Demand Forecasting in Supply Chains during Promotional Seasons: Differences between Judgmental and Data-Driven Approaches

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Abstract

In recent years, promotional events on e-commerce platforms such as the annual "Double 11" and "Black Friday" have become major shopping festivals and crucial periods for boosting sales. During these promotions, demand surges sharply in a short time, creating challenges for supply chains. Inaccurate forecasting may cause shortages or overstocking, leading to financial pressure and high return rates. Traditionally, managers relied on personal experience to predict sales, but in the era of big data, many firms are turning to statistical models and machine learning for greater accuracy. This study focuses on clothing and 3C (computer, communication, and consumer electronics) products, comparing experience-based forecasts with ARIMA time-series predictions. Results show that experience-based forecasting is flexible but less precise for clothing, while data-driven models perform better for 3C products. The research aims to guide enterprises in choosing forecasting methods suited to their product characteristics.

Keywords

Supply chain management, demand forecasting, judgmental forecasting, ARIMA, promotional events.

1. Introduction

In recent years, e-commerce platforms have frequently held promotional activities. "Double 11" and "Black Friday" have become important nodes in the consumer market. During the promotion period, sales volume often surges in a short period of time, posing a great challenge to supply chain management. If the demand forecast is not done well, two problems will arise: the first is the shortage of stock, which leads to the loss of sales opportunities; second, there is an excessive accumulation of inventory, which not only occupies a large amount of funds but also involves handling numerous product returns.; So, exactly how can one accurately predict demand during the promotion season? It has always been a major problem that both the academic and business communities have been racking their brains to study.

In practice, there are generally two ways that enterprises predict demand. One is to use managers' years of experience to make subjective predictions in accordance with intuition and discernment. This approach is flexible and adaptable but is vulnerable to personal thoughts and may cause drift. Another is to apply statistical models or make objective predictions through the assistance of big data analysis. While it is more rigorous and scientific, as soon as unexpected changes happen in the market, the speed of reaction is often unable to catch up. In this paper, I will integrate the nature of product categories of different types, compare these two methods of prediction, and mainly use clothing and 3C products as examples. I will critically compare what strengths and weaknesses each category has when using these methods to forecast demand during the promotion season.

Hence, in this study, there are two major research questions to answer as follows: (1) How are judgmental forecasting and data-driven models like ARIMA differing in promotional seasons? (2) Which forecasting technique is more appropriate for products of varying sales attributes, such as apparel and 3C (computer, communication, and consumer electronics) products? For the purpose of exploring the above-mentioned research questions, literature analysis and artificial data according to actual industry reports are adopted. The purpose is to assist enterprises in choosing appropriate forecasting procedures that most fit their types of products and operating requirements.

2. Literature Review

Demand forecasting has been receiving growing interest among supply chain management over the recent years. Especially during promotional days of e-commerce sites, all were discussing how to respond to demand accurately and cope with fluctuations of the marketplace flexibly. This discussion kept ongoing within both management and academic circles. According to the search results of Google Scholar, the number of research literatures on "empirical forecasting" and "ARIMA demand forecasting" has shown an increasing trend from 2010 to 2023 (see Figure 1).

