Intelligent Design Suggestion and Sales Forecasting for New Products in the Apparel Industry

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Abstract
This study demonstrates how algorithms can assist humans in decision-making in the apparel industry. A two-stage method including suggestions and intelligent forecasting was proposed. In the first stage, a web crawler was used to browse a B2C apparel website to identify popular products. In the second stage, machine learning methods were used to predict the sales demand for new products. Additionally, we used Google Trends to collect external information indices to adjust the demand forecasting. Our numerical study shows that the intelligent forecasting approach can effectively reduce the Mean Square Error (MSE), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE) by at least 45.79, 26.35, and 26.34 %, respectively.

Keywords
new product, suggestion, forecasting, web crawler, machine learning, Google Trend.

1. Introduction

With the rapid development of online information and e-commerce, business models have undergone considerable changes to meet the rapidly changing consumer preferences. Over the past two decades, the fashion industry has been transforming, and changes in consumption patterns have forced retailers to reduce costs and increase design flexibility and speed in the market [1]. The main trends in the fashion industry's supply chain are as follows: (1) Quick response: because customers are decision makers in the retail environment, a supply chain that can quickly respond to customer expectations is required [2]. (2) Short production: fashion trends combined with the seasonal nature of products usually result in a shorter life cycle [3]. According to the successful fashion retailer Zara, a year can be divided into 20 seasons. (3) Vertical integration: retailers can eliminate intermediaries, communicate consumer requirements directly with manufacturers, and increase production efficiency. Cooperation between retailers and manufacturers promotes product development, improves product quality, and lowers prices [4].

These trends have given rise to fast fashion, which focuses on quick, low-price, and diverse styles in small quantities, while significantly shortening the life cycle of apparel products. Consequently, retailers are constantly introducing new products. Compared to other traditional industries, the apparel industry is more consumer-oriented. Therefore, to understand consumers' needs, apparel companies need to stay ahead of market trends. Previously, designers would absorb elements from the internet, streets, fashion magazines, or even what they saw in dramas, subjectively believing that products containing these elements would be popular [5]. Typically, we cannot determine if a product will attract consumers until it has been launched. It is fortunate, if the products are hot-selling, but for products that are not selling well, the excess supply and a waste of materials are one of the main reasons why manufacturing costs cannot be reduced.

In addition, with the growing popularity of the internet and social media sites, it is becoming increasingly convenient for people to keep up with fashion trends. The faster people purchase fashion products, the more garment companies produce them. The fashion industry is the second largest polluter worldwide [6]. Owing to the rapid growth of social media, consumers are vulnerable to changes in their preferences as a result of external factors. This increases the difficulty and uncertainty of forecasting customer demand, particularly for new products, for which historical sales data are lacking. Thus, demand forecasting plays an important role in the success of apparel companies. Inaccurate forecasting may lead to product stockouts, overstock, or even the waste of manufacturing costs. Therefore, an efficient forecasting method is necessary in the apparel industry.

In recent years, artificial intelligence (AI) models have come with strong advantages, such as the capability to derive directly from the data "arbitrarily nonlinear" approximation functions, which are highly recommended and common in demand and sales forecasting in many industries [7]. AI methods can be used to predict tendencies or preferences for apparel and sales demand. Whether for a garment company or environmental protection, this will be a win-win situation.

Therefore, the objective of this study was to examine how algorithms (machine learning and web crawlers) can assist humans (designers) in making decisions (fashion design). We proposed a two-stage method that includes suggestions and intelligent forecasting to improve efficiency in the apparel industry. In the

first stage, we used a web crawler on a B2C website to identify popular products. Subsequently, the component elements of popular products are disassembled and suggested to designers for designing new products. In the second stage, we used machine learning methods on historical data to predict the sales demand for new products after they had been designed, and then incorporated external information indexes from Google Trends to reduce demand forecasting errors. This study not only helps the company know whether this product will be a hot seller before it goes public but also proves that external factors have a certain influence on predicting future trends.

The main contributions of this study are as follow:
a) Using a web crawler to support designers in fashion design and creating new products.
b) An intelligent forecasting method is proposed to predict the sales demand for new products. The objective of this method is to add external information indices to decrease the forecasting error gaps. Even without historical sales records, we can predict future demand using historical product sales that are highly similar to those of new products.

