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Management Optimization Path of Grassroots Public Service Collaboration Mechanisms in Digital Governance Scenarios

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SUMMARY: *Grassroots governance is the cornerstone of China's governance system, and the level and effectiveness of governance at the grassroots level are directly related to the development and stability of the whole national society. Based on the social survey data of grassroots public service coordination mechanism in 105 villages in Province A in 2024, the article selects the influencing factors of grassroots public service coordination and determines 14 independent variables based on one-way ANOVA and Lasso regression model, and analyzes the relevant influencing factors of the management optimization paths of the grassroots public service coordination mechanism by using multicategorical ordered logistic regression model. The results show that the clarity of the policy framework, the uniformity of regulations and standards, the orientation of assessment and incentives, the leadership and political determination, the appropriateness of the organizational structure, the adequacy of resource security, the degree of integration of platforms, the quality and security of data, the applicability of technology, the digital literacy of personnel, the awareness and ability of collaboration, the effectiveness of the training system, the degree of process optimization, and the accessibility and inclusiveness of services have a significant impact on the management optimization of grass-roots public service collaborative mechanisms. Optimization has a significant impact. It is recommended that the government improve the main governance capacity, promote the construction of a collaborative governance infrastructure platform, improve the relevant supporting mechanisms, and increase the publicity of the governance collaborative mechanism.*

KEYWORDS: *multicategorical ordered logistic regression model; one-way ANOVA; Lasso regression model; grassroots public services; digital governance*

1 Introduction

As an important link connecting people's hearts and minds, public service is the proper meaning of promoting social justice and advancing common prosperity, and is of great significance in enhancing the people's sense of gain, happiness and security, as well as in promoting the comprehensive development of the human being and the overall progress of society. However, at present, due to the development planning or economic foundation of each region, especially in the grass-roots areas, or even the phenomenon of "stagnation", the construction of grass-roots public services lags behind the city, and the development of grass-roots public services is not balanced between the areas of development [1-3]. In addition, grass-roots public services show serious problems such as uneven distribution of resources, information barriers, and insufficient synergy, resulting in low service efficiency and effectiveness [4-6]. Therefore, there is an urgent need for the development of grassroots public services to keep up with the pace of

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national modernization and ensure the realization of common wealth, and digital empowerment provides a new perspective for the equalization of grassroots public services.

The provision of digital public services by the government for the people is an important way to meet the people's needs for a better life and enhance their sense of access and happiness. The digital governance approach effectively breaks the time and space barriers, improves the level of inclusion of limited resources, greatly facilitates people's lives, meets diversified personalized needs, and promotes the social inclusion of public services [7-9]. The new round of information technology revolution led by 5G and big data, and the development of the digital society, not only accelerate the integration of digital technologies with various industries and sectors of society, but also play a significant role in promoting the digital transformation of public services in urban and rural areas, bridging the "digital divide", innovating the supply model of public services, and enhancing the precision level of public service supply [10-14]. It is worth noting that the focus of empowering public services with digital technology is to promote the equalization of basic public services in urban and rural areas, and to enhance the people's sense of access, happiness and security [15, 16]. However, in the process of public service development under digital governance, some grassroots digital public service construction has “copied and pasted” the standards and requirements of public services in other smart cities, and most grassroots service subjects have insufficient synergy, resulting in the supply of digital technology not being able to meet the demand for grassroots public services, which affects the efficiency of the supply of grassroots public services [17-21]. With the deepening of digital governance, it is important to unite multiple official departments and related social organizations, enterprises, citizens and other central subjects to carry out collaborative governance.

The article firstly explains the relevant theories of Logistic regression model and establishes the grassroots public service synergy mechanism in 105 villages within the scope of province A as the research object for investigation. Then, the following variables were initially selected as influencing factors: clarity of policy framework, uniformity of regulations and standards, assessment and incentive orientation, leadership and political determination, adaptability of organizational structure, sufficiency of resource guarantee, degree of platform integration, data quality and security, technical applicability, personnel digital literacy, collaborative awareness and ability, effectiveness of training system, degree of process optimization, accessibility and inclusiveness of services, multi-party participation mechanism, and feedback and response mechanism. Then, based on the results of single factor analysis and Lasso regression analysis, 14 independent variables such as clarity of policy framework, uniformity of regulations and standards, and appraisal and incentive orientation were selected, and a multicategorical ordered logistic regression model was applied to study the influencing factors of the management optimization paths of the grass-roots public service collaborative mechanism.