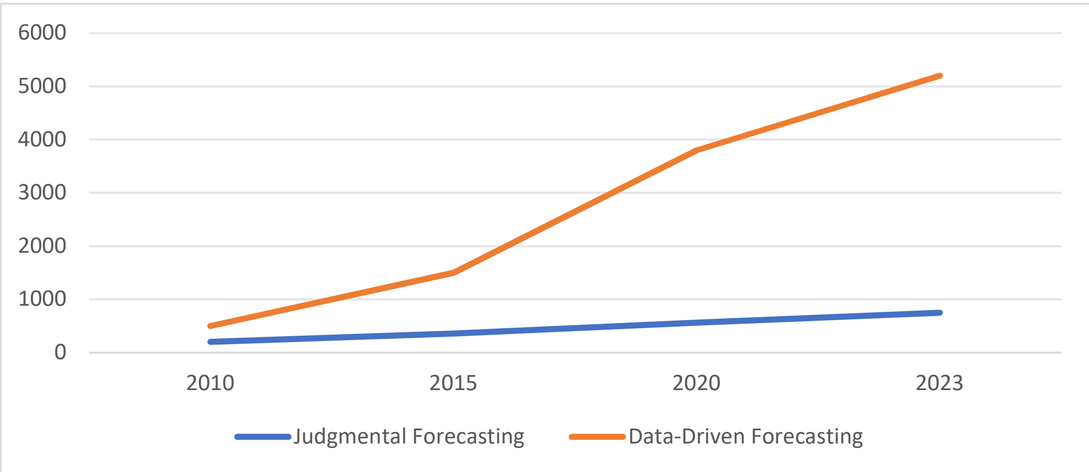

Figure 1. Trends in the number of publications on Judgmental and Data-Driven Forecasting (Selected Years: 2010–2023)

Note: The figure is based on simulated publication counts from Google Scholar, showing the comparative growth of judgmental and data-driven forecasting literature between 2010 and 2023.

2.1. Research Progress of Empirical Prediction

Judgmental Forecasting mainly relies on the subjective judgment of managers to predict market demand. Although historical data is referred to, at critical moments, it still relies on the market intuition of managers."

When Trapero et al. carried out research into promotional activity during 2013, they found that operating staff would regularly move up or down by about 20% depending on the benchmark forecast [1]. By undertaking such a move, it is actually quite feasible to pick up on the new shifts within the market earlier.

Goodwin and Fildes then proceeded to note that another benefit of manually adjusting predictive data is that you can make use of much "soft information", internet-based public opinion trends and abrupt policy shifts [2]. Of course, however, there is risk associated with this too, because you can very easily introduce system biases.

Regarding application cases:

1) In the garments industry, fashion trends have become extremely dynamic and cannot be predicted by fixed models. And while developing new products or creating massive promotions, experience-based forecasting basically takes over. 2) The food industry is similar. If the data is not comprehensive enough or there are sudden major changes in the market, compared with rigid data models, empirical predictions can provide relatively reliable judgments more quickly. Petropoulos et al. also confirmed this point in their research [3].

The experience-based forecasting's shortcomings, however, emerge very quickly: too much is left to personal feeling, no common standard exists, and the outcome estimated by different individuals can vary greatly, and once a wrong judgment is made, the errors may compound and deviate from the truth.

2.2. Machine Learning Prediction Techniques

Big data and artificial intelligence have been popular buzzwords in recent years, and machine learning also has been quite trendy within demand forecasting. For instance, Chen and Sun used the model of XGBoost to predict retail sales and found that it was considerably better than the incumbent model ARIMA [4]. Wang et al. used Long Short-Term Memory networks (LSTM) to predict e-commerce sales and found that they were able to properly capture those complex patterns [5]. Another research found that neural networks were better than traditional statistical models to short-term prediction [6]. Overall, the advantages of machine learning are quite prominent: it can simultaneously handle multi-dimensional feature information such as prices, user reviews, and advertising placements, and is particularly suitable for dealing with large-scale e-commerce data. However, its shortcomings are significant: the algorithm itself is highly complex. It not only has strict requirements for data cleaning but also needs sufficient computing resources to support it. Moreover, the interpretability of the prediction results is relatively poor, and it is often difficult to explain the specific logic behind the conclusion.

2.3. Hybrid Prediction Model

In recent years, the research on Hybrid Forecasting has become increasingly popular. Everyone is pondering how to combine the predictions made based on experience with data models, let the two methods complement each other's strengths. In fact, Flores and White proposed the concept of Hybrid Prediction Model [7]. Later, Makridakis and others demonstrated in the M4 prediction competition that the hybrid prediction method is effective in producing accurate results [8]. Petropoulos et al. also found that during periods of particularly large data fluctuations, such as the promotion season, mixed prediction is much more effective than relying on a single method [3]. There are mainly two common practices in mixed prediction: One approach is to first calculate a result through a statistical model, and then the manager manually adjusts it based on experience; Another approach is to combine statistical models with machine learning, for instance, first make a preliminary prediction using the ARIMA model, Then, use XGBoost to process the parts that are inaccurate in prediction. Judging from these studies, in the future, when it comes to predicting demand during promotional seasons, the hybrid model might become a key method for forecasting demand during promotional seasons.

