Design Studies and Intelligence Engineering
L.C. Jain et al. (Eds.)

doi:10.3233/FAIA220750

Research on Forecasting Sales of Apparel We-Media Platforms Based on Multi-Dimensional Gray Prediction Model

Haobin Lin [a,b], Yangyang Wu [a], Yutian Ke[a], and Qingyan Zhu [a, 1]
a. Jiaxing Nanhu University, Jiaxing Zhejiang 314001, China; Shanghai BONO Apparel CO., LTD. Shanghai, 201613, China;
b. Shanghai Baoniao Clothing Co., Ltd., China

Abstract: In today's rapidly developing Internet economy, people are increasingly preferring to consume and shop on self-media platforms. The change of marketing methods has brought huge business opportunities to businessmen. However, due to the problems of low threshold, wide mass clusters, few sales data samples and many channels in the sales of clothing on self-media platforms, forecasting sales of we-media platforms has become a huge headache which affects the survival of clothing enterprises. According to the characteristics of self-media apparel sales data, the article combines the literature research on gray prediction theory, selects and optimizes the multidimensional gray prediction GM (1, N) model. Besides, by means of data collection from target customers, correlation analysis, error test and model application, it reveals that the use of multidimensional gray prediction model has strong feasibility and high prediction value for the self-media platform apparel sales prediction, which provides apparel companies' sales prediction a fresh idea.
Key words: Gray theory; We-media; Sales forecasting

1. Introduction

In recent years, the country's technology and economy have continued to advance, and the Internet self-media platforms have expanded constantly. By June 2021, the size of Chinese Internet short video users has reached 888 million. Compared to December 2020, it has a simultaneous increase of 14.4 million, accounting for 87.8% of the overall size of China's Internet users. With the growth of the number of users, the self-media platform led by "TikTok" has become a new battlefield for online marketing in the apparel industry, and various brands have entered, ranging from overseas international brands, such as Nike, Adidas-neo, Uniqlo and so on. To some indigenous popular brands, such as HLA, ANTA, Semir and so forth. Similarly, the emergence of business opportunities must be accompanied by crises. Both traditional marketing channels and emerging channels have no way to avoid the competitions between many platforms. According to incomplete statistics, the clothing brands stationed in the we-media platforms generally have inventory problems, and the root causes of these problems are the lack of sales forecasting or the defects of sales forecasting methods, thus leading to the restricted development of enterprises and the decline of competitiveness. Therefore, in the competition of

[1] Corresponding author: Qingyan Zhu, Jiaxing Nanhu University, E-mail: zqy20180525@163.cm, mailing address: No. 572, Yuexiu South Road, Jiaxing, Zhejiang 314001, P.R. China

the apparel industry on the we-media platforms, sales forecasting has become a key factor affecting the competition of brands.

In early 1980, Professor Julong Deng [1] published Gray Control System. After nearly 40 years of vigorous development, gray system theory has formed a multidisciplinary structure system including analysis, control, decision making, optimization and prediction. The advantage of gray forecasting models is a small amount of calculation. Namely, people can predict based on a small number of sample data and this model can be applied to short-, medium-, and long-term forecasting. At present, gray forecasting has become ubiquitous in academic research at home and abroad, and has been studied in diverse fields such as health care, construction, and environment [3]-[8]. In the field of clothing, the one-dimensional gray prediction model GM (1, 1) with a single variable and the multidimensional gray prediction model GM (1, N) with multiple variables are the two most representative models. The gray prediction model selected in the experiments of this paper requires a comprehensive judgment in terms of the prediction accuracy and adaptability of the model. In terms of model applicability comparison, Li Juanfei [2] stated that economic factors are influenced by several factors, and the multidimensional gray model is more suitable than the unidimensional gray forecasting model to predict the developmental trend of GDP and achieve more accurate forecasting results. In the study of sales forecasting in the apparel industry, the sales of apparel products are affected by many factors, so the optimal choice of the gray model requires more comprehensive consideration. In addition, there are many factors that affect the sales of apparel on the we-media platforms, such as the number of similar visitors, collections, and purchase. Although one-dimensional GM (1,1) model can reflect the developmental trend and results of product sales, it is impossible to make a more comprehensive and accurate forecast of apparel sales based on one factor alone. According to statistics, there are plenty of apparel companies on the self-media platforms, but most of them are mainly niche apparel brands, emerging original apparel brands, and traditional apparel brands. The customer clusters of these brands are relatively small, and the sales categories are varied. When making sales forecasts, we find that the data collection is not extensive, and the cost is too high and the timeliness is poor. Since these apparel brand data are characterized by small samples and high variability, the multidimensional GM (1, N) model is more suitable for sales forecasting of apparel brands on we-media platforms. This study takes four types of apparel sales data, which are the most representative of target niche brands, as the research object, and establishes a complete multidimensional GM (1, N) model to make sales prediction for self-media apparel brands, which has certain reference value and guiding significance for predicting sales of we-media apparel enterprises.