2 Data sources and modeling

2.1 Theories Related to Logistic Regression Models

2.1.1 Theory of Classical Logistic Regression Models

In a general linear model, the value of the dependent variable y is meaningful and it is usually assumed that $y \sim N(\mu, \sigma^2)$. When y is a dichotomous variable or a variable of type 0-1, a value of y of 0 or 1 is only nominal and has no practical significance. In this case, y obeys the Bernoulli distribution, i.e., $y \sim b(1, p)$. For 0-1 type variables, the regression model needs to be improved.

(1) The regression function can no longer follow the linear regression equation, but should use a continuous curve restricted to the $[0,1]$ interval. In practice, the more widely used is the Logistic function, which is of the form:

$$y = f(x) = \frac{1}{1+e^{x}} \tag{1}$$

(2) The dependent variable y itself can only be taken as 0 or 1, and cannot be used directly as an independent variable in a regression model. Noting that P is the probability that $y=1$ and Q is the probability that $y=0$, it is clear that there is $Q=1-P$. Suppose that p independent variables $x_1, x_2, \cdots, x_p$ are observed, denoted $X = \left(x_1, x_2, \cdots, x_p\right)$. The difference with the linear model is that instead of studying the relationship between the dependent variable and the independent variable, we study the relationship between the probability P of the dependent variable taking a certain value and the independent variable.

Practical observations show that the relationship between the probability P and the explanatory variables is "S"-shaped rather than linear. The logistic function is an "S" shaped curve, so the logistic curve is generally used to describe the relationship between P and the explanatory variable X:

$$P\left(y=1 \middle| X\right) = \frac{\exp\left(\beta_0 + \beta_1 x_1 + \cdots + \beta_p x_p\right)}{1+\exp\left(\beta_0 + \beta_1 x_1 + \cdots + \beta_p x_p\right)} = \frac{\exp\left(X\beta\right)}{1+\exp\left(X\beta\right)} \tag{2}$$

Logit transformation of the above equation gives:

$$Logit\left(y\right) = \ln\left(\frac{P}{1-P}\right) = \beta_0 + \beta_1 x_1 + \cdots + \beta_p x_p = X\beta \tag{3}$$

This equation is called the classical logistic regression model, $\beta_0, \beta_1, \cdots, \beta_p$] are the parameters to be estimated.

However, in practice, it is often encountered that the dependent variable is an ordered variable with multiple levels. By generalizing the general logistic regression model, a multicategorical ordered logistic regression model can be obtained.

2.1.2 Multiclassified Ordered Logistic Regression Models

Let y be an ordered response variable with k levels and $X = \left(x_1, x_2, \cdots, x_m\right)$ be the vector of independent variables. The probability of y taking j levels is $\pi_j = P\left(y = j \middle| X\right)$, $j = 1, 2, \cdots, k$ and $\sum \pi_j = 1$. The k levels are divided into two categories: $\{1, 2, \cdots, j\}$ and $\{j+1, j+2, \cdots, k\}$ with $j = 1, 2, \cdots, k-1$. Logistic regression is performed on the multicategorical ordinal response variable according to the logistic regression model for the dichotomous response variable. When each x_i is a dichotomous, multicategorical ordered independent variable, it is necessary to fit the following $k-1$ two-categorical Logistic regression equations:

$$\sum_{1}^{j} p_j = \frac{\exp\left(a_j + \sum_{1}^{m} b_i x_i\right)}{1+\exp\left(a_j + \sum_{1}^{m} b_i x_i\right)},\ j = 1, 2, \cdots, k-1 \tag{4}$$

$$\sum_{1}^{j-1} p_{j-1} = \frac{\exp\left(a_{j-1} + \sum_{1}^{m} b_i x_i\right)}{1+\exp\left(a_{j-1} + \sum_{1}^{m} b_i x_i\right)},\ j = 2, \cdots, k-1 \tag{5}$$

