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Analysis of the Application of Information Technology in the Management of Rural Population Return Based on the Era of Big Data

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ABSTRACT

Based on rural population return management, governance theory, and information technology theory, this paper analyzes the specific performance of rural areas in managing population return and describes the overview, quantity, life status, and demographic characteristics of rural population return, as well as the current situation of rural population return management. A method of managing rural population return based on a rural population return management model constructed by a machine learning algorithm is designed. The empirical results show that the method designed in this paper is low-cost, fast, and highly accurate and is well-suited for improving and expanding the system for managing rural return flows. The research in this paper provides a reference for further promoting the transformation strategy of rural governance in the context of new urbanization.

KEYWORDS

Information Technology, Population Return, Rural Governance, Strategic Transformation

1. INTRODUCTION

With the rapid development of urbanization and industrialization after the reform and opening up, especially since the new century, the development gap between the east and west has become obvious, and the level of socio-economic development and employment opportunities in the eastern coastal areas have caused a strong siphon effect, resulting in the rapid growth and expansion of the number and scale of the cross-regional migrant population between the east and west and urban and rural areas, which has rapidly set off a large-scale wave of outbound workers (Soneka & Phiri, 2019). The rapidly increasing mobile population, along with the demographic dividend, has become a powerful booster for the country's rapid economic growth, promoting industrial restructuring and rational allocation of labor resources. Some experts and scholars analyze from the perspective of economics that the return of the migrant population is an important manifestation of the emerging wave of innovation and entrepreneurship in the process of transferring labor-intensive and resource-intensive industries to the central and western regions, which will be accompanied by the transfer and better allocation of human resources (AlBar & Hoque, 2019). If analyzed from the perspective of social integration of the mobile population, what are the important correlations between the emergence of the mobile population return phenomenon and the inability of the mobile population to integrate into the inflow

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area, and what are the factors affecting the social integration of the mobile population, all these questions need further research and response (Nyangarika & Bundala, 2020).

Based on the definition of the mobile population in existing statistical surveys, this paper defines the concept of population mobility with data and the problem under study, and enriches the theoretical connotation of the mobile population; this paper designs a new method for mobile population size estimation based on existing statistical survey methods, i.e., constructing a mobile population management model based on machine learning classification algorithm through data mining, on which Applying the capture-recapture sampling estimation method to measure the size of the mobile population and extrapolating the information such as the market share of mobile communication operators, this paper provides methodological support to be able to count more accurate data of the mobile population (Saediman et al., 2019). Compared with the existing mobile population survey methods, the population mobility measurement method based on mobile communication big data designed in this paper has been substantially improved in terms of timeliness and saving survey cost while maintaining higher accuracy, so the method can be applied to the practice of statistical survey of the mobile population, which enriches the methodological theory of mobile population survey in the statistical survey, and on this basis, for It also has an important theoretical value for the improvement and perfection of the statistical system of the mobile population. By using data mining and statistical methods, we can analyze the characteristics of communication behaviors of different groups through the use of mobile communication big data resources accumulated by mobile operators in real-time, and find a more accurate, timely, and effective method to obtain information of mobile population, to find a new way for the statistics of the mobile population (Kar et al., 2019).

This paper analyzes the social integration of rural inter-provincial migrant population from economic, social, and psychological dimensions, which is similar to the study on the citizenship of the agricultural migrant population. Therefore, based on the previous studies, we apply the symbiosis theory to analyze the social integration of the migrant population to make up for the lack of research in this field and to lay the theoretical foundation for the subsequent discussion. This paper first reviews the current status of research on mobile population size estimation and research methods. Based on the shortcomings of previous studies, this paper constructs a mobile population management model based on mobile communication big data, based on the behavioral characteristics of the population, and determines and measures the mobility of the population from the user behavior characterized by mobile communication big data. The final mobile population management model is selected by comparing the performance of this model through various classification performance criteria and theoretical analysis; the final mobile population management model is used to classify and identify the unclassified samples in the sample data, and then obtain the mobile population in the entire sample data set.

2. RELATED WORK

Information technology is effective in increasing the rate of urbanization by improving labor productivity and strengthening rural-urban linkages. Weaver M S et al. studied the correlation between the level of computer penetration and the rate of urbanization in rural areas of southern Brazil and pointed out that there is a strong positive correlation between the rate of urbanization and the level of information technology penetration, mainly because the widespread penetration of information technology can greatly improve labor productivity (Weaver et al., 2020). Karahanna E et al. analyzed the specific role of ICT in the local urbanization process by distributing questionnaires to the Newcastle, UK, area in the context of informatization, and suggested that although informatization promoted the overall urbanization development rate, the gap between informatization in different regions widened the gap of urbanization between regions (Karahanna et al., 2019). However, what needs additional attention is that the digital divide problem brought about by the application of information technology is hindering urban-rural population mobility, solidifying the urban-rural dual structure, and slowing down the urbanization process. With the continuous improvement of information technology, the damping effect of the urban-rural digital divide on the urbanization process is becoming more and more significant (Aldosari et al., 2019).