2. Principle and process of gray modeling

2.1 Grey correlation analysis

As a branch of gray system theory, gray correlation analysis is a method to measure the degree of correlation between factors according to the degree of similarity or dissimilarity between their developmental trends. The basic principle is to judge whether sequence curves are closely related according to the similarity of their geometric shapes. The closer the curve is, the greater the correlation between corresponding sequences will be, and vice versa [9].

2.2 Grey GM (1, N) model

Multidimensional gray forecasting model GM (1, N) is made up of a dependent variable and (N-1) a first-order linear dynamic model of the independent variables. It transforms an original irregular data sequence into generated regular data sequence. Then, it builds albinism differential equation through these generated data sequence. Thus, the original data of predictive value can be obtained by solving the differential equation and the following cumulative reduction.

(1) Construction of original data sequence and accumulation of generated data sequence

Let's assume that we have N sequences, $X_i^{(0)} = \left(X_i^{(0)}(1), X_i^{(0)}(2), \cdots, X_i^{(0)}(n)\right), i = 1,2,\cdots,N$, $X_i^{(0)}$ is accumulated to obtain the generated sequence:

$$X_i^{(1)} = \left(X_i^{(0)}(1), \sum_{m=1}^{2} X_i^{(0)}(m), \cdots, \sum_{m=1}^{n} X_i^{(0)}(m)\right)$$
$$= \left(X_i^{(1)}(1), X_i^{(1)}(1) + X_i^{(0)}(2), \cdots, X_i^{(1)}(n-1) + X_i^{(0)}(n)\right), \quad i = 1, 2, \cdots, N \tag{1}$$

Among them, $X_1^{(0)}$ is a sequence of dependent variables, representing the sales volume in the study. $X_i^{(0)}$ is a sequence of independent variables, namely, the number of collections, purchases and visits in the study.

(2) Construction of differential equation

The first-order differential equation of GM (1, N) model built by the accumulation is:

$$\frac{dX_1^{(1)}}{dt} + aX_1^{(1)} = \sum_{i=1}^{N-1} b_i X_i^{(1)} = b_1 X_2^{(1)} + b_2 X_3^{(1)} + \cdots b_{n-1} X_n^{(1)} \tag{2}$$

(3) Solving differential equations

$\alpha = \left(a, b_{1,}, b_{2,} \cdots, b_{n-1}\right)^T$ can be obtained by least square method as a parameter column in differential equation, $\widehat{\alpha} = (B^T B)^{-1} B^T Y$, among them,

$$B = \begin{pmatrix} -\frac{1}{2}\left(X_1^{(1)}(1) + X_1^{(1)}(2)\right) & X_2^{(1)}(2) & \ldots & X_N^{(1)}(2) \\ -\frac{1}{2}\left(X_1^{(1)}(2) + X_1^{(1)}(3)\right) & X_2^{(1)}(3) & \ldots & X_N^{(1)}(3) \\ \vdots & \vdots & \vdots & \vdots \\ -\frac{1}{2}\left(X_1^{(1)}(n-1) + X_1^{(1)}(n)\right) & X_2^{(1)}(n) & \ldots & X_N^{(1)}(n) \end{pmatrix}, Y = \begin{pmatrix} X_1^{(0)}(2) \\ X_1^{(0)}(3) \\ \vdots \\ X_1^{(0)}(n) \end{pmatrix}$$