Equation (5) minus (4) is obtained:

$$p_j = \frac{\exp\left(a_j + \sum_{1}^{m} b_i x_i\right)}{1+\exp\left(a_j + \sum_{1}^{m} b_i x_i\right)} - \frac{\exp\left(a_{j-1} + \sum_{1}^{m} b_i x_i\right)}{1+\exp\left(a_{j-1} + \sum_{1}^{m} b_i x_i\right)} \tag{6}$$

$$p_k = 1 - \sum_{1}^{k-1} p_j = 1 - \frac{\exp\left(a_{k-1} + \sum_{1}^{m} b_i x_i\right)}{1+\exp\left(a_{k-1} + \sum_{1}^{m} b_i x_i\right)} \tag{7}$$

Further deformations are available:

$$Ln\left[\frac{\sum_{1}^{j} p_j}{1-\sum_{1}^{j} p_j}\right] = a_j + \sum_{1}^{m} b_i x_i,\ \ j = 1, 2, \cdots, k-1 \tag{8}$$

Here p_j is the estimate of π_j, a_j is the estimate of the intercept, and b_i is the estimate of the partial regression coefficient β_i.

2.2 Data organization

2.2.1 Data sources and sample selection

The data for this study is derived from the Social Survey of Province A (2024). This survey investigated the collaborative mechanisms of basic public services in 105 rural areas across the province. In this paper, the survey item "Optimization of the Management Path of Public Service Collaboration Mechanism" from this survey is selected as the dependent variable, and six independent variables are chosen: institutional and policy aspects, organizational and execution aspects, technical and data aspects, human resources, processes and services, and participation and interaction. The total number of valid questionnaires in the survey was 23,928, but there were a large number of questionnaires with incomplete information such as “refused to answer” and “don't know”, which were excluded from the study, resulting in a final sample size of 10,808.

2.2.2 Overview of variables

The independent variables of this study contain six dimensions: system and policy, organization and implementation, technology and data level, human resources, process and service, and participation and interaction. Specifically, they include: clarity of policy framework, uniformity of regulations and standards, orientation of appraisal and incentives, leadership and political determination, appropriateness of organizational structure, adequacy of resources, degree of integration of platforms, quality and security of data, applicability of technology, digital literacy of personnel, awareness and capability of collaboration, effectiveness of training system, degree of process optimization, accessibility and inclusiveness of services, multiple participation mechanisms and feedback and response mechanisms.

2.3 Modeling

Since the management optimization path of the dependent variable grassroots public service collaborative mechanism includes six levels, we used ordered multicategorical logistics regression to divide the six levels of the management optimization path of the grassroots public service collaborative mechanism into four types with different interruptions, resulting in the following four regression models:

$$\ln\left(\frac{p(j\le 1)}{1-p(j\le 1)}\right)=\beta_{0j}+\left(\beta_1x_1+\beta_2x_2+\beta_3x_3+\beta_4x_4\right) \tag{9}$$

$$\ln\left(\frac{p(j\le 2)}{1-p(j\le 2)}\right)=\beta_{0j}+\left(\beta_1x_1+\beta_2x_2+\beta_3x_3+\beta_4x_4\right) \tag{10}$$

$$\ln\left(\frac{p(j\le 3)}{1-p(j\le 3)}\right)=\beta_{0j}+\left(\beta_1x_1+\beta_2x_2+\beta_3x_3+\beta_4x_4\right) \tag{11}$$

$$\ln\left(\frac{p(j\le 4)}{1-p(j\le 4)}\right)=\beta_{0j}+\left(\beta_1x_1+\beta_2x_2+\beta_3x_3+\beta_4x_4\right) \tag{12}$$

where p is the probability that the management optimization path of the grassroots public service collaborative mechanism is in the range of j, β_{0j} is a constant term, and x_1, x_2, x_3, and x_4 are the independent variables in turn.

