standardize the order of income distribution, and strengthen the transparency of income distribution. Enhance the financial capacity of residents in Anhui Province, especially those with middle and low incomes. Income determines consumption, with low to middle-income individuals having low income and no excess consumption capacity. The Engel's coefficient is high and the basic quality of life is low. The government wants to improve the consumption level and income level of residents in Anhui Province from the source, which is the key to solving the problem of insufficient consumption demand.

4.2.5 Expanding the Consumption Space of Aging Population

Anhui Province has been experiencing an aging trend since the 1990s. After the COVID-19 pandemic in 2023, the aging trend is severe, and the phenomenon of low marriage rate and fewer children is also very serious. The government is promoting and implementing policies to increase marriage and fertility rates, but cannot ignore the consumption market of the elderly. The increase in the elderly population has led to the growth of the elderly consumer group, At the same time, the improvement of living standards has led to an increase in the average age of the population in China. The consumption timeline of the elderly has been extended, and the improvement of living standards and cognitive levels has led the elderly to pursue an improvement in the quality of life in their later years. The accumulation of work throughout their lives is also richer than that of young people. Therefore, the elderly have enormous consumption potential and fully stimulate their consumption desire, Meeting the consumption needs of the elderly is an important step in improving the consumption level of residents in Anhui Province. The consumption energy of the elderly cannot be ignored and will play an important role in the increasingly aging socio-economic situation.

4.2.6 Enhancing personal value awareness

People should actively engage in self-education, pursue self-improvement and comprehensive personal development, actively devote themselves to their favorite positions, unleash personal value, and deeply recognize their responsibilities and obligations for promoting regional economic development.

In summary, the improvement of residents' consumption level and economic development level in Anhui Province is complementary and requires the joint efforts of the government, enterprises, and individuals.

REFERENCES

1.Li Heng, Yao Siyuan, Yang Rentao, et al. Analysis of Factors Influencing the Consumption Level of Urban Residents in Bengbu City, Anhui Province [J]. China Business Review, 2023, No.880 (09): 96 99. DOI: 10.19699/j.cnki.issn2096-0298.2023.09.096.

2.Li Ying, Zhuang Kejun. A Study on the Combination Prediction of Chinese Residents' Consumption Level Based on the IOWA Operator [J]. Journal of Chongqing University of Technology (Natural Science Edition), 2022, 39 (01): 92-100. DOI: 10.16055/j.issn.1672-058X.2022.0001.013.

3.You Wenqian, Zhuang Kejun. Research on China's Grain Yield Combination Prediction Based on IOWA Operator [J]. Journal of Chongqing University of Technology (Natural Science Edition), 2020,37 (05): 80-87. DOI: 10.16055/j.issn.1672-058X.2020.0005.013.