According to Chege S M et al, the current management approach for the floating population is still dominated by traditional concepts, showing a significant "two heaviness's and two lightness's" (Chege et al., 2020). In other words, there is a serious control mindset in the management of the floating population, and many local governments put too much emphasis on prevention and management, while seriously lacking a sense of service, thus forming a governance situation that emphasizes management, but not service. This traditional top-down management requires absolute obedience from the floating population while ignoring some basic needs of the floating population (Yao et al., 2019). At the same time, some of the decisions made based on the mobile population often have the performance of "experience but not science". Most of the decisions are made based on subjective experience and whim, without a reliable database and scientific basis. According to Yao B et al., it is extremely difficult to implement the basic information of the mobile population, and it is difficult to figure out the bottom number and specific information of the mobile population. Doing a good job of registering the information of the mobile population is the basic premise and fundamental support for governance and service of the mobile population (Tang & Hao, 2019). Currently, there are many problems with the existing information base based on mobile population, which makes it difficult to achieve effective management of mobile population data. Secondly, the governance of the mobile population involves many aspects and related departments, such as health care, public security, human resources, family planning, education, civil affairs, etc. Each department has a different focus on the governance and service of the mobile population, so the information collected and the data constructed also have their own bias (Chen et al., 2019). As a result, the information of the floating population has become a single entity, and the data of each organization has become a silo without disturbing each other due to the lack of sharing mechanism.

Most of the many studies based on information technology have been conducted in commercial organizations, and few information technology studies have been conducted with government agencies as the target, and the only ones that have been conducted are mostly with the U.S. federal government (Li & Li, 2019). Most of the previous studies on information technology have outlined and demonstrated the benefits of big data with the help of case studies, and the theoretical scope is too limited. There are more studies based on technical aspects, especially on how to develop and use information technology, but few of them are conducted from the perspective of social management and public service, and the only ones are too one-sided. Besides, the current discussion around information technology is only some shallow issues, there is still a lot of management and technical problems that need to be overcome, and these difficulties have produced varying degrees of interference and hindrance to the further development of information technology. Therefore, the author takes the rural population as the target and explores its governance in the mobile population from the perspective of large information technology, hoping to bring some improvement and benefit from the theoretical perspective (Batsis et al., 2019).

3. INFORMATION TECHNOLOGY-BASED STUDY OF RURAL POPULATION RETURN MANAGEMENT

3.1 Population Data Processing

Information resources can achieve long-distance real-time resource sharing through digitalization, networking, and intelligence, breaking through geographical restrictions, improving rural spatial conditions, and enhancing the quality of urbanization. However, the attribute of quasi-public goods makes it inefficient and market failure under pure market allocation, and it is difficult to effectively improve the efficiency of rural transactions, so further government regulation is needed. To analyze the network relationship between nodes within the information network, it is necessary to measure the level of information association between nodes, and the strength of information radiation is considered to be the most direct reflection of the level of information association between two rural areas, therefore, the measurement of rural information radiation is the foundation and key work of information network analysis (Alavion & Taghdisi, 2021). The information network system is the carrier of material and non-material information transmission between rural areas and rural areas.

The influence range of the radiation model presents a circle, and in the context of the gradual smoothness and modernization of the information transmission media, the geographical distance is no longer the main limitation of the information transmission process and efficiency, and considering this feature, some improvements are appropriately made to the model, as shown in equation (1). L_{ij} is the expected intensity of information flow between i and j; n_i and n_j are the information levels of rural i and rural j; G_{ij} is the information concern of rural i to rural j, and n is the statistical number of rural areas or regions. Based on the calculation of the radiation model, the relationship matrix of the information network is finally obtained (Yilmaz et al., 2019).

$$L_{ij} = G_{ij} * \frac{n_i * n_j}{n_i(n_i + n_j) + n_j(n_i + n_j)} \tag{1}$$

The spatial pattern of mobile population distribution, as the main manifestation of the level of rural urbanization development, largely demonstrates the changes in the urban system. With the widening of urban-rural and regional disparities and the gradual opening of government restrictions on household registration policies, the scale of rural population mobility is rapidly expanding.

In this paper, the level of association between nodes in the rural network is calculated mainly based on the inter-rural population migration, based on the direction and scale of population movement, and using social network analysis as a means to describe the dynamic process of group clustering and contact relations in the process of population transfer from urban to rural areas with relational data to show the specific characteristics of rural network evolution. Specifically, we construct an m × n matrix of directional relationships (row vectors represent population inflow places and column vectors represent population outflow places) to describe the directional urban relationship network of rural population flow across provinces in the period.

$$M = \begin{bmatrix} l_{11} & l_{12} & l_{1n} \\ l_{21} & l_{22} & l_{2n} \\ l_{m1} & l_{m2} & l_{mn} \end{bmatrix} \tag{2}$$

Information attention is described by citing the Baidu index. Through the Baidu index to explore the attention degree between rural areas, the search index is obtained by using the geographical area as the key entry point and another rural area as the geographical search keyword, which is used as a consideration of the attention degree between rural areas (da Costa et al., 2020). In the specific calculation, the original data fell into the interval of [0, 1] through linear transformation according to the standardization of deviation; the setting of each weight of the evaluation index system used the mean square difference weight decision method; the missing individual data within the statistical yearbook was completed by using the fitting results of three smooth splines. The calculation results of the informatization index are shown in Table 1.

