Hindawi
Journal of Electrical and Computer Engineering
Volume 2023, Article ID 9849316, 1 page
https://doi.org/10.1155/2023/9849316

Retraction

Retracted: Research on the Correlation between Information and Communication Technology Development and Consumer Spending Based on Artificial Intelligence and Time Series Econometric Model

Journal of Electrical and Computer Engineering

Received 19 December 2023; Accepted 19 December 2023; Published 20 December 2023

This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

(1) Discrepancies in scope
(2) Discrepancies in the description of the research reported
(3) Discrepancies between the availability of data and the research described
(4) Inappropriate citations
(5) Incoherent, meaningless and/or irrelevant content included in the article
(6) Manipulated or compromised peer review

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

References

[1] C. Fan, S. H. Law, S. Ibrahim, and N. A. M. Naseem, "Research on the Correlation between Information and Communication Technology Development and Consumer Spending Based on Artificial Intelligence and Time Series Econometric Model," *Journal of Electrical and Computer Engineering*, vol. 2022, Article ID 1645232, 11 pages, 2022.

Hindawi
Journal of Electrical and Computer Engineering
Volume 2022, Article ID 1645232, 11 pages
https://doi.org/10.1155/2022/1645232

Research Article

Research on the Correlation between Information and Communication Technology Development and Consumer Spending Based on Artificial Intelligence and Time Series Econometric Model

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Received 13 April 2022; Accepted 9 May 2022; Published 13 June 2022

Academic Editor: Wei Liu

In order to explore the correlation between ICT development and consumer spending, this paper uses artificial intelligence and time series econometric models to study the correlation between ICT development and consumer spending. Moreover, this paper organically combines the advantages of wavelet analysis and hidden Markov model to construct a wavelet domain hidden Markov chain model. It is used to examine the flow of information on different scales related to the development of communication technology and consumer spending, so as to infer the potential mechanism of the interaction of different traders' behaviors from the other side. Through cluster analysis, it can be seen that the correlation analysis method of information and communication technology development and consumption expenditure based on artificial intelligence and time series econometric model proposed in this paper has certain reliability. At the same time, there is a strong correlation between the development of communication technology and consumer spending.

1. Introduction

Based on artificial intelligence and time series econometric model, this paper studies the correlation between the development of information and communication technology and consumption expenditure and combines cluster analysis to explore whether there is a close relationship between the development of communication technology and consumption expenditure.

With the steady development of my country's communication industry economy, the theoretical research on the communication industry is relatively comprehensive and mature. The research on the communication industry at home and abroad is mainly carried out from the aspects of effective competition, government regulation, industrial organization research, and research on enterprise competitiveness and internationalization. From the perspective of consumers, the income of the communication industry is the expenditure of communication consumption. But at present, there are relatively few researches on communication consumption. Since the proportion of postal consumption in residents' communication consumption expenditure in recent years is very small and the change is not large, the change in communication consumption is mainly caused by telecommunication consumption. The development of the telecommunications market is particularly important. For the influence of the evolution of the telecommunications market and structure, the communication consumption of urban residents plays a leading role, while the communication consumption of rural residents is still at a relatively low level, so the relative impact is relatively small.

Advances in information and communication technologies are having a profound impact on consumer shopping behavior. In recent years, domestic and foreign research on the relationship between ICT and travel behavior has been increasing. Studies have shown that not only telecommuting significantly reduces the number of trips and travel distance, but also more noncommuting trips occur near the residence

[1]; due to the use of telecommuting, the number of trips and vehicle mileage are significantly reduced [2]; people who work entirely by telecommuting spend significantly more time shopping than those who work normally [3]; the study found a clear correlation between online shopping and in-store shopping, that is, people's knowledge. The more information they have about the things they are interested in, the more travel they take to engage in those things [4]; literature examines the relationship between shopping in stores and online shopping; Ferrell, CE considers the space and currency pair between ICT and telecommuting the influence of relationship [5]; the multitasking mode has a great influence on the application of confidence communication technology [6]; *D* studied the significant change law of personal behavior in temporal and spatial arrangement under ICT conditions. However, there are not many studies devoted to ICT application and consumer behavior, and even fewer studies in the background of China [7].

Information consumption is a process in which various types of decision-makers in society digest and absorb the existing information about decision-making, and form action plan decisions or ideological decisions through several transformations [8]. Information consumption is a continuation of the process of social information production and exchange and is a social activity for consumers to acquire information, recognize information content, and reproduce information. Information consumption is divided into living information consumption, learning information consumption, scientific research information consumption, and four levels of decision-making information consumption [9]. At present, the definition of consumption economics is generally adopted; that is, "information consumption is a consumption activity that directly or indirectly takes information products and information services as consumption objects."

The modernization level of telecommunications infrastructure is replaced by the number of fiber-optic cables laid, and the impact of telecommunications infrastructure in the USA on FIRE (financial, insurance, real estate) and manufacturing sectors is concentrated. FIRE has a significant positive impact [10]; based on the regional perspective, a Probit model is established to analyze residents' broadband customization services, and its impact on the regional economy and information economy is explained [11]. Using the input-output method to quantitatively measure the impact of the development of the telecommunications industry on the local economic growth, it shows that the output obtained from the input of the telecommunications infrastructure has the ability to indirectly create new value, thereby driving the development of the regional economy [12]. The five-stage model of universal service proposed by *En*, through the measurement technology, demonstrates that there is a strong positive relationship between the development of telecommunications and economic growth [13].

Technological innovation is the process of dissemination and adoption among potential users through certain channels, and it is pointed out that technological innovation diffusion includes three aspects, namely, inter-enterprise diffusion, intra-enterprise diffusion, and overall diffusion through the joint action of the two [14]. To summarize the connotation and essence of ICT innovation, ICT innovation mainly starts from the generation of new ideas, through the commercialization of ICT innovation and the whole process of its diffusion to potential markets, deep integration, and even technology substitution [15]. The diffusion of technological innovation is realized by two aspects: "expansion" and "scattering." "Expansion" refers to the process of expanding the production scale within the enterprise and the repeated application of technological innovation results; "scattering" refers to the process of external transfer and dissemination of the enterprise, Reference [16].