Take the derivative of the matrix to solve the $\widehat{\alpha}$ differential equation. The solution obtained is:

$$\widehat{X}_1^{(1)}(k+1) = \left(\widehat{X}_1^{(0)}(1) - \frac{1}{a}\sum_{i=2}^{n} b_i X_i^{(1)}(k+1)\right)e^{-ak} + \frac{1}{a}\sum_{i=2}^{n} b_i X_i^{(1)}(k+1)$$

(4)

(4) Calculating the predicted value

By reducing $\widehat{X}_1^{(1)}(k+1)$ incrementally, we generate:

$$\widehat{X}_1^{(0)}(k+1) = \widehat{X}_1^{(1)}(k+1) - \widehat{X}_1^{(1)}(k) \tag{5}$$

In the equation, $\widehat{X}_1^{(0)}(k+1)$ is the predicted value. Among them, k= 1,2,3... , 6 is the fitting value, and greater than or equal to 7 is the predicted value.

(5) Residual test

In order to determine the accuracy of the model, the model performance test is carried out after the model prediction. The basic principle of the model test is to compare the differences between the fitted value obtained by the $\widehat{X}_1^{(0)}(k)$ and the actual value, that is, the residual test. The model performance is judged by calculating the average relative error $\varepsilon(avg)$ and accuracy p^0 of the model, and the formula is as follows：

$$\varepsilon(avg) = \frac{1}{n-1}\sum_{k=2}^{n}\left|\frac{X_1^{(1)}(k)-\widehat{X}_1^{(1)}(k)}{X_1^{(1)}(k)}\right| \times 100\% \tag{6}$$

$$p^0 = \left(1 - \varepsilon(avg)\right) \times 100\% \tag{7}$$

The model used in this study is multi-dimensional GM (1, N), so it is necessary to calculate the average relative error $\varepsilon(avg)$ and accuracy p^0 of the model to judge the performance of the model. If the accuracy of the predicted values is greater than 85%, then the model achieves a high prediction accuracy. If the accuracy of the predicted values is between 80% and 85%, then the prediction accuracy of the model is average.

3. Construction of we-media platform sales forecast model

3.1 Selection of index factors for sales data

There are many factors affecting clothing sales forecasting. Huang Ying [10] screens key factors affecting clothing sales through GM(1, N)-Prophet combined model, thus promoting the accuracy of prediction. To select the key factors affecting clothing sales, the core is to start with the consumer's consumption habits and the related factors concerned with evaluation of the categories of the sales platforms, thus confirming the four aspects, including consumer's preference for the commodity, the population base, the purchase possibility of the commodity and the spread of the consumer's preference for the commodity. On the basis of the above four aspects for the segmentation and establishment of index factors, the number of visitors, the quantity of collection and purchase, the appeal of commodities, and spontaneous promotion degrees are established as the first-level indicators. Then, according to the primary index, the number of visitors, collection and purchase, dwelling time in average page and the number of transmitting shopping link are deemed as five secondary indexes, which are the influencing factors of commodity sales data. The hierarchical relationship of index factors is demonstrated in Table 1.

Tab1. Index factors affecting the sales forecast of the clothing industry and their division

	The first index	The second index
The index factors that affect forecasting sales of the apparel industry	The number of visitors	The volume of visitors
	The quantity of collection and purchase	The number of collection
		The number of purchase
	The appeal of commodities	Dwelling time in average page
	The degree of spontaneous promotion	The number of transmitting shopping link

3.2 Data collection and pre-processing

The research object of this paper is brand B of a certain Douyin merchant, and the sales data of the four most representative clothing products of this brand are selected for a total of 8 weeks from December 2021 to January 2022. The four clothing products are knitted leggings, pullover hoodies, casual knitted pants and stripe cardigans. The relevant sales data include sales volume, the number of visitors, collection and purchases, dwelling time in average page and the times of transmitting shopping link. Partial data of the four garments after pre-processing are shown in Table 2.