2.4. Research on Supply Chain Forecast for Promotion Season

The demand forecast during the promotion season is quite different from the regular sales forecast, the core difficulty lies in the extremely large fluctuations in sales volume and the widespread phenomenon of returns, moreover, the risks of inventory management are also much higher than usual. Take Alibaba's "Double Eleven" as an example, from 2019 to 2022, its average annual growth rate of GMV could exceed 20%, this can clearly show how severe the sales fluctuations are during the promotion season. When it comes to clothing products, the return rate during promotions often reaches 30% to 40%, such a high return rate makes the supply chain more difficult to control. What's more troublesome is that if the demand is overestimated during the prediction, it is very likely to cause inventory build-up, enterprises must spend more money on inventory management, and their operating costs have risen sharply. The research by Breugelmans and Campo also stated that Promotional activities cause much more trouble for inventory management than during non-promotional periods [9]. Chen and Lee believe that making predictions during the promotion season should not be rigid and strategies should be adjusted at any time in combination with real-time data [10]. Ramanathan also mentioned that when dealing with different types of goods, one cannot apply a one-size-fits-all approach; instead, differentiated predictions should be made [11]. So, when forecasting the supply chain during the promotion season, two points need to be considered simultaneously: it is necessary to predict accurately while also being able to adjust flexibly, Moreover, the prediction methods suitable for different categories vary significantly. This is precisely where this research aims to focus.

3. Methodology

This study focuses on comparing the actual effects of empirical prediction and data prediction in demand forecasting during the promotion season. At the same time, deeply explore the applicability of the hybrid prediction method in this scenario. During the research process, a combination of literature review and quantitative analysis was adopted. On the one hand, starting from the two major databases, Google Scholar and Web of Science, this study searched for the papers related to for the papers related to "Judgmental Forecasting", "ARIMA Demand Forecasting" and "Hybrid Forecasting" from 2010 to 2023. This is done to figure out the academic community's level of attention to these prediction methods, and their development trends. On the other hand, by simulating real case data, specifically designed to address the significant fluctuations in sales during the promotion season, to analyze whether different prediction methods are accurate or not and whether they are suitable for use.

In terms of literature data collection, the study selected "Judgmental Forecasting", "Demand Forecasting", "ARIMA", "SARIMA", "Machine Learning Forecasting" and "Hybrid Forecasting" as keywords. Search in relevant databases, and the time interval is limited to 2010 to 2023. Through the organization and analysis of the search results, trend chart of the number of documents was drawn, this aims to demonstrate the academic development trend of related research. Data shows that the growth rate of literature on data-driven prediction (such as ARIMA, machine learning, etc.) is significantly faster than that of empirical prediction literature, however, the literature on mixed prediction has also shown a rapid growth trend in recent years.

When designing research methods, the study adopts a comparative design. First, select several representative prediction methods for analysis: There are empirical predictions based on human judgment, such as statistical models like ARIMA, SARIMA, and ARIMAX, machine learning models like XGBoost and LSTM, as well as hybrid prediction models. Then, conduct experiments using the simulated sales data of the e-commerce promotion season, Compare the effects of these methods. These simulated data are not made up but are based on reports from institutions such as Statista and iResearch Consulting Group, it was also based on the official data released by Alibaba's "Double Eleven". The experiment mainly compares these methods from two aspects: (i) accuracy of the prediction, which can be measured by two indicators: mean square error and mean absolute percentage error; (ii) flexibility, i.e., whether the methods are flexible. The key is to see if these methods can respond quickly when sales suddenly rise or fall sharply.