In the theory of telecommunication demand, the demand of communication consumers is generally divided into access demand and usage demand. Therefore, the research on mobile communication consumer behavior can be divided into access demand and use demand research from the perspective of consumer demand, which basically corresponds to consumers' choice and use behavior. It mainly studies consumer demand and demand function, income, price elasticity of demand, etc. [17]. Access demand refers to the willingness of a user to join a telecommunication network and become a user of a certain operator. Access requirements have the characteristics of one-time or discrete requirements, because once a user joins the network and becomes a user of a certain network, he does not need to apply for network access repeatedly [18]. The usage requirements include requirements for various services such as local calls, long-distance calls, and data services. For usage requirements, the network access fee is equivalent to a sunk cost, so no matter how big the traffic volume is, the network access fee does not affect the consumption level. The consumption of telecommunication services (traffic volume) mainly depends on the price level of use, and the user access demand not only is related to the user access price, but also depends on the used price, which is an important difference between the access demand and the use demand [19]. Mobile communication consumers first choose and then use mobile communication products. The two decision-making behaviors have the characteristics of nonsimultaneity, but they are interrelated and interacting processes. This kind of access and use needs are called discrete continuous mixed needs of consumers. Discrete continuous mixed demand is referred to as mixed demand. Whether it is access demand or usage demand, it can be divided into aggregate demand research (aggregate model) at the macro-level and individual consumer demand research (micro-market analysis) at the micro-level from the level of discussion at home and abroad. Hybrid demand is mainly a micro-level concept [20].

2. Time Series Economic Model

2.1. Hidden Markov Model. Hidden Markov model $\{X_t, t \in N^+\}$ (HMM) is a special kind of hybrid model. If $\mathbf{X}^{(t)}$ and S^{(t)} represent the historical information from time 1 to time *t*, then the most basic situation in this type of model can be summarized by the following two equations:

$$P\left(\frac{S_t}{S_{t-1}}\right) = P\left(\frac{S_t}{S_{t-1}}\right), \quad t = 2, 3, \ldots L,$$
$$P\left(\frac{X_t}{X^{(t-1)}}, S^{(t)}\right) = P\left(\frac{X_t}{S^{(t)}}\right), \quad t \in N^+. \tag{1}$$

This model contains two parts. The first is an unobservable "parametric process" $\{S_t, t = 2, 3, \ldots L\}$ that satisfies the Markov property. In this way, when S_t is known, the probability distribution of X_t only depends on the current state S_t and has nothing to do with the previous state $S^{(t-1)}$ and the observed value $\mathbf{X}^{(t-1)}$. This dependency structure is shown by the following directed graph (Figure 1).

If the Markov chain $\{S_t\}$ has M states, then $\{X_t\}$ is called an M-state hidden Markov model. The following takes a 2-state hidden Markov model as an example to show the observation value of the hidden Markov model.

The production process is shown in Figure 2. The stationary distribution of the Markov chain $\{S_t\}$ is $\delta = (0.75, 0.25)$, the transition probability matrix is set to $\Gamma = \begin{pmatrix} 0.9 & 0.1 \\ 0.3 & 0.7 \end{pmatrix}$, and $p_i(x) = p(X_t = x/S_t = i)(i = 1, 2, L, M)$ is the conditional distribution of the observable variable X_t. It should be noted that if X_t is a discrete random variable, then p_{i} (x) is naturally a probability mass function, that is, the probability that X_t is equal to x under the condition that the Markov chain is in state i at time t. If X_t is a continuous random variable, then $p_i(x)$ can be extended to a probability density function, that is, the value of the conditional probability density function of X_t at x when the Markov chain is in state i at time t. However, in order to save space, it is written in a discrete way here; that is, the conditional distribution is marked as $p_i(x)$, and the marginal distribution is marked as $P(X_t = x)$). It is only necessary to pay attention to the specific meaning and transformation in continuous scenarios.

In applications, it is often necessary to master the distribution of X_t and the marginal distribution of high-dimensional (X_t, X_{t+k}). Therefore, the following will give some marginal distribution results when the Markov chain is homogeneous but not necessarily stationary and then some useful results when the Markov chain is stationary. Although X_t can be either continuous or discrete, this paper only considers the continuous case for the purpose of studying volatility.

2.1.1. Univariate Distribution. For the marginal distribution of an observable random variable X_t, we have

$$\begin{aligned} P(X_t = x) &= \sum_{i=1}^{m} P(S_t = i) P\left(\frac{X_t = x}{S_t = i}\right) \\ &= \sum_{i=1}^{m} u_i(t) p_i(x). \end{aligned} \tag{2}$$

Among them, $u_i(t) = P(S_t = i)$. Formula (2) can be easily re-expressed in matrix form as follows:

$$\begin{aligned} p(X_t = x) &= (u_1(t), u_2(t), \ldots u_m(t)) \begin{pmatrix} p_1(x) & & 0 \\ & \ddots & \\ 0 & & p_{im}(x) \end{pmatrix} \begin{pmatrix} 1 \\ \vdots \\ 1 \end{pmatrix} \\ &= \mathbf{u}(t) \mathbf{P}(x) 1. \end{aligned} \tag{3}$$

Among them, $P(x)$ is a diagonal matrix formed by $p_i(x)$ $(i = 1, 2, \ldots, m)$. According to the formula, it is easy to know

$$P(X_t = x) = u(1) \Gamma^{t-1} P(x) 1. \tag{4}$$

The establishment of (4) only requires that the Markov chain be homogeneous, not stationary. If the Markov chain is stationary and has a stationary distribution δ, the result will be simpler, because at this time $\delta \Gamma^{t-1} = \delta$, and (4) can be reduced to

$$P(X_t = x) = \delta \mathbf{P}(x) 1. \tag{5}$$

2.1.2. Double Variable Page Distribution. Directed graph models (DGMs) can simplify the computation of many probability distributions related to hidden Markov models. For example, the joint distribution of a set of random variables V_i $(i = 1, 2, \ldots, n)$ can be simply written as follows:

$$P(V_1, V_2, \ldots, V_n) = \prod_{i=1}^{n} P\left(\frac{V_i}{\mathrm{pa}(V_i)}\right). \tag{6}$$

Among them, $\mathrm{pa}(V_i)$ represents all "parents" (parent nodes) of the variable (node) in this Bayesian network. A detailed introduction to graphical models can be found in the literature (Jordan, 2004). The 4 random variables are X_t, X_{t+k}, S_t, and S_{t+k}. According to the structure of hidden Markov model, $\mathrm{pa}(S_t)$ is empty, while $\mathrm{pa}(S_{t+k}) = S_t, \mathrm{pa}(X_t) = S_t$ and $\mathrm{pa}(X_{t+k})$, so their joint distribution can be written as follows:

$$P(X_t, X_{t+k}, S_t, S_{t+k}) = P(S_t) P\left(\frac{X_t}{S_t}\right) P\left(\frac{S_{t+k}}{S_t}\right) P\left(\frac{X_{t+k}}{S_{t+k}}\right). \tag{7}$$