Table 2. DY order group inventory sales details

	Knit leggings						pullover hoodies					
Time/ Week	Sales volume /piece	Volume of visitors/time	Quantity of collection/piece	Quantity of purchase/piece	Dwelling time in average page/s	Transmitting the shopping link/time	Sales volume/piece	Volume of visitors/ time	Quantity of collection/piece	Quantity of purchase/piece	Dwelling time in average page/s	Transmitting the shopping link/time
1	83	23912	795	1344	0.73	74	248	52226	2034	2949	0.45	13
2	90	21073	820	968	0.56	61	296	46931	1817	2766	0.76	26
3	100	16297	639	864	0.69	35	283	41334	1556	2471	0.99	44
4	88	14277	567	770	0.96	21	193	34908	1246	1988	1.35	19
5	108	17230	715	1014	1.77	17	271	36971	1218	1977	0.46	12
6	91	15876	658	977	0.46	35	130	27932	835	1312	0.84	15
7	94	16939	679	1055	0.97	22	91	12580	479	571	0.69	35
8	90	16190	661	910	0.35	9	52	10922	370	398	1.15	27
	Casual knitted pants						Stripe cardigans					
Time/ Week	Sales volume /piece	Volume of visitors/time	Quantity of collection/piece	Quantity of purchase/piece	Dwelling time in average page/s	Transmitting the shopping link/time	Sales volume/piece	Volume of visitors/ time	Quantity of collection/piece	Quantity of purchase/piece	Dwelling time in average page/s	Transmitting the shopping link/time
1	46	7238	290	426	0.57	5	29	22868	760	904	0.43	11
2	42	6929	262	456	0.35	3	27	21831	653	814	0.44	9

3	52	6862	282	436	0.62	5	25	20465	585	842	0.55	6
4	54	8427	335	480	0.19	6	27	14480	472	576	0.43	8
5	51	7996	263	406	0.85	9	20	14873	411	557	0.28	5
6	45	6092	227	351	1.01	10	25	14639	372	529	0.62	7
7	53	6592	253	400	0.77	11	21	12366	313	437	0.58	10
8	48	7073	296	417	0.62	6	23	12826	333	479	0.49	6

3.3 Gray correlation analysis of multi-dimensional data

In a bid to boost the forecasting accuracy, dimensional reduction was carried out by gray relational degree analysis before data were substituted into the prediction model. By analyzing the gray correlation degree of the number of visitors, collection and purchase, dwelling time in average page and times of transmitting shopping link in the sales data of its four clothing products, the data obtained are shown in Table 3.

Table 3. Grey correlation analysis of sales forecast index factors

products	Volume of visitors/time	Quantity of collection/piece	Quantity of purchase/piece	Dwelling time in average page/s	Transmitting the shopping link/time
Knit leggings	0.6258	0.7166	0.6187	0.6392	0.5158
pullover hoodies	0.8913	0.8651	0.8772	0.6023	0.6017
Casual knitted pants	0.8755	0.8470	0.8327	0.6960	0.6566
Stripe cardigans	0.7529	0.6485	0.7114	0.6334	0.6467
Average	0.7864	0.7693	0.7600	0.6427	0.6052

According to the results of correlation degree in Table 3, the analysis shows that the correlation degree of the number of visitors, collection and purchase, and sales volume is greater than 0.7, and the correlation degree is comparatively strong. Nevertheless, the correlation degree of dwelling time in average page and sales volume is both lower than 0.7, and the correlation degree is comparatively weak. Therefore, in the multi-dimensional sales model prediction, the sales volume is taken as the dependent variable, and the three dimensional factors of visitor, collection and purchase volumes are deemed as the independent variables.

3.4 GM (1, N) model test

We select three influencing factors as the main factors, build GM (1, 3) model of the number of visitors, collection, purchase and sales, and obtain the coefficient vector of the model through solving. According to the above research, we test GM (1, 3) model for residuals, substitute the data predicted by the model and actual data into the formula and calculate. The residual test results of the predicted values of the four products of brand B are shown in Table 4 below.

