Grey system theory is an effective mathematical method for studying small sample data and solving poor information problems. The grey correlation model and grey prediction model in this theory have been widely used in scientific studies in various industries. Currently, it is quite difficult for China to formulate scientific policies as livestreaming e-commerce is an emerging industry with little available annual data; therefore, the use of grey system theory is crucial to the study of the future scale of livestreaming e-commerce. In this paper, of many factors influencing the development of livestreaming e-commerce, 14 predictors of livestreaming e-commerce development scale were selected to construct a grey correlation model, by which 5 main predictors were determined. Based on the predictors identified above, 4 grey prediction models of GM (1,1), DGM (1,1), NDGM (1,1), and FDGM (1,1) were constructed, and the accuracy of these models was compared. It was concluded that the NDGM (1,1) model had the best simulation effect. The NDGM (1,1) model is then used to forecast and analyse the indicators of livestreaming e-commerce development scale from 2021 to 2023, and some relevant suggestions were made. This paper applies the new modelling approach to livestreaming e-commerce studies, thus broadening the theoretical study field of livestreaming e-commerce. Moreover, the findings can help the Chinese government make more reasonable and effective decisions as a new study on livestreaming e-commerce was conducted from a different perspective in this paper.

1. Introduction

In previous e-commerce transactions, consumers can only shop according to text descriptions or picture displays. Some scholars believe that there are many unknown risks in this type of transaction [1–3]. However, with the development of internet technology, a new type of shopping, that is, livestreaming e-commerce, has emerged. It was defined by some scholars as a form of shopping that, through live streaming, visually displays information about products, enabling real-time interaction between merchants and sellers [4–6]. As a new field in e-commerce development, livestreaming e-commerce has been aided by the development of the Internet. It started in 2016 and exploded in 2019, going through three stages: the budding period, the exploration period, and the explosion period. Currently, the hottest topic “livestreaming marketing” has increased greatly from “over 100 million in a single livestream” to “over 10 billion in a single livestream.” According to the statistics from iResearch, China’s livestreaming e-commerce market scale exceeded 1 trillion yuan in 2020, which is nearly 30 times more than that of 2016 (366 trillion), as shown in Figure 1. The social and economic benefits brought by livestreaming e-commerce have attracted the attention of the Chinese government, especially in the area of rural revitalisation. The online merchants of Tabao Village have helped some villages rise from poverty and become prosperous by taking full advantage of livestreaming e-commerce development bonus period, during which the number of livestreaming room users and orders showed explosive growth. Although livestreaming e-commerce developed rapidly, there are also many problems to be solved. Moreover, it is difficult for the government to make scientific decisions since relevant annual data is relatively little and most of the available
information is grey. Therefore, the study of livestreaming e-commerce in China is of theoretical and practical significance.

2. Literature Review

2.1. Current Status of Livestreaming E-Commerce Study. Of previous studies on livestreaming e-commerce, some studies focused on certain factors existing in livestreaming e-commerce that can affect consumers’ willingness to purchase; for example, the synchronisation characteristics [7], consumer experience [8], and interface design [9] of livestreaming e-commerce platforms are highly appealing to consumers; and such characteristics of streamers as public personalisation [10] as well as professionalism and credibility [11] can also influence consumers’ shopping. On the other hand, some scholars have conducted qualitative studies on the current situation and future trends of livestreaming e-commerce [12, 13]. In addition, some scholars have also conducted quantitative studies on livestreaming e-commerce [14, 15].

Most of the existing studies on livestreaming e-commerce were conducted from a qualitative perspective because livestreaming e-commerce is an emerging industry, and relevant data is scarce. Moreover, few scholars conducted quantitative studies on which factors have an influence on the development of livestreaming e-commerce, and of these factors, those major and minor ones are still to be further studied. Furthermore, there are also fewer studies on the prediction of livestreaming e-commerce development scale because of the small sample size and the fact that the existing mathematical and statistical methods are not suitable for quantitative prediction analysis.

2.2. Current Status of Grey System Theory Research. The grey system theory is a theory proposed by Professor Deng to study the problem of “small data, small samples, and poor information.” In real life, problems such as incomplete data information are often encountered, making analysis impossible, and grey system theory can solve these problems [16–19]. Grey system theory, including grey correlation analysis and grey prediction analysis, has been widely applied in energy [20], transportation [21], agriculture [22], and other areas. Research on the optimization and application of models for grey correlation analysis has attracted extensive attention from scholars. The research on grey correlation model has changed from point correlation coefficient model to grey correlation degree analysis model based on global and global perspectives [23–25]. There are still many scholars working on optimisation and improvement around the models [26, 27]. Research on the application of grey correlation analysis models has been widely used in the evaluation of e-commerce market efficiency [28], the evaluation of e-commerce development strategies [29], and the classification of e-commerce consumer text evaluation [30]. Grey forecasting is an important part of grey system theory, which builds mathematical models based on small amounts of incomplete data information, performs data simulations, and finally makes predictions about future trends. It is more suitable for small sample forecasting than commonly used forecasting methods, such as regression analysis. Research on the optimisation and application of grey prediction models has been popular among scholars [31–34]. For example, new prediction models have been proposed to address the problem of jumping from discrete to continuous form of grey prediction models [35, 36]. Other scholars have proposed a new SAIGM model with a fractional-order cumulative operator based on the commonly used grey prediction models [37]. Research on the application of grey prediction models has found that some scholars have applied grey models to forecasting research in other areas such as cross-border e-commerce [38] and maritime regional e-commerce [39].

As an emerging industry, the existing annual data of livestreaming e-commerce are relatively small, with problems such as small sample size and poor information. It is difficult to analyse the existing annual data by conventional statistical methods, while the grey system theory can be used to analyse the data with less data, and the grey model constructed has a good fitting effect and high accuracy. At present, the research results on grey system theory in the field of livestreaming e-commerce are particularly scarce. This study can expand the applied research field of grey system theory, which has an important theoretical significance. In addition, the research results from a new research perspective on livestreaming e-commerce can provide scientific reference for government decision-making and have strong practical significance.

3. Grey System Theory

3.1. Grey Correlation Analysis Model. As an active branch of grey systems theory, grey correlation analysis is often used to analyse relevant influences, mainly including grey absolute correlation, grey relative correlation, and grey composite correlation.
3.1.1. Grey Absolute Correlation. The grey absolute correlation is a model based on the similarity of the sequence folds, independent of their spatial location. When the similarity of the folds is greater, the grey absolute correlation is greater and vice versa.

\[ X_0^0 = \left( x_0^0(1), x_0^0(2), \ldots, x_0^0(n) \right) = (x_0(1) - x_0(1), x_0(2) - x_0(1), \ldots, x_0(n) - x_0(1)) , \]
\[ X_i^0 = \left( x_i^0(1), x_i^0(2), \ldots, x_i^0(n) \right) = (x_i(1) - x_i(1), x_i(2) - x_i(1), \ldots, x_i(n) - x_i(1)) , \]  
\[ (1) \]

Making \( |s_i| = \left| \sum_{k=2}^{n-1} x_0^0(k) \right| + (1/2)x_0^0(n), \) \( |s_i| = \left| \sum_{k=2}^{n-1} x_i^0(k) \right| + (1/2)x_i^0(n), \) \( |s_i - s_0| = \left| \sum_{k=2}^{n-1} (x_i^0(k) - x_0^0(k)) \right| + 1/2 \]

Let the system behavior sequences \( X_0 \) and \( X_i \) be of the same length and both be 1-timespaced sequences, \( X_0 = (x_0(1), x_0(2), \ldots, x_0(n)), X_i = (x_i(1), x_i(2), \ldots, x_i(n)), \) then the starting point zeroing image of \( X_0 \) and \( X_i \) is

\[ 2(x_i^0(n) - x_0^0(n)) \]

3.1.2. Grey Relative Correlation. The grey relative correlation is a model constructed based on the perspective of the change rate of the sequence relative to the origin, independent of the size of the observed values in the sequence itself. There is some relationship between the change rate of any two sequences. The closer the change rate of the sequence relative to the starting point, the larger the grey relative correlation is.