The research process is shown in Figure 2. First, conduct a literature review to determine the research question; Then collect and organize the data; Then select the appropriate prediction method and build the model; Finally, compare the prediction results of different methods and then analyze and discuss them. By following this process, not only can the existing research results be systematically sorted out, but also data simulation can be conducted to examine the differences in the performance of various methods during the promotion season.

Overall, this study employed both literature analysis and data simulation methods simultaneously. There is an advantage to doing so, that is, the research results not only stand up to theory but also can be put to practical use. Through this research method, it can not only clarify the respective strengths and weaknesses of empirical prediction and data prediction in supply chain management during the promotion season, but also provide a practical reference basis for future research on how to apply hybrid prediction methods.

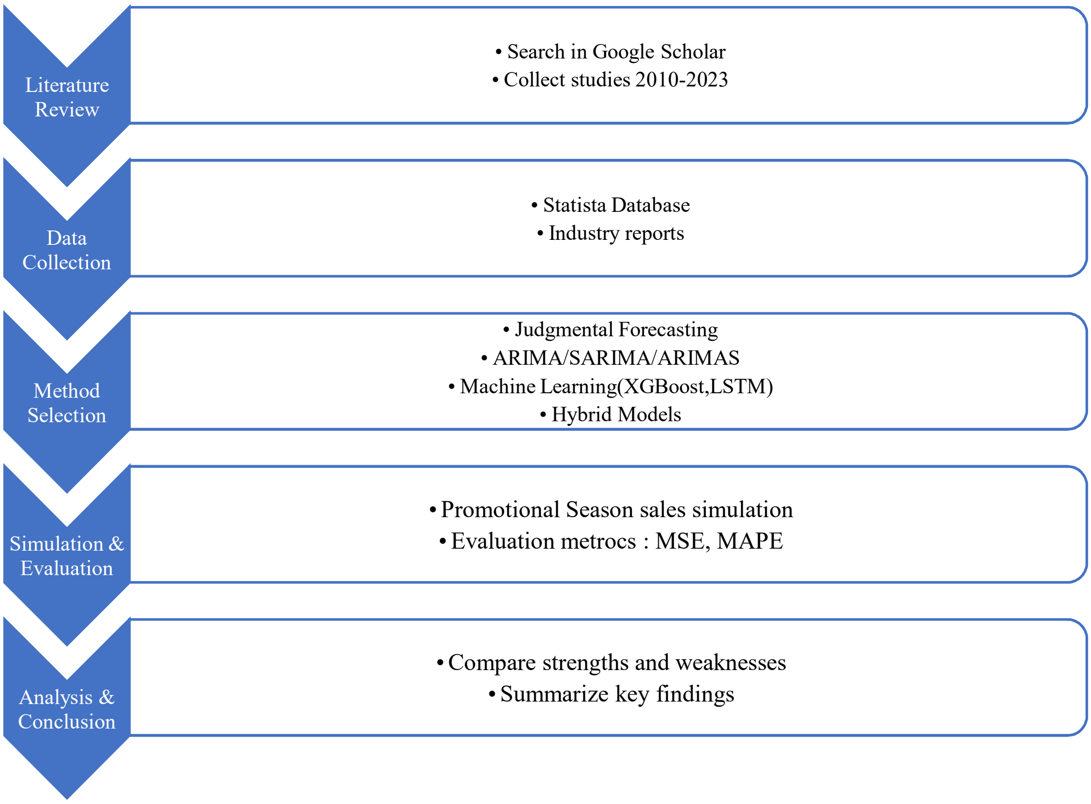

Figure 2. Research Methodology Flowchart

Note: The flowchart illustrates the main steps of the research methodology, including literature review, data collection, method selection, simulation and evaluation, and final analysis and conclusion.