Tab4.Residual test results of predicted values of four products of Brand B

Name of products	Test results	Time/week						
		2	3	4	5	6	7	8
Knit leggings	Actual sales volume/piece	90	100	88	108	91	94	90
	Predicted sales volume/piece	88	120	108	117	98	90	104
	Residual error	2.132	-20.103	-20.294	-9.336	-6.582	4.260	-13.939
	Relative error/%	2.568 %	22.336%	20.294 %	10.609 %	6.095%	4.681%	14.829%
	Average relative error/%	11.630%						
	Accuracy	88.370%						
pullover hoodies	Actual sales volume/piece	296	283	193	271	130	91	52
	Predicted sales volume/piece	272	315	242	231	157	62	45
	Residual error	23.710	-32.258	-48.809	39.993	-26.714	29.409	6.648
	Relative error/%	9.560 %	10.898%	17.247 %	20.722 %	9.858%	22.623%	7.305%
	Average relative error/%	14.030%						
	Accuracy/%	85.970%						
Casual knitted pants	Actual sales volume/piece	42	52	54	51	45	53	48
	Predicted sales volume/piece	41	65	65	56	50	57	49
	Residual error	0.763	-13.474	-10.806	-4.538	-4.920	-4.072	-0.815
	Relative error/%	1.659 %	32.080%	20.780 %	8.405%	9.647%	9.048%	1.538%
	Average relative error/%	11.880%						
	Accuracy/%	88.120%						
Stripe cardigans	Actual sales volume/piece	27	25	27	20	25	21	23
	Predicted sales volume/piece	26	31	29	28	26	22	20
	Residual error	1.159	-6.219	-2.333	-7.630	-1.040	-1.494	2.989
	Relative error/%	3.998 %	23.034%	9.331%	28.260 %	5.199%	5.976%	14.235%
	Average relative error/%	12.862%						
	Accuracy/%	87.138%						

By comparing the data in Table 4, we can find that the predicted sales volume calculated by GM (1, N) gray prediction model of four groups of different categories of clothing products is not much different from the actual sales volume. Similarly, the average relative simulation error of GM (1, N) gray prediction model for four groups of clothing products of different categories is always less than 15%. Therefore, GM (1, N) model has high prediction accuracy in clothing sales prediction of we-media platforms.

3.5 Application of GM (1, N) model

Based on the above research, the GM (1, N) model is selected for sales prediction, and the knitted leggings are selected as the prediction object. The DGM (1, 1) model is used to predict the influencing factors to get the cumulative generated value. The value is substituted into GM (1, 3) for calculation, and the sales forecast value of eight weeks between February and March 2022 is obtained.

Calculation procedures are as follows:

(1) 1-AGO sequence of system characteristic data

$$X_1^{(1)} = \left(X_1^{(1)}(1), X_1^{(1)}(2), X_1^{(1)}(3), X_1^{(1)}(4), X_1^{(1)}(5), X_1^{(1)}(6), X_1^{(1)}(7), X_1^{(1)}(8)\right)$$
$$= (92.9,\ 185.5,\ 277.8,\ 369.7,\ 461.2,\ 552.3,\ 643.1,\ 733.6) \quad (8)$$

The 1-AGO sequence of the correlation factor data series

$$X_2^{(1)} = \left(X_2^{(1)}(1), X_2^{(1)}(2), X_2^{(1)}(3), X_2^{(1)}(4), X_2^{(1)}(5), X_2^{(1)}(6), X_2^{(1)}(7), X_2^{(1)}(8)\right) =$$
$$(15039.2,\ 29665.8,\ 43891.1,\ 57726.2,\ 71181.6,\ 84267.9,\ 96995.1,\ 109373.2) \quad (9)$$

$$X_3^{(1)} = \left(X_3^{(1)}(1), X_3^{(1)}(2), X_3^{(1)}(3), X_3^{(1)}(4), X_3^{(1)}(5), X_3^{(1)}(6), X_3^{(1)}(7), X_3^{(1)}(8)\right)$$
$$= (628.9,\ 1246.4,\ 1852.8,\ 2448.3,\ 3032.9,\ 3607.1,\ 4170.8,\ 4724.4) \quad (10)$$

$$X_4^{(1)} = \left(X_4^{(1)}(1), X_4^{(1)}(2), X_4^{(1)}(3), X_4^{(1)}(4), X_4^{(1)}(5), X_4^{(1)}(6), X_4^{(1)}(7), X_4^{(1)}(8)\right)$$
$$= (993.7,\ 2002.2,\ 3025.8,\ 4064.7,\ 5119.1,\ 6189.3,\ 7275.4,\ 8377.8) \quad (11)$$