Let the sequences \( X_0 \) be of the same length as \( X_i \), and none of the initial values are 0, \( X_0 = (x_0(1), x_0(2), \ldots, x_0(n)), X_i = (x_i(1), x_i(2), \ldots, x_i(n)), \) then the initial image of \( X_0 \) and \( X_i \) is

\[ X'_0 = (x'_0(1), x'_0(2), \ldots, x'_0(n)) = \left( \frac{x_0(1)}{x_0(1)}, \frac{x_0(2)}{x_0(1)}, \ldots, \frac{x_0(n)}{x_0(1)} \right) \]
\[ X'_i = (x'_i(1), x'_i(2), \ldots, x'_i(n)) = \left( \frac{x_i(1)}{x_i(1)}, \frac{x_i(2)}{x_i(1)}, \ldots, \frac{x_i(n)}{x_i(1)} \right) \]
\[ (3) \]

and then the zeroing image of the starting point of \( X'_0 \) and \( X'_i \) is

\[ X'^0_0 = \left( x'^0_0(1), x'^0_0(2), \ldots, x'^0_0(n) \right) = (x'_0(1) - x'_0(1)), x'_0(2) - x'_0(1), \ldots, x'_0(n) - x'_0(1)) , \]
\[ X'^0_i = \left( x'^0_i(1), x'^0_i(2), \ldots, x'^0_i(n) \right) = (x'_i(1) - x'_i(1)), x'_i(2) - x'_i(1), \ldots, x'_i(n) - x'_i(1)) , \]  
\[ (4) \]

Making \( |s'_i| = \left| \sum_{k=2}^{n-1} x'_0^0(k) \right| + (1/2)x'_0^0(n), \) \( |s'_i| = \left| \sum_{k=2}^{n-1} x'_i^0(k) \right| + (1/2)x'_i^0(n), \) \( |s'_i - s'_0| = \left| \sum_{k=2}^{n-1} (x'_i^0(k) - x'_0^0(k)) \right| + 1/2 \]

Let the system behavior sequences \( X_0 \) and \( X_i \) be of the same length and both be 1-timespaced sequences, \( X_0 = (x_0(1), x_0(2), \ldots, x_0(n)), X_i = (x_i(1), x_i(2), \ldots, x_i(n)), \) then the starting point zeroing image of \( X_0 \) and \( X_i \) is

\[ 2(x_i^0(n) - x_0^0(n)) \]

The grey relative correlation is

\[ r_{0i} = \frac{1 + |s'_0| + |s'_i|}{1 + |s'_0| + |s'_i| + |s'_i - s'_0|} \]
\[ = \frac{1 + \left| \sum_{k=2}^{n-1} x'_0^0(k) \right| + (1/2)x'_0^0(n) + \left| \sum_{k=2}^{n-1} x'_i^0(k) \right| + (1/2)x'_i^0(n)}{1 + \left| \sum_{k=2}^{n-1} x'_0^0(k) \right| + (1/2)x'_0^0(n) + \left| \sum_{k=2}^{n-1} x'_i^0(k) \right| + (1/2)x'_i^0(n)} \]  
\[ (5) \]
3.1.3. Grey Composite Correlation. The grey composite correlation reflects the similarity degree between the sequences and the proximity degree of the change rate between the sequences relative to the origin. The grey composite correlation is an indicator that considers the close degree between sequences from a more comprehensive perspective, where $\theta \in [0, 1]$, usually taken as $\theta = 0.5$.

Let the length of sequences $X_0$ and $X_i$ be the same and the initial value is not 0, the grey absolute correlation of the two sequences is $\varepsilon_{0i}$ and the grey relative correlation is $r_{0i}$, then the grey composite correlation of $X_0$ and $X_i$ is

$$
\rho_{0i} = \theta \varepsilon_{0i} + (1 - \theta) r_{0i}.
$$

(6)

3.2. Grey Prediction Model. The principle of grey prediction model is that a small amount of raw data will first be processed; then the corresponding model will be established to mine, discover, and grasp the laws in the system and finally make a scientific quantitative prediction on the future development trend of the system. As mentioned earlier, the raw data needs to be processed prior to predicting the uncover laws from the seemingly disorganised raw data. Common data processing methods include cumulative generation, cumulative subtraction generation, and so on. In addition, due to problems in the system development environment and the raw data collection process, the raw data grows too fast, or data is missing, which requires the introduction of buffer operators and mean generation operators to process the raw data. Once the raw data has been processed, prediction models can be constructed. Grey prediction models include the commonly used GM (1,1) model, DGM (1,1) model, and so on. In addition, some emerging models are also included, such as NDGM (1,1) model, FDGM (1,1) model, and so on. Different grey prediction models have different modelling mechanisms, but the core of the modelling is to start the research around a small amount of known raw data, extract valuable data information, and discover the development patterns in it, so as to achieve quantitative forecasting of future changes.

3.2.1. Grade Ratio Test. Before grey predictive modelling can be carried out, the original data needs to be checked for the grade ratio test. If the test is passed, the grey prediction modelling requirements are met.

Let the original sequence $X^{(0)} = (x^{(0)}(1), x^{(0)}(2), \ldots, x^{(0)}(n))$, where $x^{(0)}(k) \geq 0, k = 1, 2, \ldots, n$, then the sequence grade ratio is $\sigma(k) = x^{(0)}(k) / x^{(0)}(k-1)$, for $k = 2, 3, \ldots, n$. When $\sigma(k) \notin (e^{-2/(n+1)}, e^{2/(n+1)})$, the original sequence can be used directly to build a model for prediction. When $\sigma(k) \notin (e^{-2/(n+1)}, e^{2/(n+1)})$, the sequence operator can be introduced to adjust the raw data. Based on a qualitative analysis of the characteristics of livestream e-commerce development, this thesis uses the second-order weakening operator to adjust the raw data.

The principle of the second-order weakening operator is as follows.

Assume the original sequence $X^{(0)} = (x^{(0)}(1), x^{(0)}(2), \ldots, x^{(0)}(n))$, make $X^{(0)}D = (x^{(0)}(1)d, x^{(0)}(2)d, \ldots, x^{(0)}(n)d)$, among $x^{(0)}(k)d = 1/n(k-1) + x^{(0)}(k+1) + \ldots + x^{(0)}(n), k = 1, 2, \ldots, n$.

Then make $X^{(0)}D^2 = X^{(0)}D D = (x^{(0)}(1)d^2, x^{(0)}(2)d^2, \ldots, x^{(0)}(n)d^2)$, among

$$
x^{(0)}(k)d^2 = 1/nk + 1/2 x^{(0)}(k)d + x^{(0)}(k+1)d + \ldots + x^{(0)}(n)d, k = 1, 2, \ldots, n.
$$

(7)

3.2.2. GM (1,1) Modelling Process. One of the most studied and applied grey prediction models is the GM (1,1) model. The GM (1,1) model represents a grey first-order and one-variable forecasting model. The modelling process of the GM (1,1) model is as follows.

Let the sequence $X^{(0)} = (x^{(0)}(1), x^{(0)}(2), \ldots, x^{(0)}(n))$, where $x^{(0)}(k) \geq 0, k = 1, 2, \ldots, n$, the 1-AGO sequences of $X^{(0)}$ is $X^{(1)}$, that is, $X^{(1)} = (x^{(1)}(1), x^{(1)}(2), \ldots, x^{(1)}(n))$, where $x^{(1)}(k) = \sum_{i=1}^{k} x^{(0)}(i), k = 1, 2, \ldots, n$.