2. Literature reviews

2.1. Fashion sales forecasting methods

In traditional forecasting methods, sales forecasting is calculated using statistical methods such as exponential smoothing, linear regression, the moving average, weighted average, Bayesian approach, and ARIMA. Reference [8] examined the applicability of the Bayesian forecasting model to fashion products and used simulated fashion product demand to demonstrate that the model generated better results than other forecasting methods. The authors in [9] considered the retail of different types of women's shoes as an example, showing that ARIMA is more accurate than the other three reliable forecasting approaches, and is generally suitable for forecasting time

series. Although statistical forecasting appears to be simple and rapid, some defects may occur. Cause statistics emphasize causality. Their operation involves inferring future predictions from historical data and can effectively predict products with stable demand. However, traditional statistical methods may not be able to obtain accurate results when faced with highly irregular issues.

AI methods have emerged owing to the increasing power of computers. In this era of information explosion, with the advantages of data and computing power, AI uses different aspects of information to solve prediction problems. Fashion sales are usually affected by selling prices, color, climate, and social media. Thus, the AI technique can be applied to forecast sales demand in the fashion industry. In the past, several studies used AI techniques for fashion sales forecasting. Reference [10] proposed an artificial neural network (ANN) model that allows nonlinear approximation functions to learn the above exogenous factors directly from data to predict women's apparel sales. The authors of [11] employed an evolutionary neural network (ENN) model to forecast fashion sales using evolutionary computation to generate an ANN. They found that ENN is suitable for products with low demand uncertainty and weak seasonal trends, but not for seasonal products. Sun et al. [12] discussed the relationship between fashion sales and some important factors affecting demand using an extreme learning machine (ELM) model. Their results showed that the ELM model was superior to several sales forecasting methods. However, the ELM is not suitable for complex tasks; it performs well for simpler tasks.

Recently, the authors in [13] studied the performance of bagging tree regression, random forest (RF) regression, and gradient boosting regression algorithms by predicting the sales demand of multiple products from different stores in the next three months; the results showed that the performance of fuzzy time series regression was the best. Reference [14] proposed a model for intuitionistic FTS forecasting based on the average length

of the interval, which enhances the forecasting result.

2.2. New product sales forecasting

The authors in [15] conducted a hybrid ANN model and fuzzy function based on the concept of comparable products and forecasted new apparel product demand considering stockouts. Reference [16] built a model that included multiple variables, and both new and historical products were represented by determinate variables, including product characteristics, internal organization, and expert opinions. In a different way, we use both internal (historical sales data) and external (Google Trends data) data to predict sales demand for new products.

Reference [17] studied large-scale fashion sales data and inferred that apparel attributes and sales factors affect demand. They used the given new-product attributes to predict demand using different machine learning methods. Recently, [18] applied AI methods such as decision trees, random forests, XGBoost, and an artificial neural network to predict textile product sales. They used a dataset to forecast sales in stores, including sales time, sales volume, and location. In a different manner, we used sales data and product features to predict the sales volume of new products. The models proposed use fewer data and are suitable for short-term or trendy products in the fashion industry. To the best of our knowledge, this is the first study that combines production design suggestions and sales forecasts. First, we help designers to design their favorite products and then provide an intelligent forecast method to predict new product sales demand in the apparel industry.