3 Empirical analysis

3.1 One-way ANOVA

In this paper, we used χ^2 test to conduct one-way ANOVA on the variables affecting the management optimization of grassroots public service collaborative mechanism, and p<0.05 indicates that the variable has a significant effect on academic achievement. The results of one-way ANOVA are shown in Table 1, where levels A~C are excellent, good and fair, respectively. The results of the one-way ANOVA show that the clarity of policy framework, uniformity of regulations and standards, orientation of assessment and incentives, leadership and political determination, adaptability of organizational structure, adequacy of resources, integration of platforms, data quality and security, applicability of technology, digital literacy of personnel, awareness and ability of synergy, effectiveness of the training system, optimization of processes, accessibility and inclusiveness of services, pluralistic participatory mechanisms, and feedback and response mechanisms have a significant impact on the academic achievement of grassroots public services. Response mechanism variables on the management optimization of grassroots public service collaboration mechanism, there are significant differences, statistically significant, so all of them will be counted as independent variables in the ordered multicategorical logistic regression model.

Table 1: Results of one-way analysis of variance

Variable	Options	A level (n=1227)	B level (n=1287)	C level (n=1140)	χ^2	p
Clarity of the policy framework (1)	The policy goals are clear and specific	455	459	247	856.365	<0.05
	Legalization of cross-departmental responsibility boundaries	435	355	415		
	Complete implementation details	337	473	478		
Uniformity of regulations and standards (2)	The degree of unification between data standards and interface specifications	258	421	499	711.854	<0.05
	Standardization of service processes	475	341	308		
	Consistency of rules for the determination of legal effect	494	525	333		
Assessment and incentive orientation (3)	The assessment indicators include collaborative performance	411	389	305	479.365	<0.05
	Incentive measures are linked to the synergy effect	348	323	307		
	The accountability mechanism is well established	468	575	528		
Leadership and political determination (4)	The degree of attention from the main leaders	416	424	239	445.65	<0.05
	The authority of cross-departmental coordination.	493	267	231		
	The ability to overcome the resistance of reform	318	596	670		
Organizational structure adaptability (5)	The institutional setup matches the collaborative requirements	365	273	386	902.365	<0.05
	The decision-making layer is connected to the execution layer level	483	434	316		
	The effectiveness of the virtual team operation mechanism.	379	853	438		
Sufficiency of resource guarantee (6)	The rationality of the allocation of fiscal funds	384	446	382	202.326	<0.05
	Coverage of technical infrastructure	257	362	487		
	Professional staffing is adequate	586	479	271		
Degree of platform integration (7)	System interconnection and interoperability level	420	216	248	99.658	<0.05
	The depth and breadth of data sharing	371	466	413		
	Platform friendliness	436	605	479		
Data quality and security (8)	The accuracy, timeliness and completeness of the data	411	242	384	58.698	<0.05
	The effectiveness of privacy protection measures	464	472	261		
	Maturity of the data governance system	352	573	495		
Technical applicability (9)	The degree of matching between technical and business requirements	407	367	242	66.596	<0.05
	The rationality of new technology application	328	499	498		
	System extensibility and compatibility	492	421	400		
Digital literacy of personnel (10)	Proficiency in using digital tools	471	367	245	85.102	<0.05
	Data analysis and application capabilities	436	374	246		
	New technology learning adaptability	320	546	649		
Collaborative awareness and ability (11)	Cross-departmental communication and collaboration skills	264	455	468	399.635	<0.05
	Service awareness and the ability to work with the masses	421	299	331		
	Problem-solving and innovation capabilities	542	533	341		
The effectiveness of the training system (12)	The pertinence and practicality of the training content	426	300	246	402.321	<0.05
	Diversity of training methods	482	284	235		
	The transformation effect of training outcomes	319	703	659		
Degree of process optimization (13)	The level of simplification and integration of business processes	309	399	417	55.659	<0.05
	Degree of integration between online and offline	268	360	407		
	Response speed and efficiency	650	528	316		
Service accessibility and	The wide coverage of the needs of different groups	433	224	429	63.985	<0.05
	The service adaptability of special groups	290	363	222		

inclusiveness (14)	Diversity of service channels	504	700	489		
Multi-participation mechanism (15)	The smoothness of public participation channels	348	330	459	70.654	<0.05
	Depth of participation of social organizations	424	390	330		
	Innovation of political and enterprise cooperation modes	455	567	351		
Feedback and response mechanism (16)	The integrity of the opinion collection system	482	216	254	569.65	<0.05
	Problem response speed and resolution quality	412	203	392		
	Continuously improved closed-loop management	333	868	494		