The immediately adjacent to the mean generating sequence of $X^{(1)}$ is $Z^{(1)}$, that is, $Z^{(1)} = (z^{(1)}(2), z^{(1)}(3), \ldots, z^{(1)}(n)) = (1/2(x^{(1)}(2) + x^{(1)}(1)), 1/2(x^{(1)}(3) + x^{(1)}(2)), \ldots, 1/2(x^{(1)}(n) + x^{(1)}(n-1)))$, of which $z^{(1)}(k) = 1/2(x^{(1)}(k) + x^{(1)}(k-1)), k = 2, 3, \ldots, n$.

The basic form of the GM (1,1) model is

$$
x^{(0)}(k) + az^{(1)}(k) = b.
$$

(8)

The least squares method is used to calculate the vectors, that is, $h = (B^T B)^{-1} B^T Y = [a, b]^T$, where $B, Y$ are

$$
B = \begin{bmatrix}
-z^{(1)}(2) \\
-z^{(1)}(3) \\
\vdots \\
-1 \\
-z^{(1)}(n) \\
\end{bmatrix},
$$

$$
Y = \begin{bmatrix}
x^{(1)}(2) \\
x^{(1)}(3) \\
\vdots \\
x^{(1)}(n) \\
\end{bmatrix}.
$$

(9)

The whitening differential equation is established as follows:
\[
\frac{dx^{(1)}}{dt} + ax^{(1)} = b. \tag{10}
\]

The time response equation for the GM (1,1) model is
\[
\begin{align*}
\bar{x}^{(1)}(k) &= \left( x^{(0)}(1) - \frac{b}{a} \right) e^{-\frac{b}{a}k} + \frac{b}{a} \\
\bar{x}^{(0)}(k) &= \bar{x}^{(1)}(k) - \bar{x}^{(1)}(k - 1).
\end{align*}
\tag{11}
\]

3.2.3. DGM (1,1) Modelling Process. The DGM (1,1) model is proposed to compensate for a shortcoming in modelling the GM (1,1) model, which is a direct jump from a discrete equation to a continuous equation. This is because the basic form of the GM (1,1) model is a discrete equation, whereas the whitening differential equation is a continuous equation. When GM (1,1) modelling is carried out, the two equations share parameters \([a,b]\) directly, which leads to errors in the results.

The DGM (1,1) model is
\[
x^{(1)}(k+1) = \beta_1 x^{(1)}(k) + \beta_2.
\tag{12}
\]

Vector \(\bar{y} = (B^TB)^{-1}B^TY = [\beta_1, \beta_2]^T\) can be calculated by the least squares method, where \(B, Y\) are
\[
B = \begin{bmatrix}
x^{(1)}(1) & 1 \\
x^{(1)}(2) & 1 \\
\vdots & \vdots \\
x^{(1)}(n-1) & 1
\end{bmatrix},
\tag{13}
\]
\[
Y = \begin{bmatrix}
x^{(1)}(2) \\
x^{(1)}(3) \\
\vdots \\
x^{(1)}(n)
\end{bmatrix}.
\]

The time response equation for the DGM (1,1) model is
\[
\begin{align*}
\bar{x}^{(1)}(k) &= \left[ x^{(0)}(1) - \frac{\beta_2}{1 - \beta_1} \right] \beta_1^k + \frac{\beta_2}{1 - \beta_1} \\
\bar{x}^{(0)}(k) &= \bar{x}^{(1)}(k) - \bar{x}^{(1)}(k - 1).
\end{align*}
\tag{14}
\]

3.2.4. NDGM (1,1) Modelling Process. The proposed NDGM (1,1) model extends the applicability of grey forecasting models from approximate chi-squared exponential sequences to approximate non-chi-squared exponential sequences, which further broadens the research area of grey forecasting applications.

The NDGM (1,1) model is
\[
\begin{align*}
\bar{x}^{(1)}(k+1) &= \beta_1 \bar{x}^{(1)}(k) + \beta_2 k + \beta_3, \\
\bar{x}^{(1)}(1) &= \bar{x}^{(1)}(1) + \beta_4,
\end{align*}
\tag{15}
\]
where \(\bar{x}^{(1)}(k)\) is the fitted value of the original sequences and \(\bar{x}^{(1)}(1)\) is the iterative base value.

Let the parameter vector \(\bar{p} = [\beta_1, \beta_2, \beta_3]^T\), \(\beta_1, \beta_2, \beta_3\) can be calculated by the least squares, that is,
\[
\bar{p} = (B^TB)^{-1}B^TY = [\beta_1, \beta_2, \beta_3]^T,
\]
where
\[
B = \begin{bmatrix}
x^{(1)}(1) & 1 & 1 \\
x^{(1)}(2) & 2 & 1 \\
\vdots & \vdots & \vdots \\
x^{(1)}(n-1) & k-1 & 1
\end{bmatrix},
\tag{16}
\]
\[
Y = \begin{bmatrix}
x^{(1)}(2) \\
x^{(1)}(3) \\
\vdots \\
x^{(1)}(n)
\end{bmatrix}.
\]

The time response equation for the NDGM (1,1) model is
\[
\begin{align*}
\bar{x}^{(1)}(k+1) &= \beta_1 \bar{x}^{(1)}(1) + \beta_2 \sum_{j=1}^{k} \beta_1^{k-j} \bar{x}(1) + \frac{1 - \beta_1^k}{1 - \beta_1} \beta_3 \\
\bar{x}^{(0)}(k) &= \bar{x}^{(1)}(k) - \bar{x}^{(1)}(k - 1).
\end{align*}
\tag{17}
\]

3.2.5. FDGM (1,1) Modelling Process. Grey prediction models were initially studied from the perspective of integer order accumulation, and thus, some scholars proposed to construct models from the perspective of fractional-order accumulation, namely the FDGM (1,1) model. The modelling mechanism of the FDGM (1,1) model is similar to the DGM (1,1) model, but fractional-order accumulation is used in the process of accumulation.

Let the nonnegative sequence \(X^{(0)} = (x^{(0)}(1), x^{(0)}(2), \ldots, x^{(0)}(n))\), whose \(r\)-order cumulative sequence is \(X^{(r)} = (x^{(r)}(1), x^{(r)}(2), \ldots, x^{(r)}(n))\), where
\[
x^{(r)}(k) = \sum_{i=1}^{k} x^{(r-i)}(i),
\tag{18}
\]
\[
C_{i,t-1} = 1, k = 1, 2, \ldots, n.
\]

The FDGM(1,1) model is
\[
x^{(r)}(k+1) = \beta_1 x^{(r)}(k) + \beta_2, \quad k = 1, 2, \ldots, n - 1.
\tag{19}
\]

Vectors \(\tilde{m} = (B^TB)^{-1}B^TY = [\beta_1, \beta_2]^T\) can be found by the least squares method, where \(B, Y\) are
\[
B = \begin{bmatrix}
x^{(r)}(1) & 1 \\
x^{(r)}(2) & 1 \\
\vdots & \vdots \\
x^{(r)}(n-1) & 1
\end{bmatrix},
\tag{20}
\]
\[
Y = \begin{bmatrix}
x^{(r)}(2) \\
x^{(r)}(3) \\
\vdots \\
x^{(r)}(n)
\end{bmatrix}.\]
The time response equation for the FDGM (1,1) model is
\[
\bar{x}^{(r)}(k+1) = \beta_1^{k} x^{(r)}(1) + \beta_2^{k} \frac{1 - \beta_1}{1 - \beta_2},
\]  
(21)

3.3. Accuracy Check. In recent years, many scholars have carried out further research around grey prediction models and thus proposed many new forecasting models, further enriching the research results of grey system theory. So how to measure the validity of these model building can be evaluated by testing the accuracy of the model; if the model passes the accuracy test, then it can be applied to real life afterwards. The commonly used accuracy testing methods are the relative error method, the correlation test, and the posteriori difference test. In this paper, the relative error method is used to test the accuracy of the model. The relative error accuracy test levels are shown in Table 1.