3. Two-phase designed model for new product sales forecasting

This section includes the following two phases. Phase 1 describes the use of a web crawler to help designers design new products, as presented in Subsection 3.1.
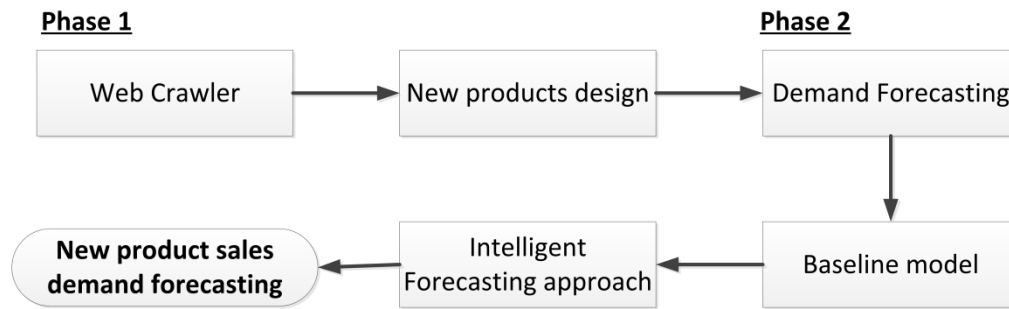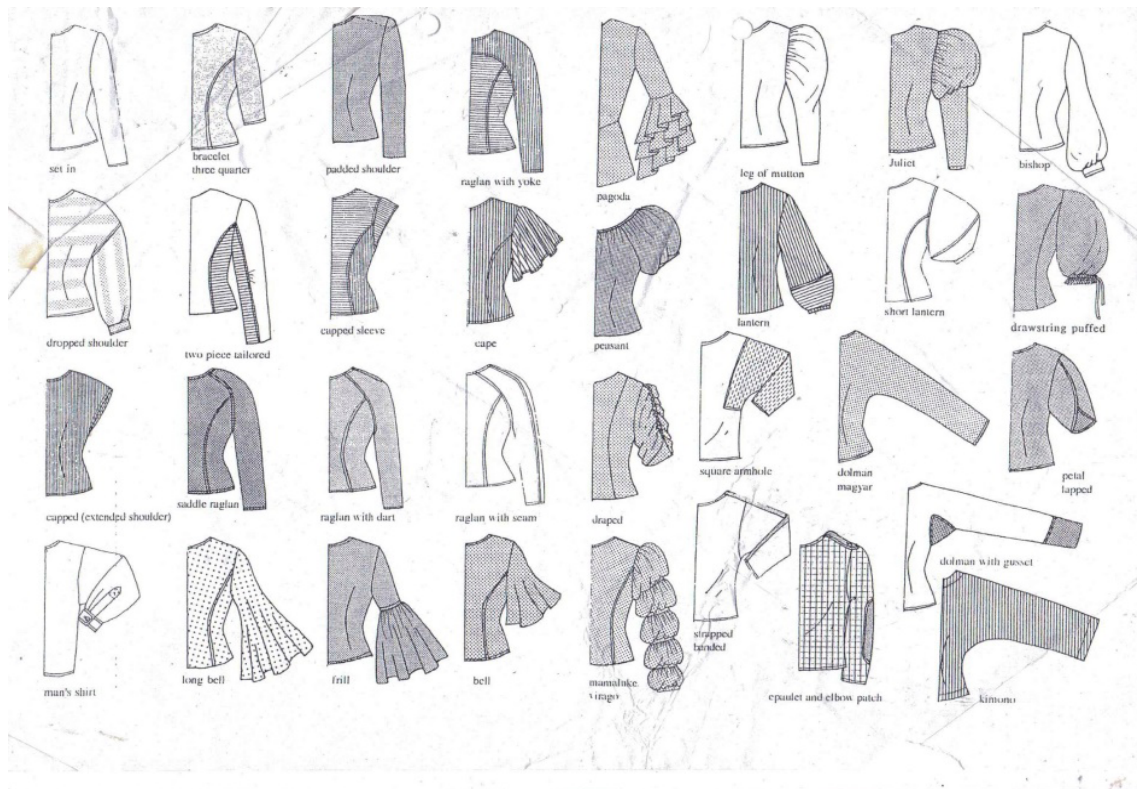
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Fig. 1. Research Framework

Fig. 2. Example for different elements based on the sleeve style
(Source: https://www.pinterest.com/pin/415175659377747162/)

Section 3.2 introduces the two demand forecasting models (baseline model and intelligent forecasting approach) in Phase 2. Figure 1 illustrates the research framework.

3.1. Phase 1: Web crawler

A web crawler is an Internet bot that can automatically browse content on the internet, such as pictures, text and videos, and can be used to obtain a large amount of public information. In Phase 1, to achieve an assisted design, we must obtain the component elements of the product; thus,

to obtain sales and product names, we use a web crawler on a certain B2C online store. We collect sales information from websites to identify popular products and elements and then provide suggestions for a new product design to designers. The product's elements include its characteristics, which could be the type of clothes, sleeves, materials used, colors, or any other thing that makes the product different or similar to others . This information can be provided through text descriptions or image recognition. Almost all B2C websites provide customer references. Figure 2 shows an example of the different elements divided based

on the sleeve styles. The result of phase 1 was a new product design. Thus, Phase 1 was used as the suggestion system for the designers.