3.2 Variable selection

The Lasso model was developed using the Glmnet package in the R software. The plot of λ values versus model error was obtained by the GCV method. The λ versus model error is shown in Figure 1. The horizontal coordinate is the logarithm of the λ value, the vertical coordinate reflects the variation of the model error, the top is the number of variables under the correspondence of the λ value, the dotted line on the left side indicates the λ value and the number of variables corresponding to the model error when the model error is the minimum, and the dotted line on the right side indicates the λ value and the number of variables corresponding to the model when it is the simplest. The number of variables in the model changes with the change of the input value, the larger the input value is, the stronger the penalty is, and the fewer the number of variables screened out in the end, the simpler the model is. Calculated by R software, when λ=0.0173, the model error is minimized, at this time the number of selected variables is 14.

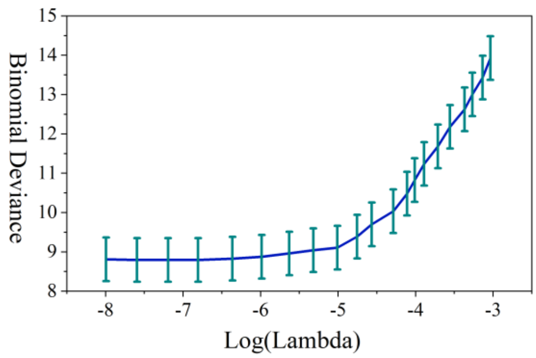

Figure 1: λ and model error

The relationship between λ values and coefficients is shown in Fig. 2. The horizontal coordinate represents the logarithm of the λ value, and the vertical coordinate represents the change status of the coefficients of each variable, which shows the variable filtering situation with the change of the λ value. It can be seen that as the value of λ continues to increase, more and more variable coefficients are contracted to zero, and the number of independent variables selected by the model becomes smaller and smaller. Therefore, unlike the traditional AIC, BIC and other methods of selecting variables, the Lasso method selects variables in a continuous and orderly process, which reduces the prediction error of the model. It can be calculated by R software that λ = 0.1369 when the number of variables selected at this time is zero.

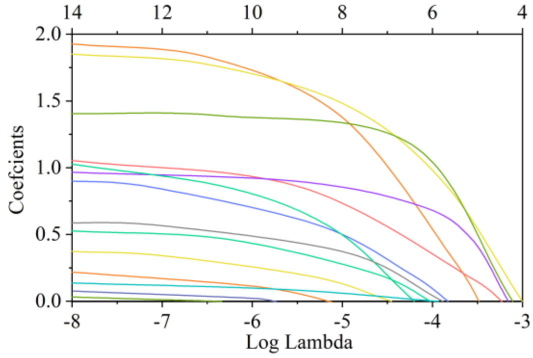

Figure 2: The relationship between λ value and coefficient

3.3 Analysis of results

3.3.1 Correlation analysis

In this paper, the data of the variables are taken for logarithmic operation, after the logarithmic operation only compresses the scale of the variables to increase the sensitivity of the independent variable to the difference of the dependent variable, and does not change the original nature of the data and the correlation relationship. The correlation statistics of the main variables are analyzed as shown in Table 2. From the results, it can be found that the independent variables are all significantly and positively correlated with the dependent variable at the 0.01 level. However, at the same time, the results of the correlation analysis indicate that the correlation coefficient between the harmonization of regulations and standards and service accessibility and inclusiveness in the study exceeds 0.80, which is a strong correlation between the two, and a covariance test is needed.