Let the original sequence \( X^{(0)} = (x^{(0)}(1), x^{(0)}(2), \ldots, x^{(0)}(n)) \), the simulated sequence is \( \hat{X}^{(0)} = (\hat{x}^{(0)}(1), \hat{x}^{(0)}(2), \ldots, \hat{x}^{(0)}(n)) \), and the relative error series is

\[
\Delta = \left( \begin{array}{c} \varepsilon(1) \\ \varepsilon(2) \\ \vdots \\ \varepsilon(n) \\
\end{array} \right) \left( \begin{array}{c} x^{(0)}(1) \\ x^{(0)}(2) \\ \vdots \\ x^{(0)}(n) \\
\end{array} \right) = \left( \begin{array}{c} x^{(0)}(1) - \hat{x}^{(0)}(1) \\ x^{(0)}(2) - \hat{x}^{(0)}(2) \\ \vdots \\ x^{(0)}(n) - \hat{x}^{(0)}(n) \\
\end{array} \right),
\]  
(22)

\( k \) point-simulated relative error can be calculated as follows:

\[
\Delta_k = \frac{\varepsilon(k)}{x^{(0)}(k)} = \left| \frac{x^{(0)}(k) - \hat{x}^{(0)}(k)}{x^{(0)}(k)} \right|.
\]  
(23)

Mean relative error can be calculated as follows:

\[
\bar{\Delta} = \frac{1}{n} \sum_{k=1}^{n} \Delta_k.
\]  
(24)

4. Selection and Determination of Indicators for Forecasting the Livestreaming E-Commerce Development Scale

4.1. Selection of Indicators for Forecasting the Livestreaming E-Commerce Development Scale. After a budding period of fumbling and exploring, livestreaming e-commerce has finally ushered in an explosive period of revelry. Livestreaming e-commerce is influenced by many factors during its development. By reading the literature and reviewing information, this paper selects livestreaming e-commerce market turnover as a quantitative indicator of the livestreaming e-commerce development scale. In addition, according to the research and analysis of Ali Research Institute and KPMG, the fact that livestreaming e-commerce is developing so rapidly is not only supported by national policies but also influenced by a variety of factors such as platforms, consumers, and streamers. Each of these players has its own role to play in the development of livestreaming e-commerce, which has finally formed an increasingly sophisticated livestreaming e-commerce ecosystem, as shown in Figure 2.

In this paper, based on the livestreaming e-commerce ecosystem, eight categories are known: platforms, livestreamers, MCN organisations, merchants, consumers, suppliers, service providers, and governments. From these eight categories, quantifiable indicators are selected as relevant influencing factors for the livestreaming e-commerce development scale, as shown in Table 2. Grey correlation analysis was used to identify the main influencing factors.

(1) Platforms: during the development of livestreaming e-commerce, Taobao livestreaming e-commerce has developed rapidly and has a relatively mature operation model, which is highly representative; thus, Taobao livestreaming e-commerce turnover was selected as an influencing factor.

(2) Livestreamers: livestreamers are an important part of the number of people working in e-commerce. As the number of people working in e-commerce increases, so does the number of livestreamers. The indicator has been chosen for the number of e-commerce employees as no official statistics are available for the number of livestreamers.

(3) MCN organisations: the development of MCN organisations has contributed to the development of livestreaming e-commerce, and many e-commerce companies now achieve commercial realisation through MCN organisations; thus, the MCN organisations market scale was selected as an influencing factor.

(4) Merchants: the livestreaming e-commerce enterprise registrations reflect the market situation. The higher the number of livestreaming e-commerce enterprise registrations, the better the development of the livestreaming e-commerce industry. This indicator was therefore chosen.

(5) Consumers: consumers are important participants in the development of livestreaming e-commerce and have an indispensable influence on livestreaming e-commerce. Considering quantifiable indicators of consumers, online livestreaming user scale and disposable income per inhabitant were selected as influencing factors.

(6) Suppliers: suppliers provide the required goods in livestreaming e-commerce, and these goods cover many categories. Combined with the current
development of the livestreaming e-commerce hot selling categories, the agricultural products e-commerce turnover, the cosmetics e-commerce turnover, the clothing e-commerce turnover, and the casual food e-commerce turnover were selected as influencing factors.

(7) Service providers: service providers offer various facilitation measures for the development of livestreaming e-commerce. For example, revenue from e-payment, IT services, and credit services in the area of e-commerce support services, which have contributed significantly to the development of livestreaming e-commerce. The service provider provides various facilities for the development of livestreaming e-commerce, among which revenues from e-payment, information technology services, and credit services in the area of e-commerce support services play a huge role in promoting the development of livestreaming e-commerce; thus, the courier service companies’ business volume and the e-commerce support services revenue were selected as influencing factors. Therefore, the courier service companies’ business volume and the e-commerce support services revenue were selected as influencing factors.

(8) Governments: the government department not only provides policy support for the development of livestreaming e-commerce but also provides a favourable business environment. The business environment includes the market environment, the economic environment, and so on. The market environment can be considered from the perspective of the e-commerce market, which has created good development opportunities for livestreaming e-commerce development. The economic environment can be considered from the perspective of the country’s economic development level, which determines the general environment for the industry development. Therefore, these quantitative indicators can be selected from the online retail transaction volume and the gross domestic product.

### 4.2. Determination of Indicators for Forecasting the Livestreaming E-Commerce Development Scale

#### 4.2.1. Data Sources

Fourteen quantifiable influencing factors were selected based on the livestreaming e-commerce ecosystem, as shown in Table 3. Using the data from 2017 to 2020 as raw data, grey correlation analysis was used to determine the relationship between each factor and the livestreaming e-commerce development scale. The final forecast indicators for the livestreaming e-commerce development scale were determined.

The data is obtained from the National Bureau of Statistics, the State Post Bureau, iMedia Research, iResearch, KPMG, Ali Research Institute, Qichacha, 100EC.CN, Foresight Industry Research Institute, China Business Industry Research Institute, National Engineering Laboratory of E-Commerce Transaction Technology, China Internet Research Institute of Central University of Finance and Economics, as well as historical data published in the financial reports of listed companies.

### 4.2.2. Forecasting Indicators for the Livestreaming E-Commerce Development Scale Based on Grey Correlation Analysis

Based on the data, the grey correlation analysis model was constructed to calculate the grey absolute correlation, grey relative correlation, and grey composite correlation between livestreaming e-commerce market turnover and each influencing factor and to determine the correlation level. Eventually, the main predictors of the livestreaming e-commerce development scale in China are determined. Based on the grey correlation analysis modelling mechanism, the model algorithm design was carried out. The grey correlation analysis modelling algorithm design process is shown in Figure 3.

The calculation process of grey correlation analysis includes solving the initial value image, solving the zeroed image of the starting point, and so on. The specific calculation process is not repeated, and the calculation results are shown in Table 4. It is generally believed that when $0.5 \leq \text{correlation} < 0.6$, the two factors have a moderate association; when $0.6 \leq \text{correlation} < 0.7$, the two factors have a strong association; when $0.7 \leq \text{correlation} < 0.8$, the two factors have a stronger association; and when $0.8 \leq \text{correlation} < 1.0$, the two factors have an extremely strong association.