Adjacent mean generated sequence of X_1':

$$Z_1^{(1)} = \left(Z_1^{(1)}(1), Z_1^{(1)}(2), Z_1^{(1)}(3), Z_1^{(1)}(4), Z_1^{(1)}(5), Z_1^{(1)}(6), Z_1^{(1)}(7), Z_1^{(1)}(8)\right)$$
$$= (139.3,\ 231.7,\ 323.7,\ 415.4,\ 506.8,\ 597.7,\ 688.4) \quad (12)$$

(2) Calculating matrix B

$$B = \begin{pmatrix} -Z_1^{(1)}(2) & X_2^{(1)}(2) & \dots & X_4^{(1)}(2) \\ -Z_1^{(1)}(3) & X_2^{(1)}(3) & \dots & X_4^{(1)}(3) \\ \vdots & \vdots & \vdots & \vdots \\ -Z_1^{(1)}(8) & X_2^{(1)}(8) & \dots & X_4^{(1)}(8) \end{pmatrix}$$

$$= \begin{pmatrix} -139.3, & 29665.8, & 1246.5, & 2002.3 \\ -231.7, & 43891.1, & 1852.8, & 3025.9 \\ -323.7, & 57726.2, & 2448.3, & 4064.8 \\ -415.4, & 71181.6, & 3033.0, & 5119.2 \\ -506.8, & 84267.9, & 3607.1, & 6189.4 \\ -597.7, & 96995.1, & 4170.9, & 7275.5 \\ -688.4, & 109373.2, & 4724.5, & 8377.9 \end{pmatrix} \tag{13}$$

(3) Parameters are obtained by least square method

Assume argument list $\alpha = (a, b_1, b_2, b_3, b_4)^T$, among them, matrix

$$Y = (\ 92.6 \quad 92.2 \quad 91.9 \quad 91.5 \quad 91.2 \quad 90.8 \quad 90.4)^T \tag{14}$$

Coefficient of system development $a = 2.0$, object-driven b=0.0; 0.4; 0.0;

According to the least square method, the time response formula of the parameter $\widehat{\alpha} = (B^TB)^{-1}B^TY$ substituting into GM（1，3） model is calculated to obtain the predicted value of the system characteristic sequence. Namely, the predicted value of the sales volume of knitted leggings in eight weeks from February to March 2022 is shown in Table 5 below.

Tab5.Final prediction results of GM (1, n) model from February to March 2022

week	1	2	3	4	5	6	7	8
Volume of visitors/piece	15039	14627	14225	13835	13455	13086	12727	12378
Quantity of collection/piece	629	618	606	595	585	574	564	554
Quantity of purchase/piece	994	1009	1024	1039	1054	1070	1086	1102
Predicted sales volume/piece	93	80	101	95	92	91	90	90

4. Conclusion and suggestions

4.1 Conclusion

By gray relational grade analysis, it is concluded that the number of visitors, collections and purchase deemed as important index factors resulting in the change of clothing sales, we establish the sales forecasting GM (1, N) model of brand B we-media platform, thus realizing "irregular distribution of small data samples" under the background of the accurate prediction of sales. In the sales process, merchants can determine which products need to be reduced inventory in the next stage, which products need to be carried out an inventory clearance in the next stage and other supply and demand strategic guidance, so as to solve the problem of inventory overstock and unstable supply and demand. It provides a new solution to the sales forecasting of we-media clothing brands, saves the prediction time on the premise of ensuring the prediction accuracy, and avoids the influence of subjective factors and environmental factors in the traditional prediction model on the forecasting.