Table 2: Statistical analysis of the correlation of the main variables

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
(1)	1													
(2)	0.528**	1												
(3)	0.392**	0.618**	1											
(4)	0.412**	0.505**	0.53**	1										
(5)	0.478**	0.508**	0.491**	0.355**	1									
(6)	0.799**	0.486**	0.523**	0.441**	0.486**	1								
(7)	0.434**	0.601**	0.495**	0.342**	0.84**	0.705**	1							
(8)	0.604**	0.369**	0.798**	0.437**	0.579**	0.688**	0.768**	1						
(9)	0.614**	0.461**	0.71**	0.425**	0.408**	0.552**	0.589**	0.719**	1					
(10)	0.519**	0.603**	0.764**	0.348**	0.613**	0.608**	0.422**	0.58**	0.722**	1				
(11)	0.694**	0.498**	0.384**	0.643**	0.333**	0.535**	0.595**	0.629**	0.446**	0.532**	1			
(12)	0.62**	0.385**	0.456**	0.684**	0.823**	0.454**	0.465**	0.533**	0.515**	0.485**	0.487**	1		
(13)	0.578**	0.77**	0.627**	0.651**	0.785**	0.718**	0.594**	0.681**	0.488**	0.472**	0.428**	0.682**	1	
(14)	0.739**	0.808**	0.355**	0.705**	0.628**	0.397**	0.546**	0.691**	0.594**	0.392**	0.621**	0.722**	0.403**	1

The results of the multicollinearity test are shown in Table 3, the VIF value is the variance inflation factor, which is used to measure the severity of multicollinearity, and it is generally believed that a VIF value of more than 10 means that there is a multicollinearity problem. In this study, the VIF value of each variable is less than 10, except for the training system effectiveness variable, the variance inflation factor of the other variables is less than 5, and the corresponding tolerance values are all greater than 0.1, which means that the variables are independent of each other, and there is no multicollinearity between the independent variables, and the subsequent analysis can be carried out.

Table 3: Multicollinearity test results

Variable	VIF	Tolerance value
(1)	3.193	0.315
(2)	3.547	0.357
(3)	4.335	0.254
(4)	4.34	0.268
(5)	4.041	0.286
(6)	3.351	0.289
(7)	3.497	0.239
(8)	3.996	0.209
(9)	3.98	0.151
(10)	6.322	0.333
(11)	3.115	0.367
(12)	4.25	0.287
(13)	4.444	0.222
(14)	3.447	0.243

3.3.2 Ordered Multi-Categorical Logistic Regression Analysis

(1) The suitability of Ordered Multicategorical Logistic with this paper

Logistic regression in which the dependent variable is a categorical variable, if the dependent variable has only two simple groups, i.e., 0 and 1 in two forms, then this is a binary Logistic regression, but the binary categorical dependent variable obviously does not satisfy the requirements of many researches, and thus there is a multivariate Logistic regression, which is a regression in which there are more than two and unordered dependent variables, and is also called a multicategorical Logisti c regression. There is also an ordered multicategorical Logistic regression, which has more than two dependent variables and is ordered. The relationship between the data type and the model chosen is shown in Table 4.

Table 4: Logistic Regression Research Model Selection Table

Independent variable	Dependent variable	Research model
Continuous variable/Categorical variable	Categorical variable (Group 2)	Binary logistic regression
Continuous variable/Categorical variable	Classification variables (multiple groups and disordered)	Multivariate Logistic regression
Continuous variable/Categorical variable	Classification variables (multiple groups and disordered)	Ordered Logistic regression

Since the dependent variable management optimization path in this paper has different classifications and there is a certain logical order between them, the variable is an ordered multicategorical variable, therefore, this paper chooses the ordered multicategorical Logistic model to analyze the influencing factors of the management optimization path of the collaborative mechanism of grassroots public services.

(2) Parallel lines test

Generally speaking, a P value greater than 0.05 indicates that the test is passed, and if it does not pass the test, the use of unordered multicategorical Logistic regression is considered. The parallel lines test is shown in Table 5. The model fitting information is shown in Table 6. p-value of 0.869 > 0.05 indicates that the parallel lines hypothesis is valid, i.e., the regression equations are parallel to each other, the effects of different values of the independent variables on the dependent variable are the same, and the subsequent ordered multicategorical Logistic regression can be performed. The significance in the model fitting information is 0.000, which is less than 0.001, indicating that the model fits well, has strong explanatory power, and can be used for significance analysis.