At the same time, the marginal distribution can be expressed as follows:

$$\begin{aligned} P(X_t = v, X_{t+k} = w) &= \sum_{i=1}^{m} \sum_{j=1}^{m} P(X_t = v, X_{t+k} = w, S_t = i, S_{t+k} = j) \\ &= \sum_{i=1}^{m} \sum_{j=1}^{m} P(S_t = i) p_i(v) P\left(S_{t+k} = \frac{j}{S_t = i}\right) p_j(w) \\ &= \sum_{i=1}^{m} \sum_{j=1}^{m} u_i(t) p_i(v) \gamma_{ij}(k) p_j(w) \\ &= u(t) \mathbf{P}(v) \Gamma^k \mathbf{P}(w) 1. \end{aligned} \tag{8}$$

If the Markov chain is stationary, then (8) can be written as follows:

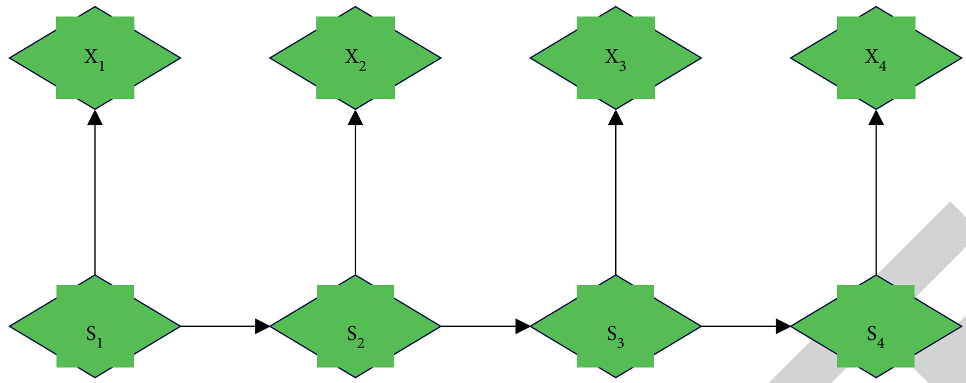

Figure 1: Directed graph representation of the underlying hidden Markov model.

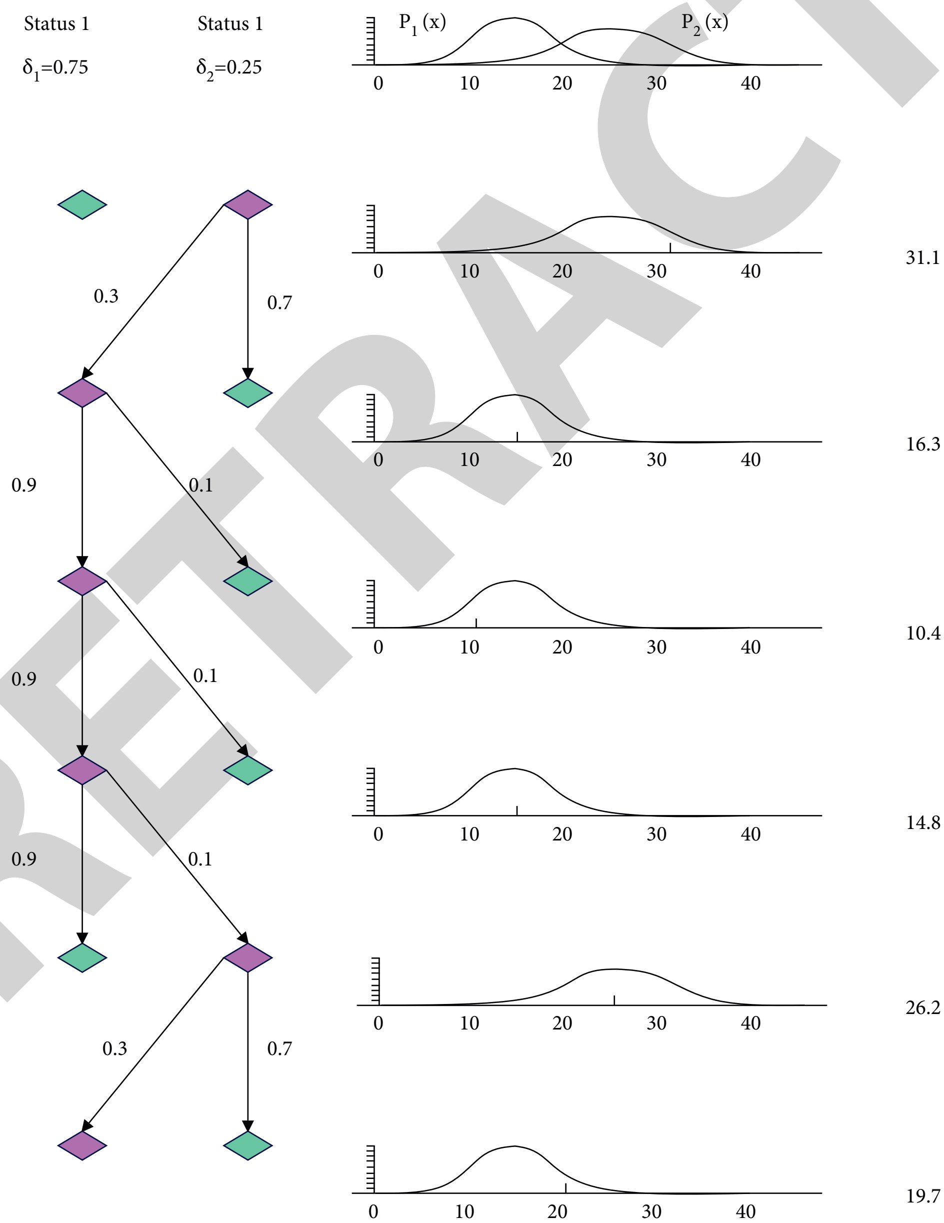

Figure 2: The generation process of the observation value of the 2-state hidden Markov model.

$$P(X_t = v, X_{t+k} = w) = \delta P(v)\Gamma^k P(w)1. \quad (9)$$

Similarly, the expression of higher-dimensional marginal distribution can be obtained. Taking the three variables in the stationary Markov chain as an example, then for any positive integer k and l, we have:

$$P(X_t = v, X_{t+k} = w, X_{t+k+l} = z) = \delta P(v)\Gamma^k P(w)\Gamma^l P(z)1. \quad (10)$$

2.2. Wavelet Domain Hidden Markov Model. According to the time series analysis in the wavelet domain, the wavelet coefficients can be regarded as the random process of the high-dimensional joint probability density function $f(W)$. Because the dimension is too high, it is difficult to use the joint probability density function to describe the dependence between different wavelet coefficients. If the different wavelet coefficients are simply considered to be independent of each other, that is, $f(W) = \prod_t f(W_t)$, the solution of the joint probability density can indeed be simplified, but the dependence of the wavelet coefficients between scales cannot be considered. Therefore, it is necessary to establish a feasible model with compromise, which can not only reflect the main correlation between wavelet coefficients, but also be easy to calculate.