An example of this is presented below. Figure 3 shows the product page of the B2C online store, where the red squares represent the content collected from the web crawler. We started collecting data from June 1, 2020, to July 31, 2020, then split product names, discarded subjective adjectives, used objective nouns as elements, and disassembled them into N elements. First, the product description provides the elements that
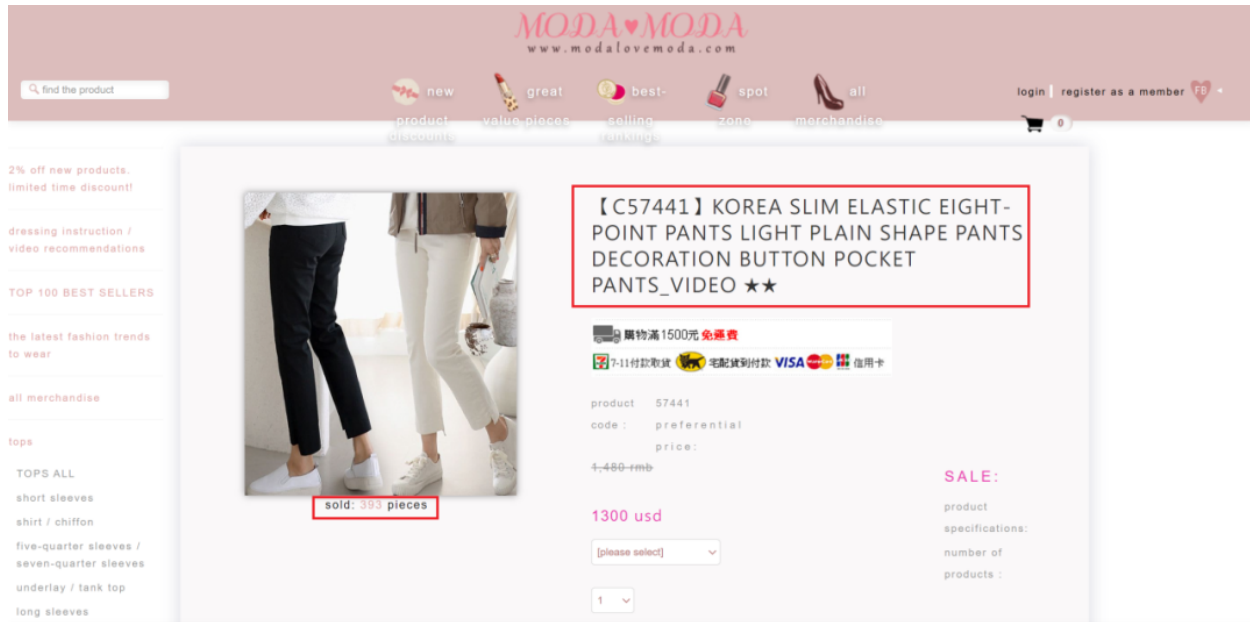
Fig. 3. Product page of the B2C online store
(Source: Retrieved April 19, 2022, from https://www.modalovemoda.com/Shop/itemDetail.aspx?mNo1=57441&m=1)

appear in them. Second, the sales of products indicates their popularity level. We can easily determine which products are popular according to the sales volume. Subsequently, we can determine the elements that appear many times in popular products. Thus, we know the most popular elements. As a result, we collected popular or preferred elements. Designers can use the results of the web crawler to create new products by reorganizing the elements, followed by Phase 2.

3.2. Demand forecasting

3.2.1. Baseline model

Owing to the lack of historical sales data for new products, sales forecasts can be made based on similar products (i.e., internal data). We selected existing products that duplicated more than three elements in the elemental composition of the new product as the internal data. For example, after Stage 1, the designer designs a new product (Item A). Item A has elements No.1-4-6-8 ($q=1$, $q=4$, $q=6$, and $q=8$). If previous products have elements (1,4,6), (1,4,6,10), and (1,6,8,13,20) and their sales volumes are 500, 1000, and 2000, respectively, the sales volume (500, 1000, 2000)

will be used as the internal data input for clustering and classification before forecasting the sales demand of Item A.

The baseline model is as follows: First, we used clustering algorithms (*K-means* and *K-medians*) to label each internal data's sales demand. Second, we constructed labels of the internal data using classification algorithms (RF and XGBoost) to predict new product labels. Finally, based on the previous steps, machine learning regression algorithms were used to predict new product sales demand. Subsequently, we combined the final prediction results with an intelligent forecasting approach to adjust the accuracy.

• *Clustering*

Because there were no sales data for new products in the past, the reason clustering was used to cluster product sales by element combinations is that it duplicates more than three elements of historical data with new products. This is also used as a pre-processing step for classification. Clustering is used to determine the relationship between the composition of elements and sales, whether it is the more duplicate elements or the key elements that cause the difference in distance from the cluster center, that is, the sales

volume. In this study, the elbow method was used to determine the K value, and the Euclidean distance was used for the calculation.