4.2 Suggestions

According to the research, with the rapid advancement of we-media economy, a mounting number of clothing brands have entered the we-media economy. Due to the short developmental time of we-media economy, the online sales model is not standardized, so the phenomenon of fast updating of clothing products and improper inventory management has emerged in this market. According to the current situation of the clothing market on the we-media platforms, the following suggestions are put forward for the development of brand B on we-media platforms based on the research results:

(1) Establish warehouse intelligence control to reasonably solve supply and demand of products

According to the results of gray correlation analysis, merchants can make timely analysis and prediction of the next stage of sales based on the sales correlation data of products such as the number of visitors and collections, and then adjust factory production and warehouse storage to avoid the phenomenon of "oversupply and promotion, under-supply and lack of sales", improve the brand supply chain, and make it a virtuous cycle within the brand sales.

(2) Determine best-sellers and long-term selling items, enhance the competitiveness and vitality of the brand

Reasonable product positioning can improve the competitiveness and vitality of clothing brands. Based on above studies, we can find that the sales volume of knitted leggings, casual knitted pants and stripe cardigans does not change largely over time. Therefore, the merchants can position these three categories as regular selling items, which serves as a way to improve the value of the brand to operate sales, help the brand to strengthen brand efficiency and build consumer loyalty. However, merchants can classify some categories such as pullover hoodies as best-sellers, since the sales volume of this kind of category soars in a period of time but slumps after a certain amount of time. As a consequence, merchants can employ the characteristics and advantages of the we-media platforms to purchase promotion and increase the attention of hot spots during the hot time of this section, so that more consumers of the we-media platforms will notice it, thus increasing the exposure and popularity of the brand.

Acknowledgements

We gratefully acknowledge the higher education research project of Zhejiang Higher Education Association (No. KT2022028) and the National College Students' innovation and entrepreneurship training program (No.202113291019) for their support, and the scientific research project of Jiaxing Nanhu University (No. N41472001-YB13) is also acknowledged.

References

[1] Deng Julong Grey control system. Journal of central China Institute of technology, 1982 (03): 9-18 DOI:10.13245/j.hust. 1982.03.002.

[2] Li juanfei, Chen Jing, Du Liying, Liu Lin, Yang Xiaopeng Application Comparison of GM (1,1) and GM (1, n) models in GDP prediction. Science and technology information (science teaching and Research), 2008 (20): 498-499

[3] Saxena Akash. Grey forecasting models based on internal optimization for Novel Corona virus (COVID-19). Applied Soft Computing Journal,2021,111.
[4] Javed Saad Ahmed,Cudjoe Dan. A novel grey forecasting of greenhouse gas emissions from four industries of China and India. Sustainable Production and Consumption,2022,29.
[5] Shi Min, permit, Wang Jue, Yin Rui, Zhang Pei Short term prediction of photovoltaic power generation based on grey correlation analysis and GeoMAN model. Journal of electrotechnics, 2021, 36 (11): 2298-2305 DOI:10.19595/j.cnki. 1000-6753. tces. two hundred thousand five hundred and thirty-eight
[6] Zhang Kaizhi, Jiang Honghua, Liu Pingzeng, Zhang Yan. Prediction of ginger planting area based on GM (1, n) model. China Journal of agricultural machinery and chemistry, 2020,41 (10): 139-143 DOI:10.13733/j.jcam. issn. 2095-5553.2020.10.021.
[7] Zhangrongyan Prediction of real estate price in Zhengzhou based on GM (1, n) model. Practice and understanding of mathematics, 2018,48 (05): 82-88
[8] Xu Qianru Research on clothing sales forecasting based on combination forecasting model. Chang'an University, 2018(1)
[9] Liu Sifeng, Guo tianbang, Dang yaoguo, etc Grey system theory and its application. Version 2 Beijing: Science Press, 1999:40-77
[10] Huang Ying, Zhang Junxi Research on sales forecast of e-commerce industry based on GM (1, n) -prophet combination model. Journal of Southwest University For Nationalities (Natural Science Edition), 2021,47 (03): 317-325