In addition, modern research found that the wavelet transform of the signal has the following properties. Aggregation: the absolute value of a wavelet coefficient is large (small), and then the coefficient value next to it will also be large (small). Persistence: the absolute value of the wavelet coefficient of a certain time scale is relatively large (small), and the absolute value of the wavelet coefficient of the adjacent scale at the same time point is also relatively large (small). These two properties indicate the correlation between the wavelet coefficients of the signal (non-noise time series). The hidden Markov tree model uses the basic hidden Markov model introduced in the paper, and the wavelet transform has a similar fork tree structure. Building a bridge between them can achieve the purpose of describing this correlation among wavelet coefficients in a compromise.

The correlation between wavelet coefficients is characterized by the transmission of coefficients between different scales; that is to say, the size of the wavelet coefficients is related to the number of related parents and affects the coefficients of their descendants. In the hidden Markov tree model, the correlation between wavelet coefficients is established by using the hidden state variables of the wavelet coefficients instead of the coefficients themselves. Therefore, the hidden Markov tree model with tree structure can effectively reflect the persistent properties of wavelet coefficients along the scale direction. Each wavelet coefficient obeys a Gaussian mixture model of M hidden states, and the M-state Gaussian hidden Markov tree model can be described by the parameter set θ:

$$\begin{aligned}\boldsymbol{\theta} &= \left\{p_{s_1}(m), \varepsilon^{m,r}_{i,po(i)}, u_{i,m}, \sigma^2_{i,m} | i \in \mathbf{I}\right.\\ &\left.= \{1, 2, \ldots, Q\}; m, r \in \{s_1, s_2, \ldots, s_M\}\right\}.\end{aligned} \quad (11)$$

Among them, the first element $p_{s_i}(m)$ is the probability distribution of the root node. Specifically, p here represents a specific probability distribution, and i represents the number of the root node. S_i corresponds to the random state of the i-th node, M represents the size of the finite state space, and I is the set of all node numbers. The second element is $\varepsilon^{m,r}_{i,pp(i)} = P(S_i = r/S_{\text{pa}(i)} = m)$, which is the conditional probability when the hidden state S_i of the i-th node is in r when the hidden state of the parent node pa (i) of the i-th node is at m. The third and fourth elements $u_{i,m}, \sigma^2_{i,m}$ are the mathematical expectation and variance of the corresponding wavelet coefficients when the hidden state of the i-th node is known to be m, respectively.

2.2.1. Parameter Estimation. For a specific financial time series in reality, even if it truly obeys the hidden Markov tree model, the specific parameters of the model are unknown most of the time. Therefore, the model parameters can only be estimated by selecting an appropriate method from the data of the only observable wavelet coefficients. Compared with the general model, the difficulty of parameter estimation of this model is that the state of each node cannot be obtained, so it is not feasible to directly use the maximum likelihood method to estimate the parameters. For such missing data problems, the EM algorithm is very effective. The core task of the EM algorithm in estimating the hidden Markov tree model is to use the parameter group (11) to fully match the wavelet tree of the observed wavelet coefficients. Each tree has Q wavelet coefficients k, namely, training $\widehat{\theta} = \text{argmax}_\theta f(\mathbf{W}/\theta)$, where $\mathbf{W} = \{W_i, i \in \mathbf{I}\}$.

The iterative process is divided into four steps:

Step 1: Initialization: the algorithm sets the initial value θ^0 of the model parameters, and the iteration index $l = 0$.

Step 2: Step E, the algorithm calculates the joint distribution $P(\mathbf{S}/\mathbf{W}, \theta^l), \mathbf{S} = \{S_i, i \in \mathbf{I}\}$ of the hidden state variables.

Step 3: M step, the algorithm sets $\theta^{l+1} = \text{argmax}_\theta E_S (\ln f(W, S/\theta)/W, \theta^l)$.

Step 4: Iteration, the algorithm judges whether to reach the convergence or stop the loop condition, otherwise, l=l+1, and the algorithm returns to Step 2 to continue the loop.

Solve for log-likelihood. From the wavelet domain hidden Markov model parameters, the likelihood function value is calculated; that is, $\ln f(W/\theta)$ is calculated

2.2.2. Training Algorithm. In the wavelet domain, the tree structure is strictly formed by the chain of wavelet coefficients, rather than by the connection of hidden states. T_i represents the subtree of wavelet coefficients corresponding to the i-th node as the root. T_i contains the wavelet coefficients W_i and all its descendants. If T_j is a subtree of T_i, then T_{ijj} is the set of wavelet coefficients after removing T_i from T_j. Without loss of generality, the wavelet coefficients can be sorted so that W_1 is at the root of the entire tree. Thus, T_1 is the tree of all observed wavelet coefficients. Each of its subtrees T_i is defined as follows:

$$\beta_i(m) = f\left(\frac{T_i}{S_i = m, \theta}\right),$$

$$\beta_{i,\mathrm{pa}(i)}(m) = f\left(\frac{T_i}{S_{\mathrm{pa}(i)} = m, \theta}\right),$$

$$\beta_{\mathrm{pa}(i)/i}(m) = f\left(\frac{T_{\mathrm{pa}(i)i}}{S_{\mathrm{pa}(i)} = m, \boldsymbol{\theta}}\right), \tag{12}$$

$$\alpha_i(m) = P\left(\frac{S_i = m, T_{1vi}}{\boldsymbol{\theta}}\right).$$

According to the properties of the hidden Markov tree model in the wavelet domain, when the state variable S_i is given, the trees T_i and $T_{i/j}$ are independent of each other. This situation makes it possible to find the probability distribution of the state variables in terms of α and β. Using Bayes' theorem, the conditional probability is obtained as follows:

$$P\left(\frac{S_i = m}{W, \boldsymbol{\theta}}\right) = \frac{\alpha_i(m)\beta_i(m)}{\sum_{m=1}^{M}\alpha_i(m)\beta_i(m)}, \tag{13}$$

$$P\left(\frac{S_i = m, S_{\mathrm{pa}(i)} = n}{W, \theta}\right) = \frac{\beta_i(m)\varepsilon_{i,\mathrm{pa}(i)}^{n,m}\alpha_{\mathrm{pa}(i)}(n)\beta_{\mathrm{pa}(i)}(n)}{\sum_{m=1}^{M}\sum_{m=1}^{M}\beta_i(m)\varepsilon_{i,\mathrm{pa}(i)}^{n,m}\alpha_{\mathrm{pa}(i)}(n)\beta_{\mathrm{pa}(i)i}(n)}. \tag{14}$$