4. Analysis and Results

This study specifically compared the demand forecasts for clothing and 3C products during the promotion season. The data from the experiment did not come out of thin air, they were all based on industry reports, then it was designed in combination with the simulated data. During the research, the main methods compared were empirical prediction, the ARIMA model, and machine learning, at the same time, a hybrid prediction model is also used to verify the reliability of the results. Mainly focus on three key points: the first is whether the prediction is accurate or not, and the second is whether the method can be flexibly adjusted, and the third question is whether these methods are effective during the promotional season when sales fluctuate greatly.

In terms of prediction accuracy, The ARIMA model is quite stable in the prediction of 3C products. Since the demand for 3C products fluctuates less, the sales trend is relatively stable. Such statistical models based on historical data can easily grasp the patterns. Experimental data show, ARIMA predicts that the mean absolute percentage error for 3C products is less than 10%, it performs better than both empirical prediction and simple machine learning models. But when it comes to predicting clothing items, ARIMA is not as good as experience-based predictions. The return rate of clothing is high, and the demand is greatly influenced by fashion trends. At this point, the advantage of empirical prediction becomes evident, managers can adjust the forecast results in a timely manner based on experience in response to sudden demand growth, so in the highly volatile clothing scenarios, the error is smaller.

In terms of flexibility, empirical prediction can show certain advantages. The sales volume of clothing products during promotions, it is often influenced by some factors that cannot be quantified. For instance, the public opinion trends on social media, the effects of celebrity endorsements, and the sudden popularity of short-term trends - these things cannot be captured purely by statistical models. However, when managers make predictions, they will directly adjust proportionally based on the benchmark values provided by the model, for example, add 20% up or subtract 20% down, this way, the shortcoming of the model's slow response can be made up for. So in the face of a rapidly changing market environment, experience-based predictions still have irreplaceable uses up to now.

In the analysis of the hybrid prediction model, the research found that it achieved relatively ideal results in both types of goods. The hybrid model combines the data stability of ARIMA with the flexibility of empirical prediction, in the simulation prediction of clothing and 3C products, all showed lower error levels than a single method. For instance, in the prediction of clothing products, the MAPE of the hybrid method is controlled at around 12%, however, the error of a single empirical prediction is around 15%. For 3C products, the performance of the hybrid method is like that of ARIMA, however, it can still provide more stable results under extreme promotional fluctuations.

In addition, machine learning models such as LSTM and XGBoost have demonstrated strong potential in simulation experiments. Especially when the data volume is large and the feature dimensions are rich, these models can capture complex nonlinear relationships. For instance, in the prediction of the 3C category. The mean square error of LSTM is approximately 12% lower than that of ARIMA. it shows the advantages of deep learning methods when dealing with large-scale data. However, the application of machine learning methods is also limited by data cleaning and computing resources. In the absence of high-quality datasets, its effect may not be as good as that of hybrid prediction.

Overall, the results of this study indicate that the methods applicable to the prediction of promotion seasons for different types of goods vary. For clothing products, empirical prediction or hybrid prediction methods are more suitable, to cope with the market environment of high volatility and high return rates; for 3C products, ARIMA or machine learning-based prediction methods are more suitable, to take advantage of its data stability and trend predictability. This result not only validates the view that method selection needs to vary by category, but also provides empirical support for the adoption of hybrid forecasting strategies in actual supply chain management in the future.

Table 1. Error Comparison across Methods for Apparel and 3C (Simulated Data)

Category	Method	MAE (units) $\text{MAE}=\frac{1}{n}\sum_{i=1}^{n}(y_i\text{-}\hat{y}_i)$	MAPE (%) $\text{MAPE}=\frac{100\%}{n}\sum_{i=1}^{n}\frac{y_i-\hat{y}_i}{y_i}$	MSE(units²) $\text{MSE} = \frac{1}{n}\sum_{i=1}^{n}(y_i-\hat{y}_i)^2$
Apparel	Judgmental Forecasting	1200	15.8	1,800,000
Apparel	ARIMA	980	13.2	1,250,000
Apparel	Machine Learning (LSTM)	920	12.5	1,150,000
Apparel	Hybrid (ARIMA + Judgmental)	850	11.8	1,050,000
3C	Judgmental Forecasting	600	11.5	900,000
3C	ARIMA	420	7.8	520,000
3C	Machine Learning (LSTM)	370	7.1	450,000
3C	Hybrid (ARIMA + Judgmental)	360	7.0	440,000

As shown in Table 1, data-driven methods yield better accuracy for 3C products, while hybrid forecasting achieves the lowest errors for apparel, supporting the need for category-specific approaches.