Both *K*-Means and *K*-Medians are popular center-based clustering algorithms used to find k centers, where k is the number of clusters that should be mentioned in advance, and it minimizes the total distance between the cluster center and each point. Their main concept is to randomly generate k centers, one for each cluster, calculate the distance from each point to the centers, assign each point to the nearest centers, recalculate the centers, and redistribute them until the centers remain unchanged. The biggest difference between the two algorithms is that the center of *K*-Means is determined by the average, whereas for *K*-Medians it is determined by the median.

• *Classification*

In this study, two machine learning methods (RF and XGBoost) were utilized to solve classification and regression problems. The two machine learning methods are illustrated as follows:

RF is a classifier composed of multiple decision trees that provide predictive models for classification and regression.

The RF algorithm steps for both classification and regression are as follows [19]:

1. Select N bootstrap samples from the original data.
2. For each of the bootstrap samples, grow an unpruned classification or regression tree.
3. At each node, the best split is randomly selected from all feature subsets instead of the complete feature set.
4. All predictions of N bootstrap samples are aggregated to predict new data; majority votes are used for classification, and the average for regression.

Therefore, splitting the learning process of the classifier is a random process. This means that the elements were randomly selected, and the entropy values were calculated. Next, the smallest entropy value is chosen as the root node and then randomly re-selected and split. In the case of a random forest, the split feature points are randomly selected, multiple parallel decision trees are established, and the final classification result is determined by a majority vote. In this study, the final result is represented by probability. For example, there are three groups (1,2,3), and the random forest creates 100 decision trees. Each decision tree has a final classification result of 20 percent in Class 1, 30 percent in Class 2, and 50 percent in Class 3. The final result is Class 3, with the highest probability (50 percent).

The authors in [20] proposed the **XGBoost algorithm**, which is a tree-ensemble model that uses the principle of tree boosting. XGBoost is an extreme gradient boosting algorithm. Boosting is a machine learning method that can reduce the bias in supervised learning. XGBoost emphasizes the elite theory, that is, each round of training increases the weight of the low error rate in the basic model and reduces the weight of the high error rate in the basic model. This is different from RF using the bagging method, which indicates that the samples are randomly selected in each round of training. In addition, it implements a loss function and penalty function in the objective

function to measure the complexity of the model. In addition, XGBoost uses a greedy algorithm to continuously split and construct multiple decision trees, and determines the final result by weighting. In each (split) step, the best choice from the current step was selected. Thus, the final results are extreme. For example, the final result is 99 percent in Class 3 and only 1 percentage in Classes 1 and 2.

Classification is a supervised learning method. The goal was to assign labels to test samples based on the features of the training samples. Based on the clustering results, we applied two classification methods, RF and XGBoost, to predict the label of a new product. To determine the influence of elements on sales demand, we used N elements disassembled from the product's name as features and clustering results as labels. The features are shown in Equation (1), O_j represents each internal data containing element j, where $j=1,2,3,\ldots, N$ indicates element $N\sim1$.

$$O_j = \begin{cases} 1, contain\ element\ j \\ 0, otherwise \end{cases}, j = 1,2,\ldots N \quad (1)$$

After training, we obtain the label of a new product based on the probability of being assigned to each label. As per the rule, the highest probability determines the label to which it belongs. Therefore, we obtained the probability of each internal datum for each label and used these probabilities in the next step.

• *Machine learning regression*

In this section, to predict new-product sales demand, we used RF and XGBoost regressions. In the previous steps, we identified the labels of both the internal data and the new product and the probability of each label. In this section, the input features are the new product elements, the probability of each label, the cluster center, and the constant. We now introduce them individually.

1. The new product element is C_j, where $j=1,2,\ldots N$ (elements). Specifically, we select the elements contained in the new product as C_j, where $C_j=0$ or 1 indicates whether the internal data contain element j or not.

2. The probability of each label is P_K, where $K=1,2,\ldots k$ (clusters), and P_K represents the probability that internal data are assigned to each label.
3. The cluster center is U, where U represents the cluster center of the group to which the internal data belong.
4. The constant is T, where T is obtained by multiplying the probability of each label by the center of each cluster.

In addition, we chose some common hyperparameters for the random forest and XGBoost, such as the learning rate or controlling the number of iterations to reduce the learning rate, or the penalty coefficient to avoid overfitting. The output data represent the real sales demand for each internal data point. After training, we obtain the prediction results for the new product.