In order to deal with the situation that the total number K of trees is greater than 1, the number of trees is represented by superscript, and the set of wavelet coefficients and the set of hidden state variables are re-denoted as $W = \{W^1, W^2, \ldots, W^K\}$ and $S = \{\mathbf{S}^1, \mathbf{S}^2, \ldots, S^K\}$, respectively. The wavelet coefficient subsets and state variable subsets in each tree use vector $W^k = (W_1^k, W_2^k, \ldots, W_Q^k)$ and vector $S^k = (S_1^k, S_2^k, \ldots, S_Q^k)$, respectively. In order to realize the E step of the EM algorithm, the upward-downward algorithm is used independently for each tree in the K wavelet trees. From formulas (13) and (14) and parameter estimation $\theta = \theta^l$, the marginal distributions $P(S_i^k = m/W^k, \theta^l)$ and $P(S_i^k = m, S_{\mathrm{pa}(i)}^k = n/W^k, \theta^l)$ of the hidden state variables can be calculated. After calculating the distribution of the hidden state variables, we can directly calculate the following:

$$p_{S_i}(m) = \frac{1}{K}\sum_{k=1}^{K} P\left(\frac{S_i^k = m}{W^k, \boldsymbol{\theta}^l}\right),$$

$$\varepsilon_{i,\mathrm{pa}(i)}^{n,m} = \frac{\sum_{k=1}^{K} P\left(S_i^k = m, S_{\mathrm{pa}(i)}^k = n/W^k, \theta^l\right)}{K p_{S_{p(i)}}(n)},$$

$$u_{i,m} = \frac{\sum_{k=1}^{M} W_i^k P\left(S_i^k = m/W^k, \boldsymbol{\theta}^l\right)}{K p_{S_i}(m)}, \tag{15}$$

$$\sigma_{i,m}^2 = \frac{\sum_{k=1}^{K}\left(W_i^k - u_{i,m}\right)P\left(S_i^k = m/W^k, \theta^l\right)}{K p_{S_i}(m)}.$$

It is not difficult to see that the training estimates for all elements $p_{s_i}(m), \varepsilon_{i,\mathrm{pa}(i)}^{n,m}, u_{i,m}$, and $\sigma_{i,m}^2$ in the above four parameter subsets of $i \in \{1, 2, \ldots, Q\}, m, n \in \{s_1, s_2, \ldots, s_M\}$ are the weighted average estimates of the independent estimates of K wavelet trees.

2.3. Statistical Characteristics of Wavelet Coefficients of Financial Time Series. Since the orthogonal discrete wavelet transform (DWT) has a certain function of decorrelation, the wavelet coefficient series is often regarded as a white noise process in data processing. Then, the statistical correlation information among the wavelet coefficients is not exploited in the modeling. However, in fact, for high-frequency financial time series, the assumption of irrelevance and Gaussian property of wavelet coefficients will no longer hold. The reasons mainly come from the following three aspects. First, for most of the high-frequency financial time series, the wavelet coefficients after wavelet decomposition usually exhibit sparse properties. The sparse property here means that most of the wavelet coefficients are relatively small, but the large wavelet coefficients can represent the singular characteristics of the original financial time series and contain most of the fluctuation information of the original financial series, but are relatively few in number. Secondly, the wavelet coefficient series as a whole presents the statistical distribution characteristics of "spike peaks and thick tails." Finally, various complex correlation structures exist in raw financial time series, so it is practically impossible to generate approximately uncorrelated series of wavelet coefficients.

Because the wavelet coefficients of the financial fluctuation time series after discrete wavelet transform are sparse, an unobservable state series can be defined and linked with each wavelet coefficient. High fluctuation state s_1 corresponds to large wavelet coefficients, and low fluctuation state s_2 corresponds to small wavelet coefficients. Then, the conditional Gaussian distribution of wavelet coefficients is established based on the hidden state; that is, the wavelet coefficient series under the condition of high fluctuation state s_1 obeys the Gaussian distribution $f_{w/s}(w/S = s_1)$ with zero mean and large variance. The wavelet coefficient series under the condition of low fluctuation state s_2 obeys the Gaussian distribution $f_{w/s}(w/S = s_2)$ with zero mean and small variance. Formula is as follows:

$$f_w(w) = \sum_{i=1}^{2} f_{w/s}\left(\frac{w}{S = s_i}\right)P(S = s_i). \tag{16}$$

In order to establish the probability model between wavelet coefficients of different time scales, a hidden Markov tree model with Cr tree structure is introduced here. The model utilizes the typical binary tree structure of discrete wavelet transform (DWT) and assumes that the tree structure composed of state variables corresponding to wavelet coefficients satisfies the first-order Markov model. This paper presents a schematic diagram of the one-dimensional discrete wavelet transform decomposition structure and one-dimensional hidden Markov tree model. Among them, the white dots represent the "hidden" state variables corresponding to each coefficient, and the black dots represent the wavelet coefficient variables. As can be

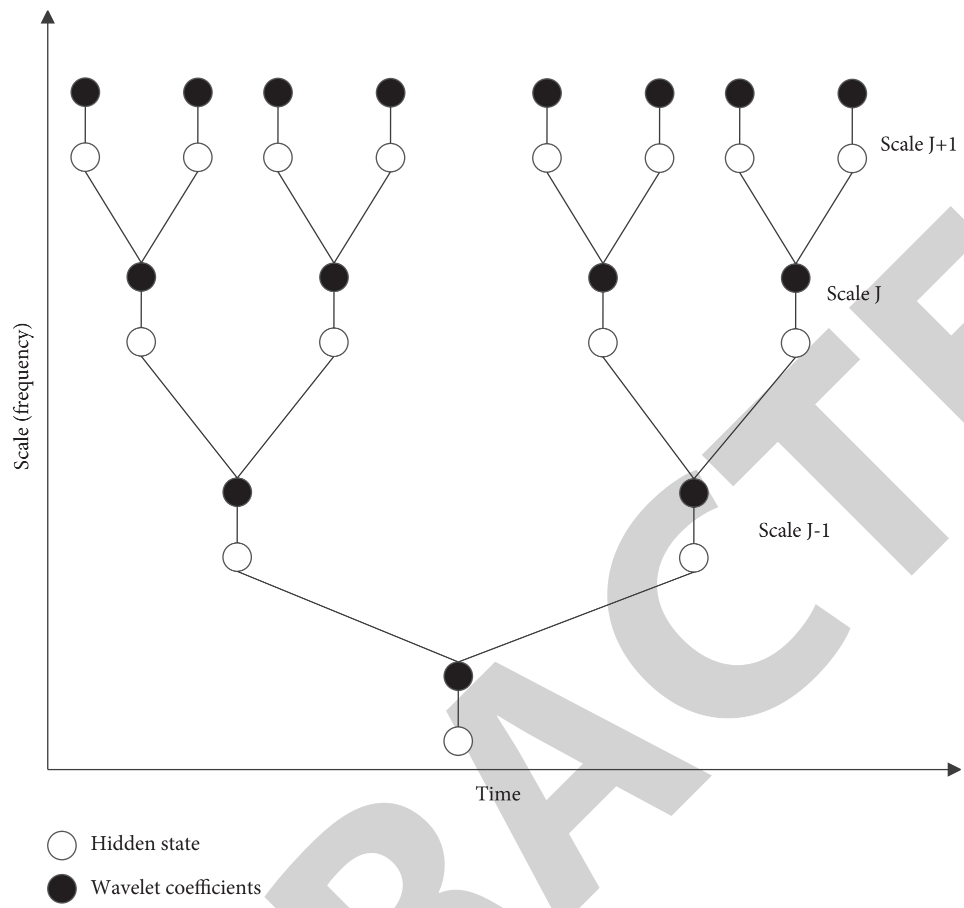

Figure 3: Hidden Markov tree model structure in wavelet domain.