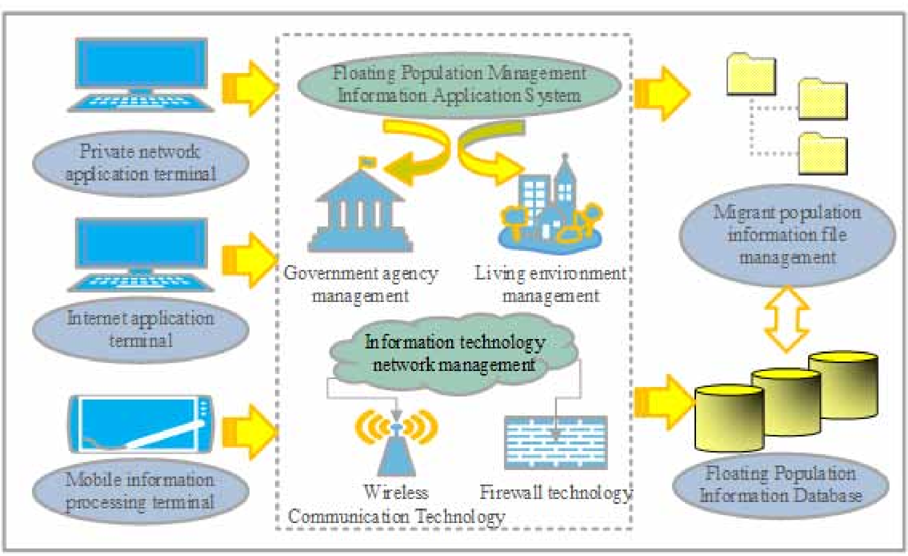
Table 1. Informationization index system

Indicator type	Indicator name	Indicator details
1	Infrastructure Index	Ownership rate of televisions, fixed phones, mobile phones, and computers
2	Use index	Number of Internet users per 100 people
3	Knowledge index	Education Index
4	Environment and Effect Index	The value-added of the information industry accounts for the proportion of GDP
5	Information consumption index	Information consumption coefficient

3.2 Rural Return Management Model

Big data management of rural migrant population includes: collecting information, transmitting information, storing information, and applying the information for migrant population, etc. This process is the whole process of information management of the migrant population by applying information technology means in combination with big data. The formation of a complete science and technology system is too specific technology means and methods combined for different aspects of the use of different information processing as support. This mobile population information management technology system contains four parts: mobile population information database and management application system and mobile information processing terminal and modern communication network (Simões et al., 2020). Among them, it is the information database that stores the mobile population information link issues, the information application system that collects and applies the mobile population information, the modern communication network system that carries out the mobile population information transmission, and the mobile information collection equipment system that carries out the mobile population collection and application. The specific information management technology system is shown in Figure 1.

Figure 1. Mobile population information service management technology system



Under the Internet and big data information technology, policies in various fields of society have been adjusted, for example, in the governance of the floating population, government departments at all levels have introduced information management systems to provide more comprehensive services for the floating population with the help of e-government systems, and can continuously improve the governance capacity. By building a scientific management information platform and achieving the goal of stability maintenance with the help of science and technology, it can strengthen the synergy between various departments and actively participate in stability maintenance work, and improve the management science and effectiveness of stability maintenance management. The scientific stability maintenance risk governance system has realized the deep reform of the management mode, the high coordination of management resources, and the effective application of emergency management technology. Through this system, it can be seen that the system has played a great regulating function in the process of population governance and has become an effective tool for this governance.

The random forest algorithm is mainly through the self-service resampling method, repeatedly generating training samples and test samples, where the training samples are used to construct multiple decision trees, thus combining them into a random forest, and the test set is used to test the classification effect of the random forest, and the results are determined by the number of votes in the classification tree (Harmanny & Malek, 2019). The result is determined by the number of votes in the classification tree. In this method, multiple training samples are generated to produce decision trees with the same distribution, and the correlation between these decision trees and their classification effect determines the classification error of the random forest algorithm. The variables for each node in the random forest algorithm are not selected among all the variables but are generated from a randomly selected fraction of the variables.

Suppose we want to solve the binary classification problem for the original dataset Data with sample size n as shown in equation (3), where X_i denotes the 'i-th' training sample and X_i Î M_n, and Y_i is the categorical variable.

$$Data = \{(X_i, Y_i)\}, i \subseteq [1, n] \tag{3}$$

The binomial tree is trained on T sub-datasets (D_1, D_2, D_T) separately, and the output of equation (4) is used for the classification problem of one sample x.

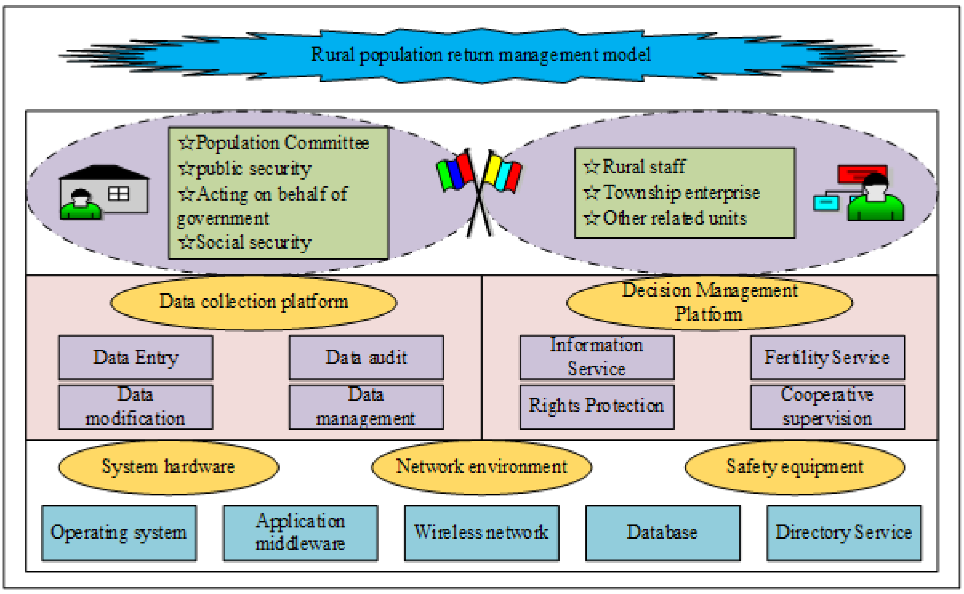
$$F(x) = \sum_{i=1}^{n} f(x_i) \tag{4}$$