3.2.2. Intelligent forecasting approach

Recently, many researchers have demonstrated the value of social media information in operational management. To reduce out-of-sample forecasting errors, the authors in [21] showed how to use social media information from Facebook. Reference [22] supported the results of [21] by showing that Google Trends can improve out-of-sample forecasting errors. The above studies discussed the B2C industry, that is, customer activities directly affect demand, and these two authors used social media sites to capture customer behavior as external information to improve the accuracy of sales forecasting. This study considers the sales demand for new products in the B2C apparel industry. We used Google Trends search indices for specific search terms, which are elements of new products and are used as external information indices. For example, if a new product A has eight elements, we checked Google Trends to determine the number of times those elements were searched. A longer search time for this element indicates higher potential demand for the product.

Figure 4 shows the application of external data to the baseline model to obtain an improved demand-forecasting framework. We set a crucial threshold to measure external indices and used multiple regression analysis to transform the external data into demand-sense adjustments.

In the baseline model, we assume that the new-product sales demand is D, which is a function of the new-product elements, the probability of each label, the cluster center, and the constant:

$$D = f^{baseline}(C_1, \ldots C_N, P_1, \ldots P_k, U, T) \quad (2)$$

Based on the results of the baseline model, we selected internal data with the same label as the new product and divided them into two groups for regression analysis to adjust demand forecasting. We set the difference between the sales and demand forecasting of the baseline model as r, and the error value as R. Sales data were obtained from the sales of products with the most similar elements. The R value was used to determine whether to generate an increasing or decreasing demand-sense adjustment. The fluctuation range of R indicated the quality of the prediction model. If R fluctuated within a certain range, a discriminative prediction model was used. In this case, the model is a type of supervised learning that uses the category identification information of the training data, abstracts the data to different degrees, defines features, and uses the features to simplify the learning problem. In contrast, if the fluctuation range of R is too extreme, we need to try other stronger prediction models. The new-product sales forecast values in this study are learned using a discriminant method. If a large database is built, it can be extended to a generative model, which is a type of unsupervised learning that uses observed data to learn the joint probability distribution of samples and labels to make predictions.

S^A is an equation of the demand sense adjustment of addition for the internal data, which is $r > +R$; and S^B is an equation of the demand sense adjustment of subtraction for the internal data, which is $r < -R$. Equations (3) and (4) describe these
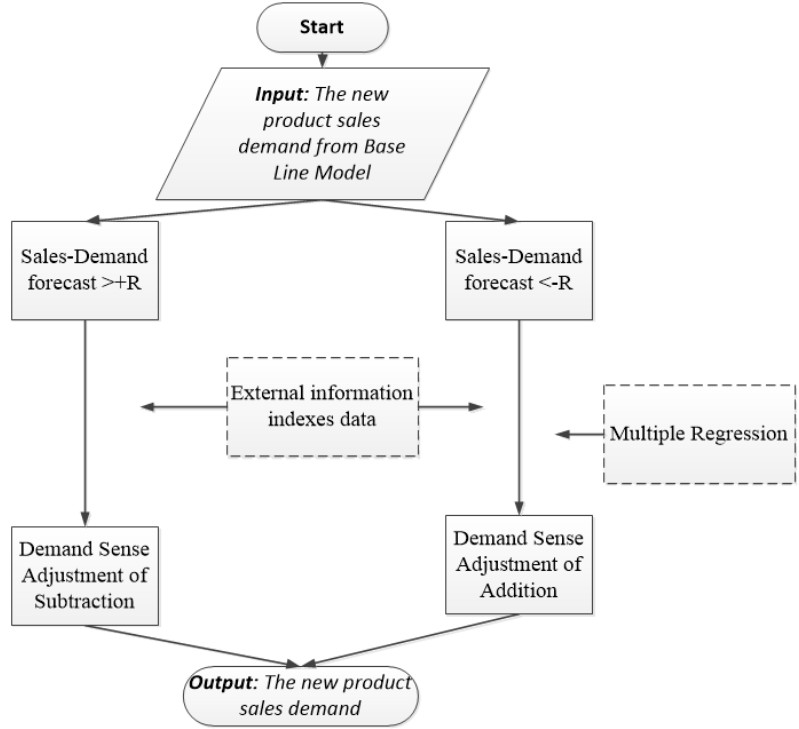

Fig. 4. Intelligent forecasting approach framework

two multiple regressions, respectively. where S^A and S^B represent addition and subtraction, respectively.