seen from Figure 3, the degree of dependence of the parent-child nodes in this model corresponds to the transmission strength of the corresponding coefficient states between the scales. This transfer strength can also be measured by the transition probability between the states of the parent and child nodes in the HMT model. Therefore, HMT can theoretically effectively evaluate the dependence of wavelet coefficients between different time scales.

By integrating GMM and HMT models, a two-state wavelet hidden Markov model (WHMM) can be obtained. It can simultaneously solve the modeling of the non-Gaussian edge distribution of the wavelet coefficients at each scale and the vertical dependence between the wavelet coefficients at each scale. For any node i in the wavelet tree, its parent and child nodes are denoted as $\mathrm{pa}(i), c(i)$, respectively, and the state of the parent and child nodes is determined by the state probability $\varepsilon_{i,\mathrm{pa}(i)}^{m,r}$. The set of all node indicators is denoted as I, and $W = \{W_i, i \in I\}, S = \{S_i, i \in I\}$. In summary, the model parameters of WHMM include the following: (1) $P_{S_1}(m)$, the probability distribution of the root node S_1; (2) $\varepsilon_{i,\mathrm{pa}(i)}^{m,r} = P_{S_i/S_{p(i)}}(S_i = r/S_{pa(i)} = m)$, that is, the conditional probability of $S_i = r$ under the condition of $S_{\mathrm{pa}(i)} = m$; (3) $u_{i,m}, \sigma_{i,m}^2$, that is, the mean and variance of the wavelet coefficient W_i under the condition of state $S_i = m$.

$$\theta = \left\{P_{s_i}(m), \varepsilon_{i,\mathrm{pa}(i)}^{m,r}, u_{i,m}, \sigma_{i,m}^2, \quad i \in I; m, r \in \{s_1, s_2\}\right\}. \tag{17}$$

3. Model Construction and Parameter Analysis

As a supply channel of market information, communication infrastructure plays the role of an information technology support assistant in terms of the "New Economic Growth Theory," which can convey advanced technologies more quickly and accurately, thereby promoting economic growth in an all-round way. Moreover, good communication infrastructure promotes the development of related industries, improves the quality of related industries, promotes the development of new industries, and promotes the optimization and upgrading of industrial structures. In order to achieve the transaction of farmers selling grain and manufacturers purchasing grain, people only need to consult by telephone, operate online, receive goods on the spot, and pay online, which saves transaction time for farmers and manufacturers and avoids unnecessary troubles. With the construction of communication infrastructure, the financial planning and personnel management of industrial manufacturers have been gradually optimized. The systematic management method and business model not only save expenses, but also improve efficiency, thus promoting the rapid development of the industry. A good communication infrastructure has created an online shopping platform. Such a new consumption model has inspired people's new thinking about consumption and stimulated people's new consumption needs. When the optimization and upgrading

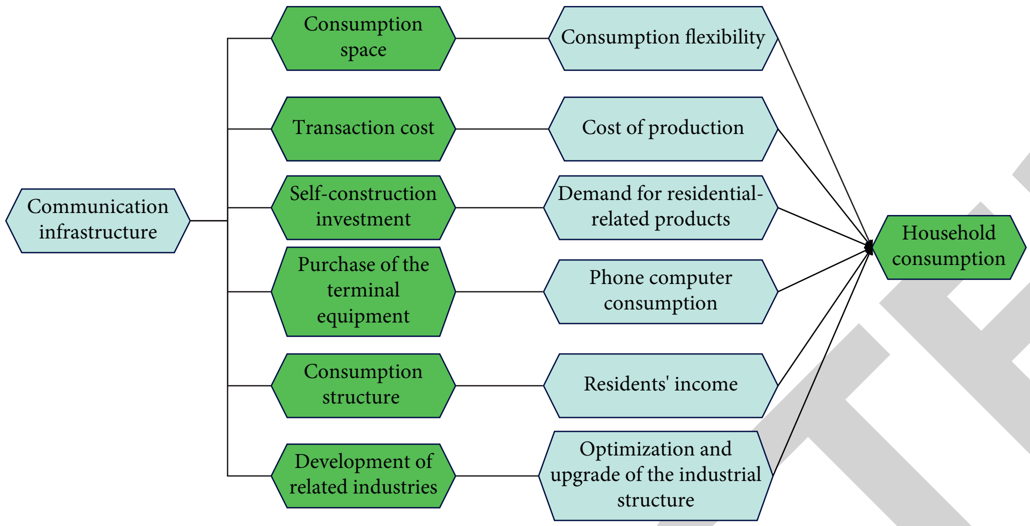

Figure 4: The mechanism of communication infrastructure on residents' consumption.