The basic principle of random forest algorithm variable selection is to randomly split each node and obtain the significant variables by comparing the errors generated before and after each node split. The classification result of the random forest algorithm combines the classification results of multiple decision trees, and by randomly generating a large number of decision trees, the classification ability of the random forest algorithm can be substantially improved. Thus, the random forest algorithm has many advantages over the previous two algorithms, as it can handle a large number of input variables, is insensitive to noise, and has good noise tolerance. The learning speed is fast, the importance of variables can be evaluated while performing classification, and it has good model generalization ability (Firissa et al., 2019).

3.3 Model Design And Evaluation

The samples are first divided into training and test sets according to the principle of equal proportions between classes, and then the training set samples are used to construct artificial neural network-based mobile population management models, and then the test set is used to test the classification performance of each classification model, and the classification results of each model are compared and analyzed according to various judgment criteria, to select the model with the best classification performance and generalization ability as the mobile population management model. Finally, the selected optimal model is used as the final mobile population management model to predict the prediction set composed of samples, and then obtain the mobile population samples in the whole sample data. The rural population return management model of this paper is shown in Figure 2.

Figure 2. Rural Return Management Model



To obtain the model with optimal classification and generalization ability, this paper chooses the cross-validation method to measure the accuracy of each classification algorithm. Cross-validation is a statistically very practical method for cutting data samples into smaller subsets. Its basic principle is to group the data sets, with one part as the training set and the other part as the test set. The model is first trained using the training set, and after the training is completed, the model obtained from the training is tested using the test set to evaluate the performance of the model. The cross-validation method can help us obtain as much valid information as possible from the limited sample data, and it is a common method for evaluating the classification performance of a model because it can avoid the model from falling into local extremes by learning from multiple perspectives. Cross-validation generally tries to satisfy two conditions: first, the number of samples in the training set should be more than the number of samples in the test set; second, the training and test sets should be sampled evenly, that is, the training and test sets should maintain the same inter-class structure as the original sample set.

There are nearly 50,000 data in the sample set used to build the mobile population management model in this paper, which is a large amount of data. Considering the computational cost and accuracy, this paper adopts the 10-fold cross-validation method commonly used in K-fold cross-validation to test the model performance, i.e., the original sample set is divided into 10 groups equally according to the principle of a constant ratio between classes, each sub-sample set is used as a test set, and the remaining In this way, 10 models are obtained, and the average performance of the 10 models is used as the evaluation result of the model on the classification performance, to obtain a reliable model error estimate.

The model design in this paper uses the LP estimator in the two-sample estimation when estimating the mobile population. The LP estimator is shown in equation (5) and the LP variance value is shown in equation (6). Where *m*i is the marked fraction of the recaptured sample in the recapture sampling, and Y is the sum of the co-weighted fractions in the n times sampling. This co-weighted estimator takes into account the contribution of the recaptured sample to the overall size, which increases the confidence of the estimation.

$$G(LP) = \frac{\sum_{i=1}^{m} X_i \sum_{j=1}^{n} X_j}{Y} \tag{5}$$

$$AVG(G(LP)) = \frac{X_1^2 * X_2}{Y^3}(X - Y) \tag{6}$$

The contact point of the security management of the mobile population in urban villages under information technology is in the network. The network referred includes both the Internet and the Internet of Things, and whether the network is smooth determines whether the command is smooth. The Internet of Things connects things to the Internet through sensors, radio frequency identification, and sensing network to realize information exchange and communication. The security management of the mobile population in urban villages in the context of information technology bundles people, things, and networks into one and selects things according to the needed information, broadening the amount of information access and transmitting valuable information for the security management of the mobile population.