In terms of grey absolute correlation, $X_6$, $X_9$, $X_1$, $X_7$, and $X_4$ ranked in the top five, indicating that the series line of these five influencing factors is very similar to the series line of livestreaming e-commerce transactions, and there is a close relationship between them. In terms of grey relative correlation, $X_1$, $X_4$, $X_7$, $X_3$, and $X_4$ ranked in the top five, indicating that there is a close relationship between the rate of change of these five influencing factors relative to the starting point and the rate of change of livestreaming e-commerce transactions relative to the starting point. In terms of grey composite correlation, $X_1$, $X_6$, $X_9$, $X_4$, and $X_7$ ranked in the top five, indicating a more comprehensive view of the relationship between these five influencing factors and the value of livestreaming e-commerce transactions, as shown in Figure 4.

The correlation results show that the correlation between the five factors of $X_1$, $X_4$, $X_6$, $X_7$, and $X_9$ on livestreaming e-commerce transaction amount reached above 0.6, indicating a closer connection with livestreaming e-commerce transaction amount; thus, these influencing factors are selected as the forecast indicators of livestreaming e-commerce development scale, and the data used below will be modelled and predicted based on the data of $X_1$, $X_4$, $X_6$, $X_7$, and $X_9$, so as to predict livestreaming e-commerce more comprehensively.
5. Livestreaming E-Commerce Development Scale Forecast

5.1. Ratio Test. The ratio test for the sequence $X_0 = (366, 1400, 4338, 10500)$ is $n = 4$, $\sigma (k) = x^{(0)} (k - 1)/x^{(0)} (k) = (366/1400, 1400/4338, 4338/10500) = (0.2614, 0.3227, 0.4131) \notin (e^{-2/4+1}, e^{2/4+1}) = ((0.6703, 1.4918))$, and it can be seen that the step-ratio test does not pass. The sequence after the introduction of the second-order weakening operator $D^2$ is

$$X_0 D^2 = (6870.67, 7777.22, 8959.50, 10500.00). \quad (25)$$

The test is then carried out on the $X_0 D^2$ grade ratio as follows:

$$\sigma (k) = \frac{x^{(0)} (k - 1)}{x^{(0)} (k)} = \left( \frac{6870.67}{7777.22}, \frac{7777.22}{8959.50}, \frac{8959.50}{10500.00} \right) = (0.8834, 0.8680, 0.8533) \notin (e^{-2/4+1}, e^{2/4+1}) = (0.6703, 1.4918), \quad (26)$$
and it can be seen that the $X_0D^2$ modelling requirements are met by the grade ratio test.

The ratio tests were carried out for $X_1$, $X_4$, $X_6$, $X_7$, and $X_9$ according to the above steps, and the results are shown in Table 5.

### 5.2. Grey Prediction Modelling Process

This paper takes sequence $X_0$ as an example and details the modelling process for GM (1,1), DGM (1,1), NDGM (1,1), and FDGM (1,1), and the modelling process for other sequences will not be repeated.

#### 5.2.1. GM (1,1) Modelling Process

The sequence is 

$$X_0 = (x_1, x_2, x_3, x_4) = (366, 4,338, 10,500, 4,300)$$

and it can be seen that the $X_0D^2$ modelling requirements are met by the grade ratio test.

The ratio tests were carried out for $X_1$, $X_4$, $X_6$, $X_7$, and $X_9$ according to the above steps, and the results are shown in Table 5.

### Figure 3: Grey correlation analysis algorithm design flow.

#### Table 3: Raw data.

<table>
<thead>
<tr>
<th>Serial</th>
<th>Influencing factor</th>
<th>2017</th>
<th>2018</th>
<th>2019</th>
<th>2020</th>
</tr>
</thead>
<tbody>
<tr>
<td>$X_0$</td>
<td>Livestreaming e-commerce market turnover (billion yuan)</td>
<td>366</td>
<td>1,400</td>
<td>4,338</td>
<td>10,500</td>
</tr>
<tr>
<td>$X_1$</td>
<td>Taobao livestreaming e-commerce turnover (billion yuan)</td>
<td>200</td>
<td>1,000</td>
<td>2,500</td>
<td>4,300</td>
</tr>
<tr>
<td>$X_2$</td>
<td>Number of people working in e-commerce (10,000 people)</td>
<td>4,250.32</td>
<td>4,700.65</td>
<td>5,125.65</td>
<td>6,015.33</td>
</tr>
<tr>
<td>$X_3$</td>
<td>MCN organisations market scale (billion yuan)</td>
<td>78</td>
<td>112</td>
<td>168</td>
<td>245</td>
</tr>
<tr>
<td>$X_4$</td>
<td>Livestreaming e-commerce enterprise registrations (jia)</td>
<td>698</td>
<td>1,121</td>
<td>1,548</td>
<td>6,939</td>
</tr>
<tr>
<td>$X_5$</td>
<td>Online live streaming user size (billion yuan)</td>
<td>3.98</td>
<td>4.56</td>
<td>5.04</td>
<td>5.26</td>
</tr>
<tr>
<td>$X_6$</td>
<td>Disposable income per inhabitant (yuan)</td>
<td>25,974</td>
<td>28,228</td>
<td>30,733</td>
<td>32,189</td>
</tr>
<tr>
<td>$X_7$</td>
<td>Agricultural products e-commerce turnover (billion yuan)</td>
<td>1,723</td>
<td>2,305</td>
<td>3,975</td>
<td>6,107</td>
</tr>
<tr>
<td>$X_8$</td>
<td>Cosmetics e-commerce turnover (billion yuan)</td>
<td>83.9</td>
<td>103.6</td>
<td>151.6</td>
<td>198.8</td>
</tr>
<tr>
<td>$X_9$</td>
<td>Clothing e-commerce turnover (billion yuan)</td>
<td>6,725.7</td>
<td>8,205.4</td>
<td>10,133.7</td>
<td>10,944.4</td>
</tr>
<tr>
<td>$X_{10}$</td>
<td>Casual food e-commerce turnover (billion yuan)</td>
<td>761</td>
<td>969</td>
<td>1,202</td>
<td>1,475</td>
</tr>
<tr>
<td>$X_{11}$</td>
<td>Courier service companies’ business volume (billion pieces)</td>
<td>400.6</td>
<td>507.1</td>
<td>635.2</td>
<td>833.6</td>
</tr>
<tr>
<td>$X_{12}$</td>
<td>E-commerce support services revenue (trillion yuan)</td>
<td>1.12</td>
<td>1.3</td>
<td>1.8</td>
<td>2.09</td>
</tr>
<tr>
<td>$X_{13}$</td>
<td>Online retail transaction volume (trillion yuan)</td>
<td>7.18</td>
<td>9.01</td>
<td>10.63</td>
<td>11.76</td>
</tr>
<tr>
<td>$X_{14}$</td>
<td>Gross domestic product (billion yuan)</td>
<td>832,035.9</td>
<td>919,281.1</td>
<td>986,515.2</td>
<td>1,015,986.2</td>
</tr>
</tbody>
</table>

Let $x^{(0)}(k) + az^{(1)}(k) = b$; parameter $a, b$ can be solved by the least squares method, that is, $\hat{h} = (B^TB)^{-1}B^TY = [a, b]^T$, where $B, Y$ are

\[
B = \begin{bmatrix}
-10759.28 & 1 \\
-19127.641 & 1 \\
-28857.391 & 1 \\
7777.22 & 1 \\
8959.50 & 1 \\
10500.00 & 1
\end{bmatrix}
\]

\[
Y = \begin{bmatrix}
-10759.281 \\
-19127.641 \\
-28857.391 \\
7777.22 \\
8959.50 \\
10500.00
\end{bmatrix}
\]

Calculate to get $a = -0.15, b = 6128.81$, which leads to the following whitening differential equation:

\[
\frac{d}{dt}x^{(1)}(t) = (B^TB)^{-1}B^TY + a, \quad x^{(1)}(0) = X_0.
\]
Table 4: Results of correlation calculations.