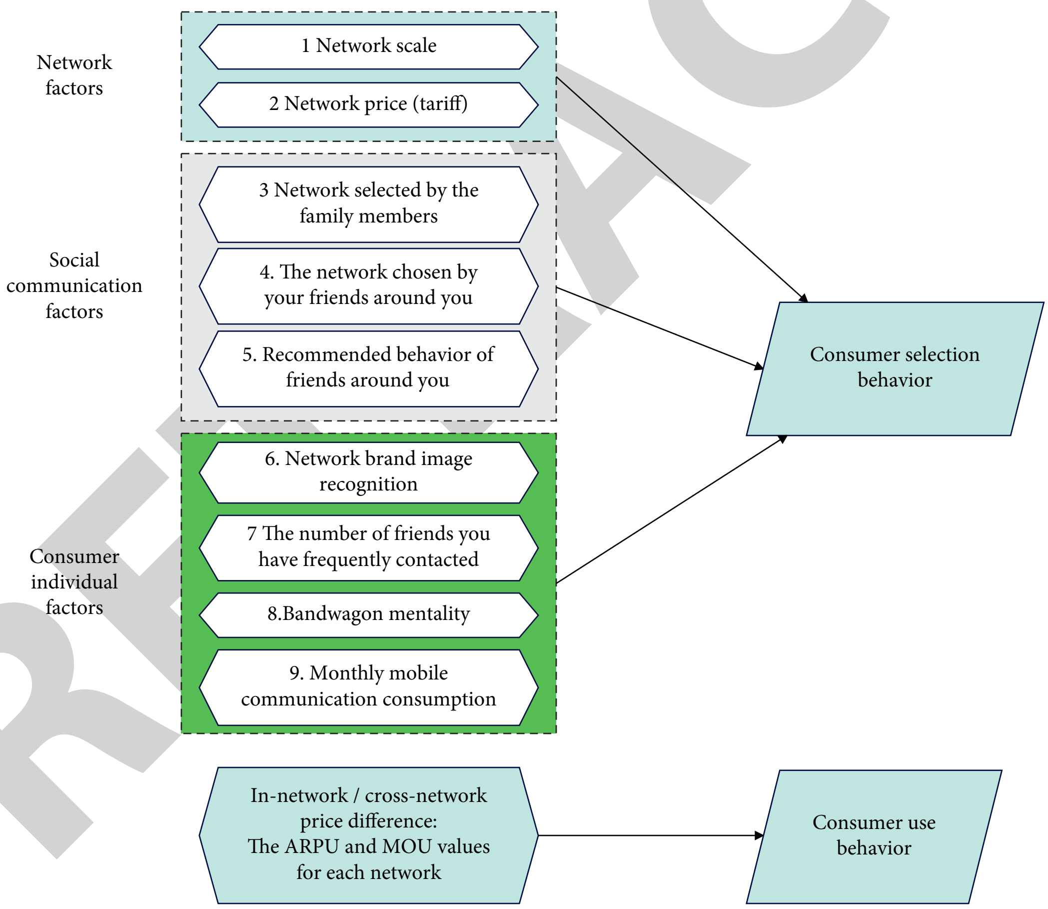

Figure 5: Theoretical framework of mobile communication users' consumption behavior.

of the industrial structure drive the regional economic development and the improvement of people's living standards, people naturally increase their consumption expectations and improve their consumption levels. The effect mechanism of communication infrastructure on household consumption is shown in Figure 4.

This article only examines consumers' choices and usage behaviors in the three networks of Mobile *G*, China Unicom, and China Unicom C. According to the above three influencing factors in this paper, the theoretical framework of mobile communication user consumption behavior as shown in Figure 5 is constructed.

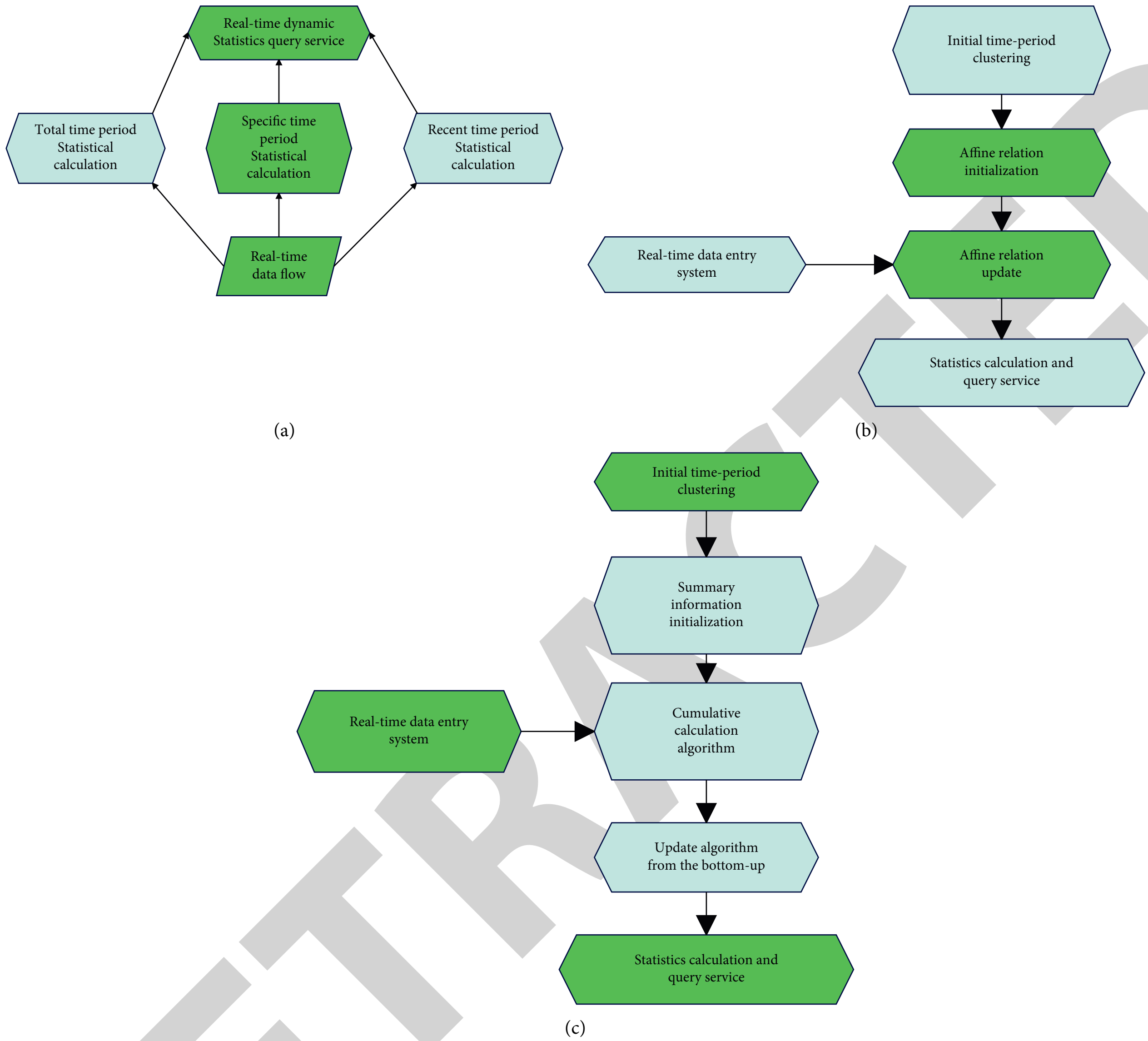

Figure 6: Time series econometric model diagram. (a) Overall design diagram of the system. (b) Landmark window processing process. (c) Sliding window multi-layer processing process.

The system not only needs to satisfy the three query requests of users, but also provides an accurate time series statistical analysis function for the multivariate time series data mining processing technology. Therefore, the basic function template of this system is shown in Figure 6. There are three times in Figure 6(a), in which the lower layer, the middle layer, and the upper layer correspond to the system input, the calculation function module of the system, and the query function module of the system, respectively. The following will mainly introduce the middle layer of the system, that is, three functional modules. For the first query request, the query function implementation module is shown in Figure 6(b). It proposes a large sliding window multi-layer statistics calculation scheme, and its query function implementation module is shown in Figure 6(c).