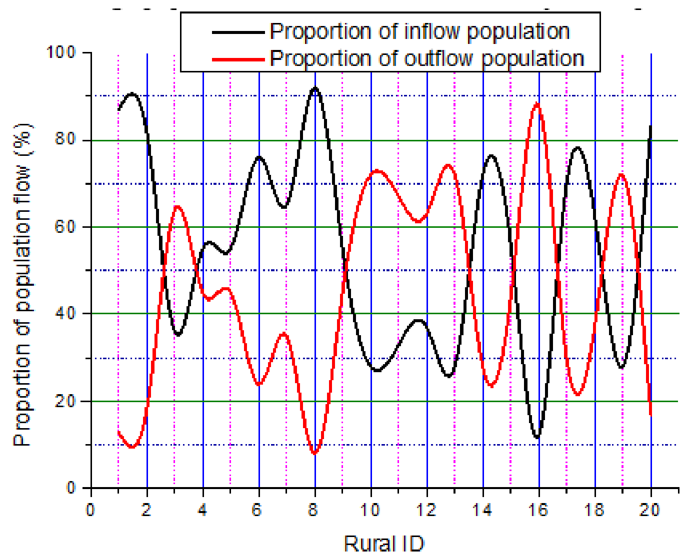
4. ANALYSIS OF RESULTS

4.1 Statistical Analysis Of Rural Population Return

In total, this paper examines the mobility of the population in 20 rural areas as shown in Figure 3. From the line graph of the flow status of the rural mobile population, the rural areas with more outflows have fewer inflows in each of the rural areas studied. The three rural areas with the highest number of outflows are Rural 10, Rural 13, and Rural 16, each accounting for as much as 70-85% of the population and over 36% overall. The areas with more inward population are Rural 1, Rural 8, Rural District 17, and Rural 20, which account for 90.1%, 90.3%, 81.3%, and 78.6 respectively, with an overall percentage of 73.2%. The three rural areas with high population outflow are all relatively economically backward areas and areas with large population bases, while the seven rural areas with high population inflow are all economically developed in coastal areas.

With the rapid development of big data technology, the connection between information technology and government management and social services has become increasingly close, and in the government's social risk management, the same information technology network technology can be used to build a grid-based governance platform to divide the activity area of each township into a grid, real-time inspection of the monitored grid based on a unified urban digital management platform, various types of information within each jurisdiction of the township Information aggregation, classification and summarization of risk factors, to facilitate the active discovery of risk issues under the management of the township government, to achieve emergency treatment, thereby

Figure 3. Rural inter-provincial migrant population movement



strengthening the collaborative governance of social risk management and improving the level of intelligent governance of social risks. In this system, big data information technology on the one hand can accurately monitor various data of rural returnees in township areas, dynamically monitor and effectively evaluate risk issues, and inspect and record various data indicators from all aspects and angles, while the high-speed flow of information can help each township perceive risk changes and provide early warning for the possible outbreak of risk issues, which helps the government take preventive measures to, on the other hand, it can clarify the division of responsibilities among various management departments of the township government and achieve effective supervision of government departments. Big data information technology can aggregate social risk management resources, facilitate the integration and mobilization of various resources for social risk management by the township government, achieve scientific and efficient social risk management, and ensure normal social operation in rural areas.

Due to the accelerating urbanization of rural areas, the return flow of the population has increased dramatically. The population registration of a rural area in 2020 shows that the 2020 mobile population has a total of 1324 people, of which 431 originate from urban areas, 314 from counties and cities, 160 are from other cities in the province, 213 are from counties, 187 are from foreign cities and 179 are from foreign counties. Based on field research combined with statistical analysis, the author summarizes the current information and structure of the floating population as shown in Figure 4.

4.2 Model Analysis Of Rural Return Management

In this section, the Vanish simulation platform is used to import the rural population return management model into the computer in the context of information technology, and the simulation is carried out for the rural population return evolution system, and finally, the current and future trends of urbanization development are obtained, as shown in Figure 5. From Figure 5, it can be seen that the level of rural urbanization always maintains a rapid development trend under the joint action of the main driving force, the slave-driving force, and the rural construction level, showing a growth trend similar to the exponential function, the growth rate of the main driving force is higher than that of the slave-driving force, and the construction pace of the rural area is too stable, and its construction level rises weakly.

Figure 4. Age characteristics of the rural returnee population

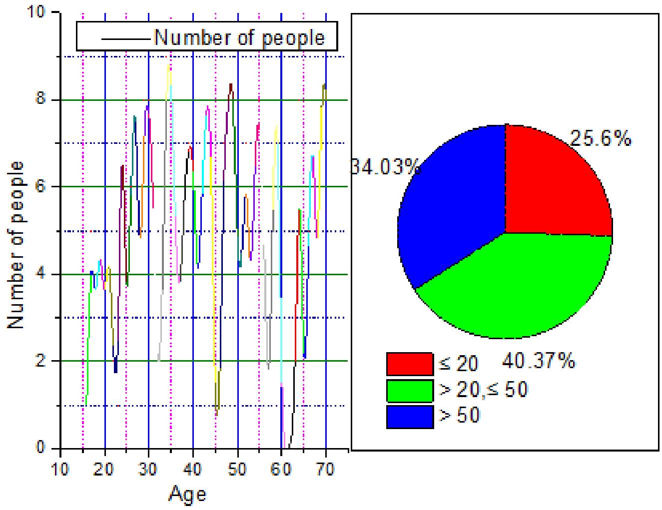
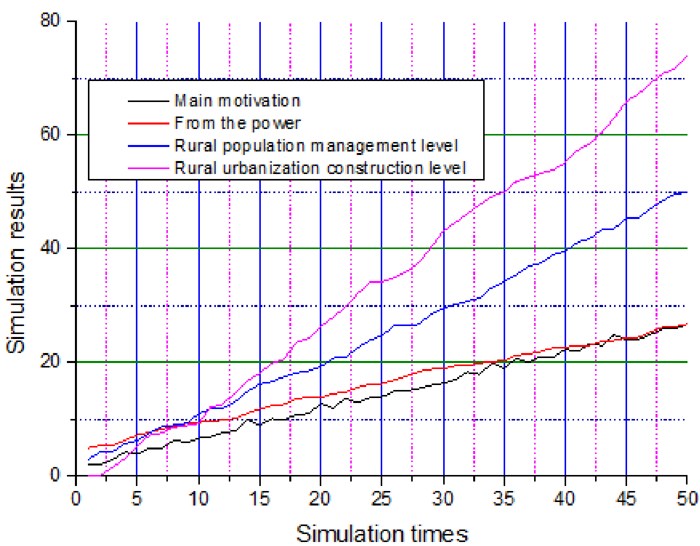