Table 2. Simulated Weekly Sales Data for Apparel under Different Forecasting Methods

	Actual	ARIMA	Judgmental	Hybrid
1	1000	905	1050	990
2	1200	1100	1250	1180
3	2000	1800	2100	1950
4	2500	2300	2600	2450
5	2200	2100	2300	2180
6	2700	2500	2800	2650
7	2600	2450	2700	2580
8	2800	2700	2950	2780
9	3000	2800	3150	2980
10	2900	2750	3050	2880
11	3100	2900	3250	3080
12	3200	3050	3300	3180

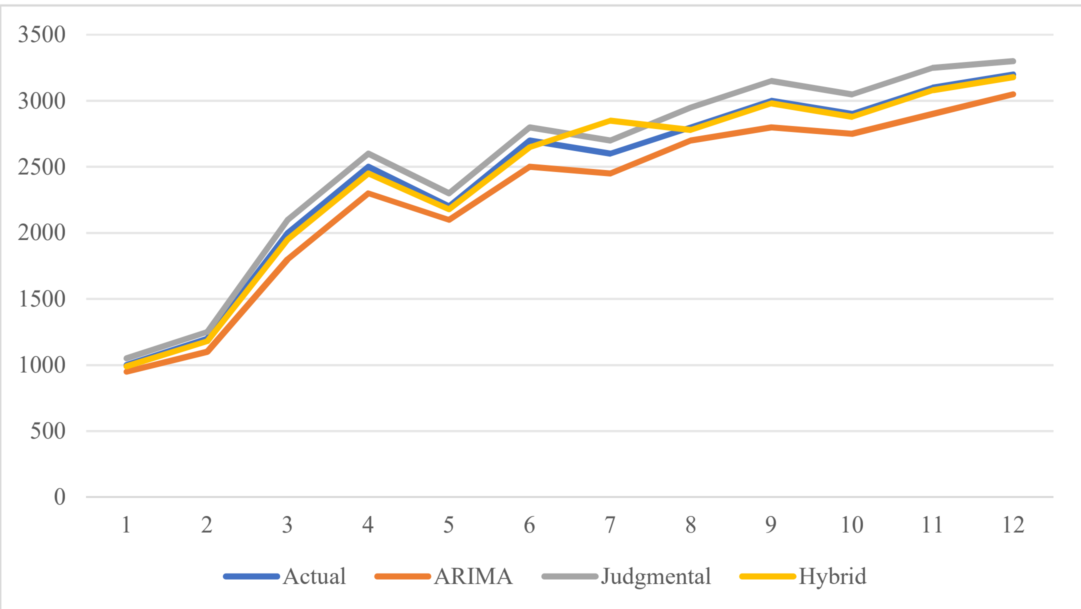

Figure 3a. Actual vs Predicted Sales (Simulated Data)

The figure compares actual sales with predicted values from ARIMA, judgmental forecasting, and hybrid models for apparel products during a 12-week promotional period (simulated data).