<table>
<thead>
<tr>
<th>Serial</th>
<th>Influencing factor</th>
<th>Grey absolute correlation</th>
<th>Grey relative correlation</th>
<th>Grey composite correlation</th>
<th>Affiliation level</th>
</tr>
</thead>
<tbody>
<tr>
<td>X₁</td>
<td>Taobao livestreaming e-commerce turnover</td>
<td>0.7556</td>
<td>0.9684</td>
<td>0.8620</td>
<td>Extremely strong association</td>
</tr>
<tr>
<td>X₂</td>
<td>Number of people working in e-commerce</td>
<td>0.6096</td>
<td>0.5182</td>
<td>0.5639</td>
<td>Moderate association</td>
</tr>
<tr>
<td>X₃</td>
<td>MCN organisations market scale</td>
<td>0.5103</td>
<td>0.5564</td>
<td>0.5334</td>
<td>Moderate association</td>
</tr>
<tr>
<td>X₄</td>
<td>Livestreaming e-commerce enterprise registrations</td>
<td>0.7181</td>
<td>0.6212</td>
<td>0.6697</td>
<td>Strong association</td>
</tr>
<tr>
<td>X₅</td>
<td>Online livestreaming user scale</td>
<td>0.5001</td>
<td>0.5191</td>
<td>0.5096</td>
<td>Moderate association</td>
</tr>
<tr>
<td>X₆</td>
<td>Disposable income per inhabitant</td>
<td>0.9977</td>
<td>0.5159</td>
<td>0.7568</td>
<td>Stronger association</td>
</tr>
<tr>
<td>X₇</td>
<td>Agricultural products e-commerce turnover</td>
<td>0.7495</td>
<td>0.5610</td>
<td>0.6552</td>
<td>Strong association</td>
</tr>
<tr>
<td>X₈</td>
<td>Cosmetics e-commerce turnover</td>
<td>0.5072</td>
<td>0.5397</td>
<td>0.5235</td>
<td>Moderate association</td>
</tr>
<tr>
<td>X₉</td>
<td>Clothing e-commerce turnover</td>
<td>0.8473</td>
<td>0.5275</td>
<td>0.6874</td>
<td>Strong association</td>
</tr>
<tr>
<td>X₁₀</td>
<td>Casual food e-commerce turnover</td>
<td>0.5500</td>
<td>0.5325</td>
<td>0.5412</td>
<td>Moderate association</td>
</tr>
<tr>
<td>X₁₁</td>
<td>Courier service companies’ business volume</td>
<td>0.5277</td>
<td>0.5338</td>
<td>0.5307</td>
<td>Moderate association</td>
</tr>
<tr>
<td>X₁₂</td>
<td>E-commerce support services revenue</td>
<td>0.5001</td>
<td>0.5303</td>
<td>0.5152</td>
<td>Moderate association</td>
</tr>
<tr>
<td>X₁₃</td>
<td>Online retail transaction volume</td>
<td>0.5004</td>
<td>0.5277</td>
<td>0.5141</td>
<td>Moderate association</td>
</tr>
<tr>
<td>X₁₄</td>
<td>Gross domestic product</td>
<td>0.5151</td>
<td>0.5161</td>
<td>0.5156</td>
<td>Moderate association</td>
</tr>
</tbody>
</table>

![Figure 4: Comparison of the three correlations.](image)

Table 5: Results of each serial ratio test.

<table>
<thead>
<tr>
<th>Serials</th>
<th>Original sequence</th>
<th>Grade ratio test sequence</th>
<th>(X_iD_i^2) serial</th>
<th>Grade ratio test sequence</th>
</tr>
</thead>
<tbody>
<tr>
<td>X₀</td>
<td>(366, 1,400, 4,338, 10,500)</td>
<td>(0.2614, 0.3227, 0.4131)</td>
<td>(6,870.67, 7,777.22, 8,959.50, 10,500.00)</td>
<td>(0.8834, 0.8680, 0.8533)</td>
</tr>
<tr>
<td>X₁</td>
<td>(200, 1,000, 2,500, 4,300)</td>
<td>(0.2000, 0.4000, 0.5814)</td>
<td>(3,075.00, 3,433.33, 3,850.00, 4,300.00)</td>
<td>(0.8956, 0.8918, 0.8953)</td>
</tr>
<tr>
<td>X₂</td>
<td>(698, 1,121, 1,548, 6,939)</td>
<td>(0.6227, 0.7242, 0.2231)</td>
<td>(4,240.42, 4,795.06, 5,591.25, 6,939.00)</td>
<td>(0.8843, 0.8576, 0.8058)</td>
</tr>
<tr>
<td>X₃</td>
<td>(25,974, 28,228, 30,733, 32,189)</td>
<td>(0.9202, 0.9183, 0.9548)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>X₄</td>
<td>(1,723, 2,305, 3,975, 6,107)</td>
<td>(0.7475, 0.5799, 0.6509)</td>
<td>(4,701.13, 5,092.33, 5,574.00, 6,107.00)</td>
<td>(0.9232, 0.9136, 0.9127)</td>
</tr>
<tr>
<td>X₅</td>
<td>(6,725.7, 8,205.4, 10,133.7, 10,944.4)</td>
<td>(0.8197, 0.8097, 0.9259)</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
The time response equation for the GM (1,1) model is
\[
\begin{align*}
\ddot{x}(k+1) &= 6870.67 \times 1.30^k - 1174.15, \\
\dot{x}(0) &= \ddot{x}(1) - \dot{x}(1)(k-1).
\end{align*}
\] (36)

The resulting simulation sequence is
\[
\ddot{X} = (6870.67, 7777.22, 8959.50, 10500.00).
\] (37)

5.2.4. FDGM(1,1) Modelling Process. Let us take \( r \) to be 1/2 and \( \beta_1, \beta_2 \) obtained according to the least square method. And 
\[
\ddot{m} = (B^T B)^{-1} B^T Y = [\beta_1, \beta_2]^T
\] are as follows, respectively:
It is calculated that $\beta_1 = 1.03, \beta_2 = 4033.02$.

The time response equation for the FDGM (1,1) model is

$$\frac{1}{\sqrt{k}} = 141304.67 \times 1.03^{(k-1)} - 134434.$$  \hspace{1cm} (39)

The resulting simulation sequence is

$$\tilde{X} = (6870.67, 7688.49, 9092.49, 10466.78).$$  \hspace{1cm} (40)

The above modelling steps are carried out with $X_9$ as an example, and the sequence modelling results are shown in Table 6. The modelling process for other sequences is consistent with the modelling mechanism of $X_9$. The detailed process of modelling is omitted, and the modelling results are shown in Tables 7–12.

Considering from the perspective of model accuracy check, it can be seen from Table 1 that the four model MAPE $< \alpha = 0.01$ of $X_9$, $X_1$, $X_6$, and $X_7$ have an accuracy of level 1. The four model MAPE $< \alpha = 0.05$ of $X_4$ and $X_9$ have an accuracy of level 2. The models constructed for these sequences above all meet the requirements. Based on the results of the simulations, the fitting effects of the four models for $X_{10}$, $X_1$, $X_4$, $X_6$, $X_7$, and $X_9$ are plotted as shown in Figure 5. Considering the four models of the sequences from the perspective of fitting effects, it can be seen that $X_7$ is a relatively good fit, in which the relative errors of the GM (1,1) model, DGM (1,1) model, and NDGM (1,1) model are less than or equal to the other sequences. Considering the relative errors of the four models, the NDGM (1,1) model has the smallest relative error and the highest simulation accuracy compared to the other three models in sequences $X_9$, $X_1$, $X_4$, $X_6$, $X_7$, and $X_9$. In summary, the NDGM (1,1) model was selected as the prediction model for the subsequent development scale of livestreaming e-commerce.