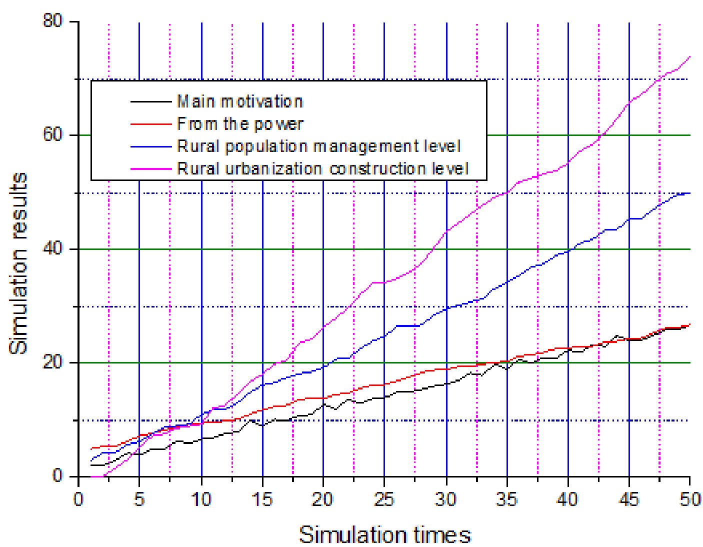
Figure 5. Trends in the evolution of rural population management systems



According to the model design of 3.3, the first sample is drawn from all cell phone numbers in the period from January 20 to February 10, 2019, to obtain a capture sample, and the number is marked, and the second sample is drawn from all cell phone numbers in the period from June 10 to June 30, 2020, to obtain a recapture sample, where the number of samples already marked in the first capture is m, so that capture and recapture two-sample sampling is carried out, and this process is repeated 10 times to obtain the results of the estimated quantity about the mobile population size estimation as shown in Figure 6. The estimated value obtained from Figure 6 is the size of the mobile population in the region among the subscribers of Unicom operators from January to June 2020, and to obtain the total size of the mobile population in the region, this paper uses information such as the market share of mobile operators in the region for appropriate and appropriate extrapolation.

The township government lacks "rethinking" on the modern social and economic development model, and purely pursues performance related to its interests. Not only is it indifferent to the risks hidden behind the phenomenon of economic development, but also lacks awareness of the sources of rural risks, and only focuses on the aftermath of the risk. Emergency management ignores the early identification and early warning of risks and lacks advanced and non-traditional risk management concepts. At present, under the promotion and encouragement of national policies, all towns and villages gradually realize the benefits of entrepreneurship and employment for rural returnees to rural economic development, fully implement national and provincial decisions and deployments on employment and entrepreneurship, and continuously improve support policies. However, the township government simply enjoys the economic dividends brought by the returning population and does not think about the danger in peace.

Figure 6. Original estimates of the size of the mobile population

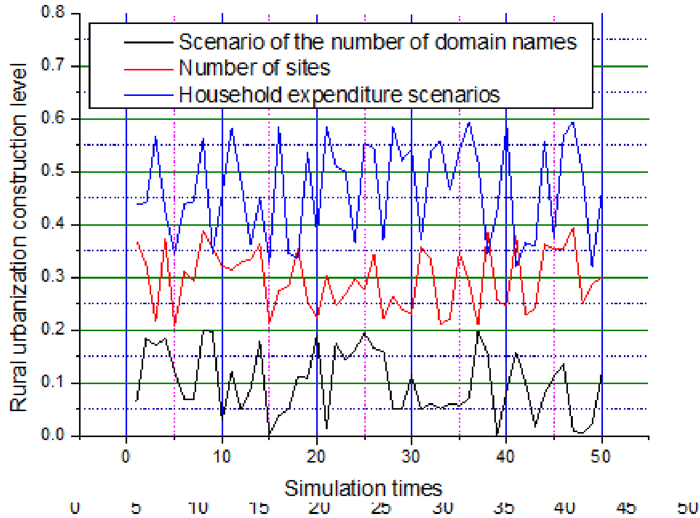


4.3 Information Analysis

Information resource preference includes three indicators: the average annual communication expenditure per household, the number of websites and the number of domain names, which represent the consumption level of information resources, the richness of Internet information, and the possession level of Internet resources, respectively. These three indicators are introduced into two scenarios: the baseline scenario and the focused development scenario, in which the indexes in the baseline scenario are taken as the original data, while the indexes in the focused development scenario are taken as two times the values in the baseline scenario. The simulation results of the information resource preference scenario can be obtained by comparing the rural urbanization level in the focused development scenario with that in the baseline scenario, as shown in Figure 7.