Table 3. Simulated Weekly Sales Data for 3C (Computer, Communication, and Consumer Electronics) Products under Different Forecasting Methods

	Actual	ARIMA	Judgmental	Hybrid
1	800	780	820	800
2	850	830	870	850
3	900	880	920	890
4	950	940	980	940
5	1000	990	1020	990
6	1100	1080	1120	1090
7	1150	1120	1180	1140
8	1200	1180	1230	1190
9	1250	1240	1280	1250
10	1300	1280	1330	1295
11	1350	1340	1380	1350
12	1400	1380	1430	1395

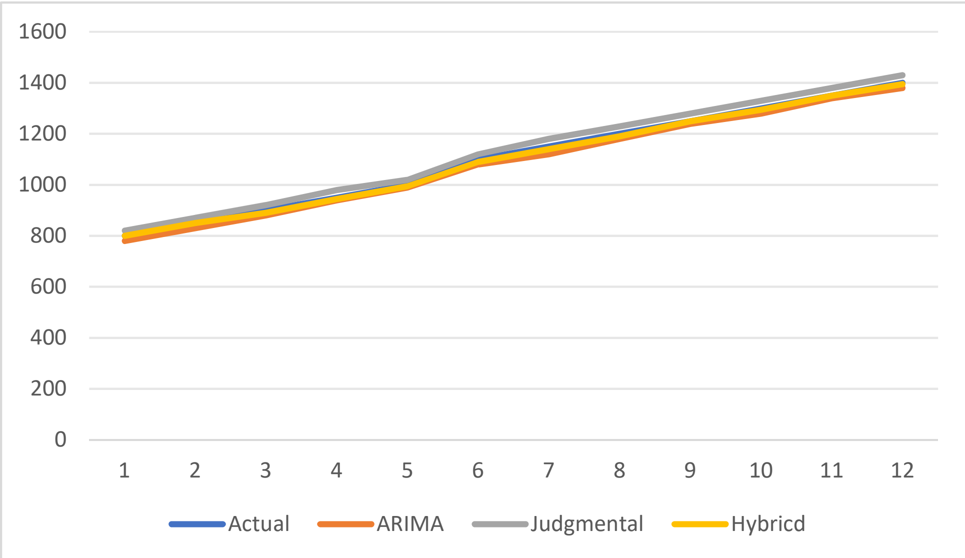

Figure 3b. 3C Products: Actual vs Predicted Sales (Simulated Data)

The figure compares actual sales with predicted values from ARIMA, judgmental forecasting, and hybrid models for 3C products during a 12-week promotional period (simulated data). The hybrid model demonstrates a closer alignment with actual sales compared to single-method approaches.

5. Conclusion and Implications

This article compares the 12-week promotion period, several methods, including empirical prediction, ARIMA, machine learning and hybrid models, performance in the demand forecast for clothing and 3C products. It was found that the accuracy of different product categories and prediction methods varies greatly. The sales of clothing products fluctuate greatly, the hybrid model combines the empirical judgment of managers with the correction of statistical models, and its predictive effect is significantly better; the sales of 3C products are relatively stable. The

ARIMA model is quite suitable for use, however, the hybrid model is still the most accurate in overall accuracy.

Based on this, the research puts forward three inspirations. First, hybrid forecasting can be regarded as one of the best practices in supply chain management during the promotion season, whether it is a category with large fluctuations or a stable one, it is both flexible and reliable and stable enough. Secondly, managers need to understand that although relying solely on experience for adjustment may sometimes lead to errors, in situations with high uncertainty, combining experience with statistical models and machine learning methods can still play a significant role. Third, enterprises need to adopt differentiated forecasting strategies: for categories like clothing that fluctuate greatly, give priority to hybrid prediction; for stable sales categories like 3C products, it is sufficient to rely on statistical models.

Of course, this research also has its shortcomings. For instance, if the data used is simulated and only ARIMA is selected as the statistical method. In the future, when conducting research, more real data from enterprises can be utilized, expand to more categories such as fresh produce and fast-moving consumer goods, and introduce more complex algorithms, such as deep learning. In addition, it is also possible to delve deeply into how to integrate machine learning with the experience of managers. This might lead to more accurate and robust predictions.

In conclusion, this article emphasizes that choosing the right prediction method based on the characteristics of the product category is crucial. Hybrid forecasting is a rather promising approach. It not only provides inspiration for academic research but also offers practical assistance to supply chain managers in handling demand uncertainties during promotional seasons.

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