5.3. Forecast and Analysis of the Development Scale of Livestreaming E-Commerce. Based on the calculation and analysis in Section 4 of the article, the livestreaming e-commerce market turnover and the main forecast indicators related to the livestreaming e-commerce development were selected as the raw data for the forecast, namely Taobao livestreaming e-commerce turnover ($X_1$), livestreaming e-commerce enterprise registrations ($X_4$), disposable income per inhabitant ($X_9$), agricultural products e-commerce turnover ($X_7$), and clothing e-commerce turnover ($X_9$). The NDGM (1,1) models for $X_9$, $X_1$, $X_4$, $X_6$, $X_7$, and $X_9$ were constructed by processing the historical data of the above indicators, and finally, the forecast values for 2021–2023 were derived, as shown in Table 12.

The forecast results show that the livestreaming e-commerce forecast indicators are all growing from 2021 to 2023, with the livestreaming e-commerce market transaction value growing at a rapid rate. This is closely related to the clothing e-commerce market turnover, online retail sales of agricultural products, and Taobao livestreaming e-commerce transaction volume, as shown in Figure 6. Clothing and agricultural products, as hot categories in livestreaming e-commerce transactions, are inseparable from people’s lives. In 2023, the clothing e-commerce market transaction scale will reach 1,148,878 billion yuan, after which the development momentum will be relatively stable. Agricultural products e-commerce compared to clothing e-commerce development trend will be faster, thanks to the support of the national rural revitalization strategy, in 2023 is expected to reach 807.166 billion yuan. The penetration rate of the livestreaming e-commerce industry will be higher in the future, and the live revenue generated by these two categories will account for a larger proportion of the many categories. Taobao, as the earliest platform to start laying out livestreaming e-commerce, has been changing its live platform operation strategy over the past few years, and the livestreaming e-commerce business model has become increasingly mature. With the support of national policies, Taobao’s livestreaming e-commerce transactions will continue to grow in the future and will reach 587.732 billion yuan in 2023. In addition, the future of the livestreaming e-commerce industry is promising. Some businessmen will target these good opportunities and create livestreaming e-commerce businesses, and the number of such businesses will grow in the future. With the country’s economic growth, the per capita disposable income of the population is increasing and will reach 33,813.08 yuan by 2023. Nowadays, people are more and more demanding for a better life and want to taste the world’s food without having to leave home. Livestreaming e-commerce is a way of shopping that can meet this demand. As a result, the growth in disposable income per capita will also lead to people spending more on live shopping.

5.4. Future Development Strategies and Suggestions of Livestreaming E-Commerce. So far, livestreaming e-commerce has seen an increase in both market transaction volume and its growth rate, as shown in Figure 7. Moreover, with the
5.4.1. Optimise the Construction of Livestreaming Platform and Promote Taobao Livestreaming Model. As the first to start laying out livestreaming e-commerce, Taobao enjoyed quite rapid growth in livestreaming e-commerce with the development of the Internet and the support of national policies. However, after the improvement of industry ecology, other livestreaming e-commerce platforms, such as TikTok livestreaming e-commerce and Kuaisu livestreaming e-commerce, appear. These livestreaming platforms will divide the user traffic pool up, and thus, the growth of Taobao livestreaming transactions in the later stage will slow down (see Figure 8). From livestreamers working in monotonous livestreaming rooms to the emergence of intelligent livestreaming robots, Taobao livestreaming platform is constantly being adjusted and optimised to improve the consumer shopping experience. As VR and artificial intelligence technologies appear one after another, Taobao livestreaming platform has created more new models, new ways of streaming platforms to plan a livestreaming e-commerce business blueprint based on their own situations through learning from Taobao’s successful experience.

Table 6: Sequence $X_0$ four prediction models modelling results.

<table>
<thead>
<tr>
<th>Models</th>
<th>GM (1,1) model</th>
<th>DGM (1,1) model</th>
<th>NDGM (1,1) model</th>
<th>FDGM (1,1) model</th>
</tr>
</thead>
<tbody>
<tr>
<td>Variables</td>
<td>$a = -0.15, b = 6128.81$</td>
<td>$\beta_1 = 1.16, \beta_2 = 6628.33$</td>
<td>$\beta_1 = 1.30, \beta_2 = -1174.15, \beta_3 = 6869.62$</td>
<td>$\beta_1 = 1.03, \beta_2 = 4033.02$</td>
</tr>
<tr>
<td>Serials</td>
<td>Modelling data</td>
<td>Simulated data</td>
<td>Simulation errors</td>
<td>Simulated data</td>
</tr>
<tr>
<td>$X_0(1)$</td>
<td>6,870.67</td>
<td>6,870.67</td>
<td>0</td>
<td>6,870.67</td>
</tr>
<tr>
<td>$X_0(2)$</td>
<td>7,777.22</td>
<td>7,731.74</td>
<td>0.58%</td>
<td>7,747.67</td>
</tr>
<tr>
<td>$X_0(3)$</td>
<td>8,959.50</td>
<td>8,988.91</td>
<td>0.33%</td>
<td>9,009.89</td>
</tr>
<tr>
<td>$X_0(4)$</td>
<td>10,500.00</td>
<td>10,450.49</td>
<td>0.47%</td>
<td>10,477.74</td>
</tr>
<tr>
<td>MAPE</td>
<td>0.46%</td>
<td>0.38%</td>
<td></td>
<td>0.21%</td>
</tr>
</tbody>
</table>

Table 7: Sequence $X_1$ four prediction models modelling results.

<table>
<thead>
<tr>
<th>Models</th>
<th>GM (1,1) model</th>
<th>DGM (1,1) model</th>
<th>NDGM (1,1) model</th>
<th>FDGM (1,1) model</th>
</tr>
</thead>
<tbody>
<tr>
<td>Variables</td>
<td>$a = -0.11, b = 2898.05$</td>
<td>$\beta_1 = 1.12, \beta_2 = 3070.42$</td>
<td>$\beta_1 = 1.08, \beta_2 = 142.03, \beta_3 = 3045.32$</td>
<td>$\beta_1 = 0.96, \beta_2 = 1994.13$</td>
</tr>
<tr>
<td>Serials</td>
<td>Modelling data</td>
<td>Simulated data</td>
<td>Simulation errors</td>
<td>Simulated data</td>
</tr>
<tr>
<td>$X_1(1)$</td>
<td>3,075.00</td>
<td>3,075.00</td>
<td>0</td>
<td>3,075.00</td>
</tr>
<tr>
<td>$X_1(2)$</td>
<td>3,433.33</td>
<td>3,432.37</td>
<td>0.03%</td>
<td>3,436.19</td>
</tr>
<tr>
<td>$X_1(3)$</td>
<td>3,850.00</td>
<td>3,840.20</td>
<td>0.25%</td>
<td>3,844.93</td>
</tr>
<tr>
<td>$X_1(4)$</td>
<td>4,300.00</td>
<td>4,296.49</td>
<td>0.08%</td>
<td>4,302.29</td>
</tr>
<tr>
<td>MAPE</td>
<td>0.12%</td>
<td>0.09%</td>
<td></td>
<td>0.09%</td>
</tr>
</tbody>
</table>

Table 8: Sequence $X_4$ four prediction models modelling results.