Table 5: Parallel line test

Model	-2 logarithmic likelihood	Kafan	Degree of freedom	Significance
Null hypothesis	38.594			
Conventional	26.356	11.326[c]	17	0.869

Table 6: Model fitting information

Model	-2 logarithmic likelihood	Kafan	Degree of freedom	Significance
Only intercept	91.263			
Ultimately	38.594	53.569	6	0.000

(3) Analysis of regression results

The results of ordered multicategorical logistic regression analysis of the main variables are shown in Table 7. As can be seen from the table, the clarity of policy framework, uniformity of regulations and standards, assessment and incentive orientation, leadership and political determination, organizational structure suitability, adequacy of resource security, degree of integration of platforms, data quality and security, applicability of technology, digital literacy of personnel, synergy awareness and capacity, effectiveness of training system, process optimization, service accessibility and inclusiveness passed the significance test, and all of them are significant at the 0.05 level. 0.05 level, indicating that the management optimization path of the grassroots public service coordination mechanism is influenced by the clarity of policy framework, uniformity of regulations and standards, assessment and incentive orientation, leadership and political determination, organizational fitness, adequacy of resource security, degree of integration of platforms, data quality and security, applicability of technology, digital literacy of personnel, awareness and ability of coordination, effectiveness of the training system, degree of optimization of processes, accessibility and inclusiveness of services. The influence of the degree of accessibility and inclusiveness of services.

Table 7: The results of ordered multi-class Logistic regression analysis

Variable	Estimation	Standard error	wald	freedom	Significance	95% confidence interval	
						Lower limit	Upper limit
(1)	6.528	3.224	4.167	1	0.1	0.245	12.849
(2)	3.175	2.606	1.499	1	0.228	8.398	1.948
(3)	2.387	1.143	4.208	1	0.005	0.097	4.72
(4)	5.282	2.601	4.185	1	0.023	2.192	10.429
(5)	2.019	0.908	4.664	1	0.073	0.216	3.858
(6)	3.26	1.464	4.746	1	0.053	0.324	6.156
(7)	6.281	3.281	4.205	1	0.138	0.196	12.758
(8)	2.266	2.551	1.53	1	0.28	-8.37	1.957
(9)	3.482	1.234	4.153	1	0.137	0.123	4.652
(10)	5.414	2.622	4.235	1	0.024	2.061	10.298
(11)	2.092	1.957	4.781	1	0.009	0.122	3.931
(12)	3.259	1.542	4.793	1	0.05	0.161	6.034
(13)	3.656	2.065	4.085	1	0.032	0.326	12.356
(14)	4.595	3.659	4.213	1	0.121	0.231	8.985

4 Conclusion

Based on the Comprehensive Social Survey (CGSS) data, this article explores the factors influencing the management optimization path of the grassroots public service collaborative mechanism, using ordered multicategorical logistics regression models. The conclusions drawn from the article are as follows:

(1) From the results of correlation statistical analysis of the main variables, the correlation coefficient of the uniformity of regulations and standards and the accessibility and inclusiveness of services exceeds 0.80, which indicates that the correlation between the two is strong, and that the uniformity of regulations and standards has a more important impact on the accessibility and inclusiveness of the collaborative mechanism of public services.

(2) In the ordered multinomial Logistic regression analysis results of the main variables, all the variables were significant at the 0.05 level. This indicates that the management optimization path of the collaborative mechanism for grassroots public services is influenced by the clarity of the policy framework, the uniformity of regulations and standards, the orientation of assessment and incentives, leadership and political determination, organizational structure compatibility, the sufficiency of resource guarantee, the degree of platform integration, data quality and security, technical applicability, personnel digital literacy, collaborative awareness and ability, the effectiveness of the training system, the degree of process optimization, and the accessibility and inclusiveness of services.

Based on the conclusions of the above study, the government should optimize the management in four aspects: strengthening the overall management, improving the response and linkage mechanism, perfecting the supporting mechanism, and fostering diversified subjects. Specifically, strengthening integrated management can be done by building an office information platform, constructing a holistic collaboration mechanism, and establishing a coordination and communication mechanism. Improving the response and linkage mechanism can be carried out by extending it to municipal units and emphasizing the voice of the public. Improving the supporting mechanism can be carried out from the aspects of increasing the financial guarantee, improving the governance capacity of the main body and optimizing the supervision and assessment mechanism. Cultivating pluralistic subjects can be carried out in terms of widely publicizing the concept of shared governance, broadening participation channels and improving the mechanism for coordinating interests.

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