$$S^A = C_j * \alpha_j * E_j + \varepsilon_t \quad (3)$$

$$S^B = C_j * \beta_j * E_j + \varepsilon_t \quad (4)$$

$$C_j = \begin{cases} 1, contain\ element\ j \\ 0, otherwise \end{cases}, \ j = 1,2,\ldots N \quad (5)$$

E_j, as the external information indices, represent the data from three months ago to the present, where j represents the elements of the new product. $C_j = 0$ or 1 represents whether the new product contains element j. To measure the correlation between r and external information index data E_j, we set the crucial threshold value θ. α_j and β_j are set up by a regression analysis between the dependent variable of r and the regressors of external information index data E_j, which is greater than θ. Additionally, ε_t is the intercept in the regression analysis.

Finally, we design an intelligent forecasting approach, as shown in Equation (6). We combined the results of the baseline model with demand sense adjustments, including the addition and

subtraction of external information index data.

$$S_t = D + S^A + S^B \quad (6)$$

4. Numerical example

According to the forecasting steps mentioned earlier, in this section, we use actual data to compare the improvement in accuracy of different forecasting models. Section 4.1 discusses the elements filtered from the results of the data crawler and the composition of the new product design. Section 4.2 demonstrates the results of the intelligent forecasting approach with the implemented demand-sense adjustment. Furthermore, we compared the accuracy of sales predicted by the forecasting methods mentioned in Section 3 with the actual sales of new products in August.

4.1. Design new products

In this subsection, we used a web crawler on an online shopping store that specializes in women's apparel and collected the sales data of all 112 products from June

1, 2020, to July 31, 2020. We then filtered out the tops of all the products. We split the product names, discarded subjective adjectives, used objective nouns as elements, and disassembled them into 83 elements. These elements make the products different from or similar to other products. The split elements and sales volume are provided by the apparel store, which is split using natural language processing. Subsequently, designers attempted to create new products based on the popular elements. Consequently, eight items were created that could be considered new products.

The results of the element combinations for new products are as follows:

1. Item A (contains eight elements): tee, short sleeve, long version, spliced, plain, split, T-shirt, and frill.
2. Item B (contains six elements): tee, short sleeve, neck, plain, light, and shear.
3. Item C (contains eight elements): tee, plain, loose, vest, swing, crew neck, skater, and sleeveless.
4. Item D (contains six elements): tee, short sleeve, neck, plain, T-shirt, and pocket.
5. Item E (contains seven elements): tee, neck, plain, vest, full, wrap-over, and sleeveless.
6. Item F (contains seven elements): tee, short sleeve, splice, cotton T-shirt, crew neck, cap sleeve, and drape.

4.2. Baseline model and intelligent forecasting approach

Based on the new products we designed in Section 4.1, we generated forecasted sales demand in the following month (August 2020) through the baseline model and then applied an intelligent forecasting approach for adjustment. In this study, the performance of these approaches was evaluated based on the forecasting errors of new product sales in August 2020. Three evaluation metrics, the mean squared error (MSE), root-mean-square error (RMSE), and mean absolute percentage error (MAPE), were used to measure the performance of the different methods.

Item	Real Sales	Baseline Model	Intelligent Forecasting Approach
A	57	49.51	59.15
B	2	12.61	0.60
C	10	20.22	12.11
D	13	25.99	7.57
E	86	144.70	112.58
F	65	51.45	55.02

Table 1. Demand forecasting results after demand sense adjustment

	Intelligent Forecasting Approach		
	MSE	RMSE	MAPE
A	4.64	2.15	3.78%
B	1.97	1.40	70.17%
C	4.46	2.11	21.11%
D	29.45	5.43	41.75%
E	706.60	26.58	30.91%
F	99.51	9.98	15.35%

Table 2. Evaluation metrics of intelligent forecasting approach

In *the intelligent forecasting approach*, we used the constituent elements of each new product as external information indices and Google Trends to collect the search volumes of the elements. Moreover, we selected internal data with the same label as the new product and measured the correlation of external information indices by setting crucial thresholds and applying multiple regression analysis to obtain demand-sense adjustments.

Based on the results of the baseline model for each new product, we implemented an intelligent forecasting approach, the results of which are presented in Table 1. Table 2 presents the evaluation metrics used to measure the performance of each item using the intelligent forecasting approach.