In this paper, different clustering data are screened and modeled, and the effect of training set and test set is analyzed. Moreover, in this paper, the result data generated by different clusters are combined and output. The clustering data modeling is shown in Figure 7.

After the above model is constructed, the correlation between the development of communication technology and consumer support is analyzed, the system of this paper is constructed through the simulation platform, the experimental research results are counted, and the results shown in Figure 8 are obtained.

Through the above cluster analysis, we can see that the method for analyzing the correlation between information and communication technology development and consumer expenditure based on artificial intelligence and time series

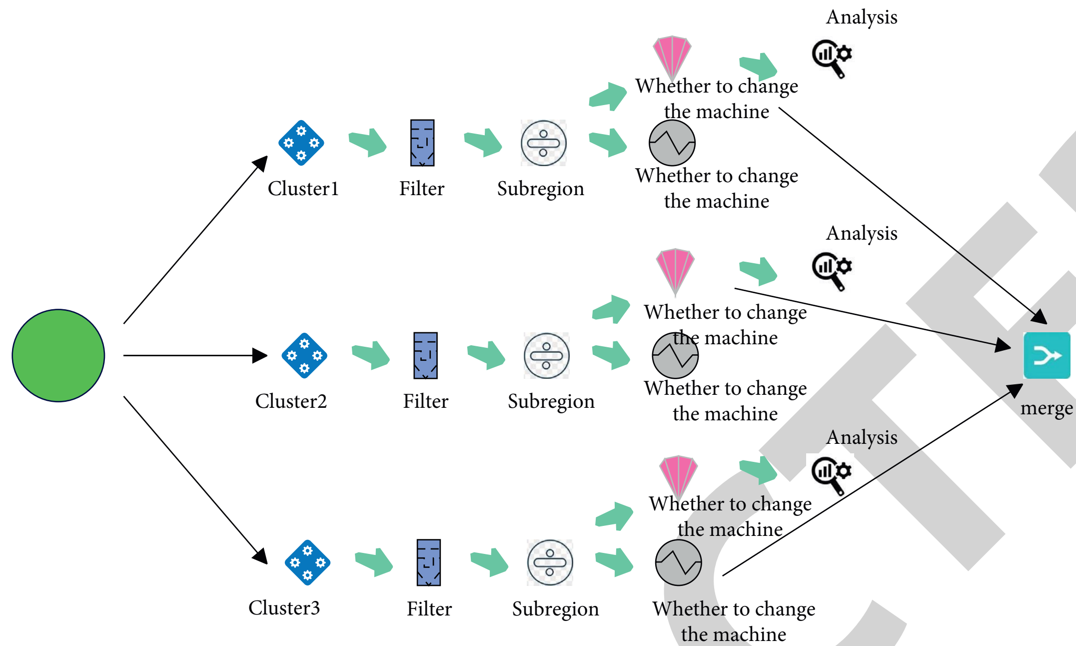

FIGURE 7: Clustering data modeling.

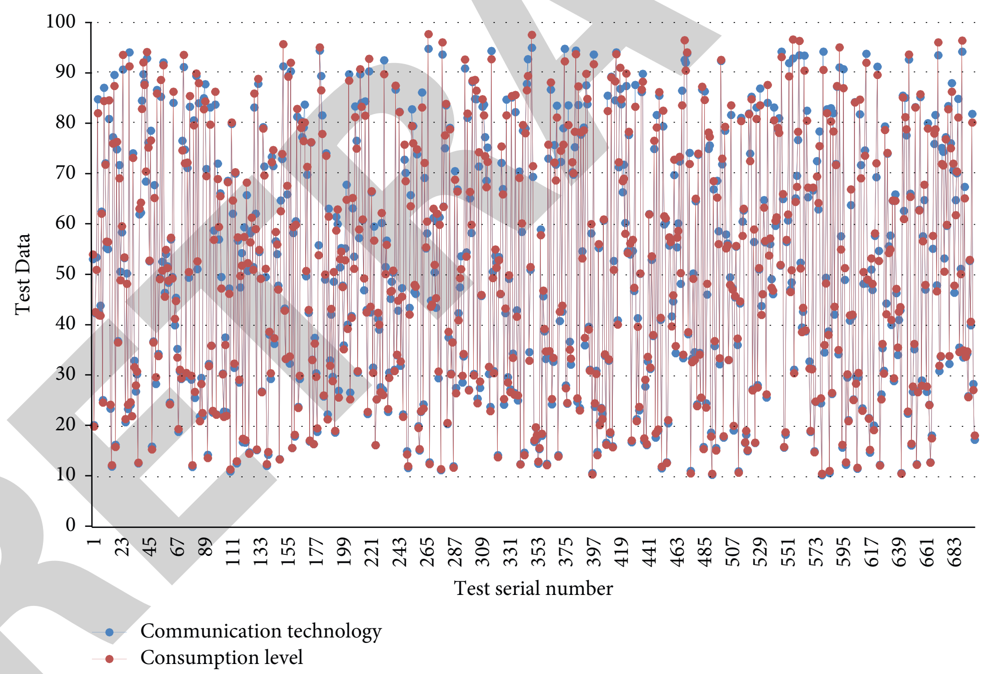

FIGURE 8: Cluster analysis of the correlation between the development of communication technology and consumer spending.

econometric model has certain reliability. At the same time, there is a strong correlation between the development of communication technology and consumer spending.

4. Conclusion

With the rapid development of computer science and technology, spatial data mining technology has become mature. Compared with the previous statistical methods, spatial data mining technology can better reflect the spatial correlation of economic indicators and can more objectively and accurately reflect the changes of certain economic indicators in a certain area and a certain period of time. With the popularization of mobile communication network, mobile phone has become an important communication tool in recent years, and mobile terminal can be regarded as an emerging tool of e-commerce for browsing and payment services. In addition, the demand for communication will increase with the development of the economy, and the increase in GDP will increase the amount of people's communication. Based on artificial intelligence and time series econometric model, this paper studies the correlation between the development of information and communication technology and consumption expenditure and combines cluster analysis to explore whether there is a close relationship between the development of communication technology and consumption expenditure. Cluster analysis shows that the correlation analysis method of information and communication technology development and consumption expenditure based on artificial intelligence and time series econometric model proposed in this paper has certain reliability. At the same time, there is a strong correlation between the development of communication technology and consumer spending.

Data Availability

The labeled dataset used to support the findings of this study is available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Acknowledgments

This study was sponsored by Universiti Putra Malaysia.

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