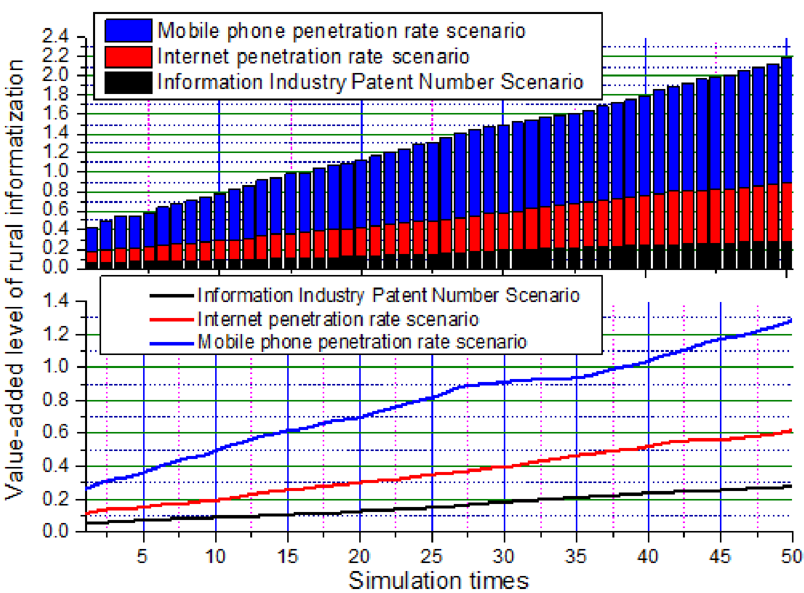
The information industry preference scenario includes only one variable, the number of legal person units in the information industry, which directly reflects the scale of the information industry. The value of the index in the benchmark scenario is unchanged, and the number of legal person

Figure 7. Evolutionary trends of rural urbanization under information resource preference policies



units in the information industry in the focused development scenario is twice that in the benchmark scenario. The simulation results of the urbanization level in the focused development scenario minus the benchmark scenario are shown in Figure 8. The number of information industry patents in the information technology preference scenario has the highest rate of increase in the level of rural urbanization, the impact of Internet penetration ranks second, and the impact of cell phone penetration is the lowest.

Figure 8. Trends in rural-urban evolution under IT preference policies



Actively promote the slow shift from rough to precise development of mobile population management, and promote the supply of public services to gradually achieve consistency with the needs of the mobile population. The frequent mobility of the floating population, coupled with the lack of autonomy to go to the relevant institutions in the location to register information, leads to the fact that the information on the floating population on file often differs greatly from the actual floating population. Based on the combination of the Internet and a large database, a public service platform is built, and information sharing system is created, dynamic monitoring and real-time data updates are carried out around the mobile population, and information from different categories, sources, and dimensions are integrated, analyzed, utilized and shared. The authorities can systematically and extensively analyze and understand the attitudes and perceptions of public services from all regions and all types of mobile groups, to make improvements and adjustments and enable the mobile population to enjoy more relevant, personalized, and convenient public services. The public services will be closer and closer to the real needs of the mobile population, and the public supply will gradually shift from supply-oriented to demand-oriented, replacing passive provision with active provision, so that the mobile population can enjoy more humane services.

It is feasible to use mobile communication user communication records to estimate population mobility. To explore the method of estimating the size of the floating population, this article is based on the characteristics of population behavior, judges and measures the mobility of the population from the user behavior represented by mobile communication big data, and builds a management model of the floating population based on the random forest algorithm. On this basis, the total size of the floating population was estimated using the method of capturing and capturing two samples concurrently. This method greatly reduces the cost of population statistics, simplifies the sampling survey, has high precision, and solves the problem of timeliness of floating population statistics, so it can be used as a supplementary method to apply to existing floating population statistics practices.

5. CONCLUSION

In this paper, based on determining the optimal set of variables, the random forest classification model, which is commonly used in machine learning algorithms, was used to construct the models separately, and then the prediction results of the test set were obtained, and the models were evaluated according to three evaluation criteria: correctness rate, F-measure value, and AUC value, and the performance of the random forest model was the best, and its prediction accuracy and generalization ability were the best, so the model based on the prediction results for the unclassified samples also show that the accuracy and interpretability of the random forest algorithm-based mobile population management model are better. In this paper, we explore the future trend of rural urbanization in the context of information and use scenario analysis to set information resources, information technology, and information industry as control variables to introduce the rural urbanization management model in the context of information. In this paper, when constructing the identification variables for mobile communication users' mobile population characteristics, the characteristics are based on the call behavior characteristics of migrant workers among the mobile population, and less consideration is given to the call behavior characteristics of the mobile population studying and doing business in the area, mainly because the data attributes obtained in this paper are insufficient, which limits the construction of identification variables to a certain extent. Based on the above study, this paper hopes that the government statistics department will improve the relevant statistical system in the mobile population statistics system, make it clear that the government statistics department has the responsibility of collecting and processing big data in the form of legal regulations, and formulate strict terms to protect users' privacy.