The improvements in the intelligent forecasting approach relative to the baseline model are summarized in Figure 5. From the comparison of the performance of the intelligent forecasting approach with that of the baseline model, the intelligent forecasting approach was observed to be more accurate than the baseline model. The relative MSE improvement ranged from 45.79% to 98.25%, the relative RMSE from 26.35% to 86.80%, and the relative MAPE improvement from 26.34% to 94.72%, which were calculated as follows:

$$Relative\ Improvement = \frac{Baseline\ MSE - Intelligent\ Forecasting\ MSE}{Baseline\ MSE} \quad (7)$$

5. Conclusion

This study proposes a two-stage method, including suggestions and intelligent forecasting, to improve the sales forecasting of new products in the apparel industry. First, we used a web crawler to decompose the results into elements to determine which elements were popular and preferred. These results can be used as a reference by designers when designing new products. Second, we show how to predict sales demand for new products from similar items and improve the forecasting model when combined with external information indexes. The core value of this study is the application of algorithms (machine learning and web crawlers) to assist humans (designers) in making decisions (fashion design). We combine market trends with demand forecasting and external information indices to reduce forecasting errors. The results showed that compared with other machine learning models (RF and XGBoost), the intelligent forecasting approach can effectively reduce the MSE, RMSE, and MAPE by at least 45.79 %, 26.35 %, and 26.34 %, respectively. The
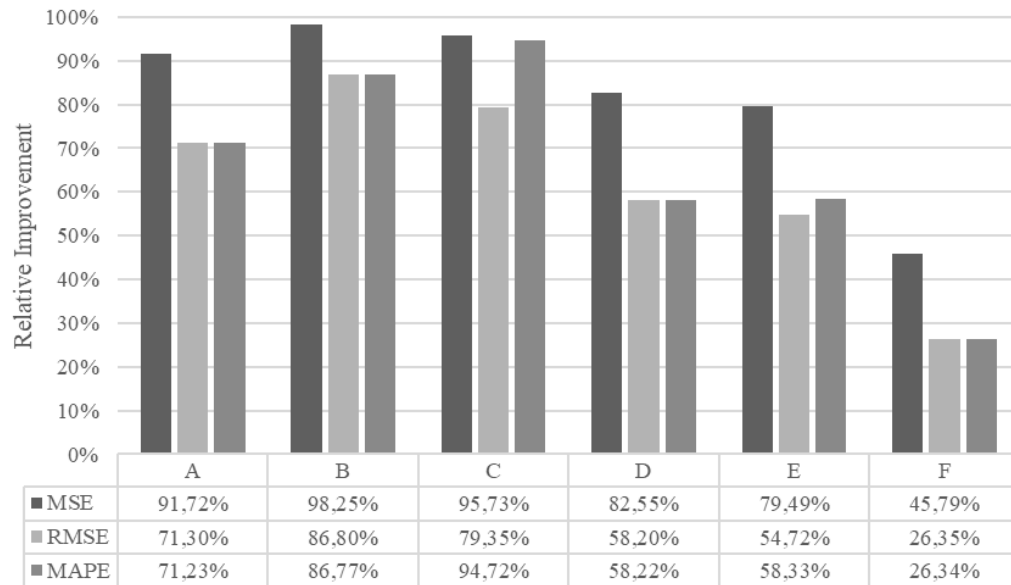
	A	B	C	D	E	F
■ MSE	91,72%	98,25%	95,73%	82,55%	79,49%	45,79%
■ RMSE	71,30%	86,80%	79,35%	58,20%	54,72%	26,35%
■ MAPE	71,23%	86,77%	94,72%	58,22%	58,33%	26,34%

Fig. 5. Relative improvement for different forecasting models

intelligent forecasting approach proposed can be an effective method for the B2C industry to forecast new product demand. Our proposed model is useful and suitable for the fashion industry, where the selling period is shorter than a few months and designers should design new products as soon as possible.

The demand forecasting method used in this study can be studied further. We provide the following suggestions: Based on this forecasting method, we can forecast the sales demand of products throughout their life cycle. This study uses a machine learning-based method with implemented demand-sense adjustments. In future studies, we plan to conduct experiments with additional machine learning algorithms to enhance the performance of the baseline model. External information indices can also be obtained from other aspects, such as observing people's recent preferences on other social media sites. In addition to investigating the search volume for new product elements in the apparel industry, it can also be extended to product styles or colors. This study uses nondigital product elements or features to make predictions. In the future, we may consider verifying whether this method can be applied to other products that are also represented by product features. Furthermore, it is not limited to the fashion industry, but can be tested in other B2C industries or supply chain network design problems [23-25].

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