<table>
<thead>
<tr>
<th>Models</th>
<th>GM (1,1) model</th>
<th>DGM (1,1) model</th>
<th>NDGM (1,1) model</th>
<th>FDGM (1,1) model</th>
</tr>
</thead>
<tbody>
<tr>
<td>Variables</td>
<td>$a = -0.19, b = 3482.94$</td>
<td>$\beta_1 = 1.21, \beta_2 = 3846.38$</td>
<td>$\beta_1 = 1.69, \beta_2 = -2525.58, \beta_3 = 4383.10$</td>
<td>$\beta_1 = 1.11, \beta_2 = 2090.94$</td>
</tr>
<tr>
<td>Serials</td>
<td>Modelling data</td>
<td>Simulated data</td>
<td>Simulation errors</td>
<td>Simulated data</td>
</tr>
<tr>
<td>$X_4(1)$</td>
<td>4,240.42</td>
<td>4,240.42</td>
<td>0</td>
<td>4,240.42</td>
</tr>
<tr>
<td>$X_4(2)$</td>
<td>4,795.06</td>
<td>4,709.34</td>
<td>1.79%</td>
<td>4,725.71</td>
</tr>
<tr>
<td>$X_4(3)$</td>
<td>5,591.25</td>
<td>5,683.74</td>
<td>1.65%</td>
<td>5,705.69</td>
</tr>
<tr>
<td>$X_4(4)$</td>
<td>6,939.00</td>
<td>6,859.75</td>
<td>1.14%</td>
<td>6,888.88</td>
</tr>
<tr>
<td>MAPE</td>
<td>1.53%</td>
<td>1.41%</td>
<td></td>
<td>1.41%</td>
</tr>
</tbody>
</table>
5.4.2. Encourage Enterprises to Carry Out Livestreaming E-Commerce, Further Driving Consumption for a Win-Win Situation. The quantity of livestreaming e-commerce enterprise registration is increasing year by year, and the growth rate of the above registration is also rising year by year, as shown in Figure 9. Since livestreaming e-commerce is now in bonus period, the government should introduce relevant policies to guide and encourage more enterprises to carry out livestreaming e-commerce business, with relevant supervision and guidance strengthened, so as to create a good market operation environment. In addition, with the improvement of China’s economic strength, the per capita disposable income of residents is increasing, but the growth rate will slow down later (see Figure 10), which is affected by COVID-19. The emergence of COVID-19 urges many consumers to shop online from a livestreaming room, which brings many new opportunities for livestreaming e-commerce. In order to further expand the livestreaming e-commerce market scale, e-commerce enterprises should precisely align with the market to upgrade consumption, create their own distinctive brands, form industrial clusters, cultivate and develop new consumer hotspots, and develop more differentiated and targeted commodities, thereby stimulating consumer purchases, meeting consumers’ pursuit of excellent goods, and achieving a win-win situation between enterprises and consumers.

5.4.3. Enrich the Categories of Livestreaming E-Commerce Products and Attach Great Importance to Products with Local Characteristics. As shown in Figures 11 and 12, the transaction volume of the clothing e-commerce market is still
Table 12: Livestreaming e-commerce forecast indicator values for 2021–2023.

<table>
<thead>
<tr>
<th></th>
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<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>$X_0$</td>
<td>6,870.67</td>
<td>7,777.22</td>
<td>8,959.50</td>
<td>10,500.00</td>
<td>12,507.26</td>
<td>15,122.70</td>
<td>18,530.59</td>
</tr>
<tr>
<td>$X_1$</td>
<td>3,075.00</td>
<td>3,433.33</td>
<td>3,850.00</td>
<td>4,300.00</td>
<td>4,786.00</td>
<td>5,310.87</td>
<td>5,877.72</td>
</tr>
<tr>
<td>$X_4$</td>
<td>4,240.42</td>
<td>4,795.06</td>
<td>5,591.25</td>
<td>6,939.00</td>
<td>9,220.40</td>
<td>13,082.25</td>
<td>19,619.38</td>
</tr>
<tr>
<td>$X_6$</td>
<td>25,974.00</td>
<td>28,228.00</td>
<td>30,733.00</td>
<td>32,189.00</td>
<td>33,035.28</td>
<td>33,527.17</td>
<td>33,813.08</td>
</tr>
<tr>
<td>$X_7$</td>
<td>4,701.13</td>
<td>5,092.33</td>
<td>5,574.00</td>
<td>6,107.00</td>
<td>6,696.80</td>
<td>7,349.45</td>
<td>8,071.66</td>
</tr>
<tr>
<td>$X_9$</td>
<td>6,725.70</td>
<td>8,205.40</td>
<td>10,133.70</td>
<td>10,944.40</td>
<td>11,285.24</td>
<td>11,428.53</td>
<td>11,488.78</td>
</tr>
</tbody>
</table>

Figure 5: Four model fits for $X_0$, $X_1$, $X_4$, $X_6$, $X_7$, and $X_9$. 
rising, but the growth rate is slower. Compared with clothing e-commerce, online retail sales of agricultural products have a strong future growth momentum, with a relatively fast growth rate. As the number of farmer-assisting livestreams is increasing year by year, and China gives strong support to the revitalization of the countryside. Local governments should vigorously develop local specialties and seize the opportunity of developing livestreaming e-commerce and
special agricultural products, thus forming a regional agglomeration and demonstration effect of live-streaming e-commerce. Among the bestselling categories of live-streaming e-commerce, clothing and food, which are closely related to people’s lives, occupy a large portion. With the growing maturity of the live-streaming e-commerce ecosystem, the scenario of “everything can be sold by live-streaming” is gradually taking shape. In the near future, the categories involved with live-streaming will be more colorful and diversified, and the live-streaming goods will be complete. Live-streams concerning different content, like tourism and education, will seize new opportunities for live-streaming e-commerce.

6. Conclusion

Previous studies on live-streaming e-commerce are mostly based on qualitative analysis. In this paper, live-streaming e-commerce development was studied quantitatively with a new approach from a new perspective. Firstly, quantifiable indicators were selected, based on the live-streaming e-commerce ecosystem, to construct a grey correlation analysis model, by which the quantitative indicators affecting the live-streaming e-commerce development scale were determined from many factors; these indicators include Taobao live-streaming e-commerce transaction volume, the quantity of live-streaming e-commerce enterprise registrations, disposable income per inhabitant, online retail sales of agricultural products, and the transaction volume of the clothing e-commerce market. Secondly, based on these quantitative indicators, four grey forecasting models, namely GM (1,1), DGM (1,1), NDGM (1,1), and FDGM (1,1), were constructed to conduct the data simulation of live-streaming e-commerce market transaction volume and influencing factors. Finally, NDGM (1,1) model with higher prediction accuracy was selected after comparison. Thirdly, NDGM (1,1) model is used to predict the future development scale and forecast indicators of live-streaming e-commerce. The forecast results show that the future development momentum of live-streaming e-commerce will continue to be strong, and its transaction value will reach 18,503.59 billion yuan by 2023. However, if we want to make the live-streaming e-commerce industry healthy and sustainable, we need to develop special industries and come out with an innovative path adapted to local conditions; for example, China’s southeastern coastal region has incubated special industries such as Haining leather and Hangzhou women’s clothing due to its developed manufacturing industry. At the same time, a regional industrial cluster has been formed. In this region, online and offline integration development has activated the energies of upstream and downstream live-streaming e-commerce industry chains and of the market players including live-streaming platforms and suppliers. In addition, an industrial ecosystem that matches the development needs of live-streaming e-commerce industry has been created to be more conducive to the long-term and stable development of live-streaming e-commerce.

The disadvantages of this paper include that the results obtained will be affected to a certain extent because there is a certain subjective factor in the process of selecting the indexes for the live-streaming e-commerce development influence factors. In addition, a single grey prediction model was used to predict the live-streaming e-commerce development scale in this paper. In the future, combined prediction models may be adopted to improve the prediction accuracy of the models, so as to study the live-streaming e-commerce development scale more accurately.

Data Availability

In this paper, the data are from the National Bureau of Statistics, national post office, media consulting, KPMG, check ali institute, enterprises, social network, forward-looking industry institute, zhongshang industry research institute, e-commerce trading technology national engineering laboratory, central university of finance and economics institute of the Chinese Internet, as well as the comprehensive results of historical data of listed companies.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Acknowledgments

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References