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REFERENCES

Alavion, S. J., & Taghdisi, A. (2021). Rural E-marketing in Iran; Modeling villagers' intention and clustering rural regions. *Information Processing in Agriculture*, *8*(1), 105–133. doi:10.1016/j.inpa.2020.02.008

AlBar, A. M., & Hoque, M. R. (2019). Factors affecting the adoption of information and communication technology in small and medium enterprises: A perspective from rural Saudi Arabia. *Information Technology for Development*, *25*(4), 715–738. doi:10.1080/02681102.2017.1390437

Aldosari, F., Al Shunaifi, M. S., Ullah, M. A., Muddassir, M., & Noor, M. A. (2019). Farmers' perceptions regarding the use of information and communication technology (ICT) in Khyber Pakhtunkhwa, Northern Pakistan. *Journal of the Saudi Society of Agricultural Sciences*, *18*(2), 211–217. doi:10.1016/j.jssas.2017.05.004

Batsis, J. A., Naslund, J. A., Zagaria, A. B., Kotz, D., Dokko, R., Bartels, S. J., & Carpenter-Song, E. (2019). Technology for behavioral change in rural older adults with obesity. *Journal of Nutrition in Gerontology and Geriatrics*, *38*(2), 130–148. doi:10.1080/21551197.2019.1600097 PMID:30971189

Chege, S. M., Wang, D., & Suntu, S. L. (2020). Impact of information technology innovation on firm performance in Kenya. *Information Technology for Development*, *26*(2), 316–345. doi:10.1080/02681102.2019.1573717

Chen, M., Ye, C., Lu, D., Sui, Y., & Guo, S. (2019). Cognition and construction of the theoretical connotations of new urbanization with Chinese characteristics. *Journal of Geographical Sciences*, *29*(10), 1681–1698. doi:10.1007/s11442-019-1685-z

da Costa, C. B., Peralta, F. S., & Ferreira de Mello, A. L. S. (2020). How has teledentistry been applied in public dental health services? An integrative review. *Telemedicine Journal and e-Health*, *26*(7), 945–954. doi:10.1089/tmj.2019.0122 PMID:31573410

Firissa, O., Seyoum, T., & Abegaz, F. (2019). Effect of drip lateral spacing and mulching on yield, irrigation water use efficiency and net return of onion (Allium cepa L.) at Ambo, Western Shoa, Ethiopia. *Journal of Horticulture and Forestry*, *11*(4), 62–69. doi:10.5897/JHF2019.0583

Harmanny, K. S., & Malek, Ž. (2019). Adaptations in irrigated agriculture in the Mediterranean region: An overview and spatial analysis of implemented strategies. *Regional Environmental Change*, *19*(5), 1401–1416. doi:10.1007/s10113-019-01494-8 PMID:31178659

Kar, A., Pachauri, S., Bailis, R., & Zerriffi, H. (2019). Using sales data to assess cooking gas adoption and the impact of India's Ujjwala programme in rural Karnataka. *Nature Energy*, *4*(9), 806–814. doi:10.1038/s41560-019-0429-8

Karahanna, E., Chen, A., Liu, Q. B., & Serrano, C. (2019). Capitalizing on health information technology to enable digital advantage in US hospitals. *Management Information Systems Quarterly*, *43*(1), 113–140. doi:10.25300/MISQ/2019/12743

Li, S., & Li, X. (2019). The mechanism of farmland marginalization in Chinese mountainous areas: Evidence from cost and return changes. *Journal of Geographical Sciences*, *29*(4), 531–548. doi:10.1007/s11442-019-1613-2

Nyangarika, A., & Bundala, F. S. M. (2020). Socio-Economic Factors Affecting Deposits Growth in Sacco's Development Case of Geita Tanzania. *International Journal of Advance Research and Innovative Ideas in Education*, *6*(2), 1273–1288.

Saediman, H., Mustika, L. N., & Tufaila, M. (2019). Cost And Return Analysis Of Rice Farming And Brick Making In South Konawe District Of Southeast Sulawesi. *International Journal of Scientific & Technology Research*, *8*(10), 835–838.

Simões, F., Rocha, R., & Mateus, C. (2020). Beyond the prophecy success: How place attachment and future time perspective shape rural university students intentions of returning to small islands. *Journal of Youth Studies*, *23*(7), 909–925. doi:10.1080/13676261.2019.1645312

Soneka, P. N., & Phiri, J. (2019). A Model for Improving E-Tax Systems Adoption in Rural Zambia Based on the TAM Model. *Open Journal of Business and Management*, *7*(2), 908–918. doi:10.4236/ojbm.2019.72062

Tang, S., & Hao, P. (2019). The return intentions of China's rural migrants: A study of Nanjing and Suzhou. *Journal of Urban Affairs*, *41*(3), 354–371. doi:10.1080/07352166.2017.1422981

Weaver, M. S., Robinson, J. E., Shostrom, V. K., & Hinds, P. S. (2020). Telehealth acceptability for children, family, and adult hospice nurses when integrating the pediatric palliative inpatient provider during sequential rural home hospice visits. *Journal of Palliative Medicine*, *23*(5), 641–649. doi:10.1089/jpm.2019.0450 PMID:31808722

Yao, B., Shanoyan, A., Peterson, H. H., Boyer, C., & Baker, L. (2019). The use of new-media marketing in the green industry: Analysis of social media use and impact on sales. *Agribusiness*, *35*(2), 281–297. doi:10.1002/agr.21581

Yilmaz, S. K., Horn, B. P., Fore, C., & Bonham, C. A. (2019). An economic cost analysis of an expanding, multi-state behavioural telehealth intervention. *Journal of Telemedicine and Telecare*, *25*(6), 353–364. doi:10.1177/1357633X18774181 PMID:29754561