

A Sales Prediction Model Adopted the Recency-Frequency-Monetary Concept

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Abstract

Predicting future sales is intended to control the number of existing stock, so the lack or excess stock can be minimized. When the number of sales can be accurately predicted, then the fulfillment of consumer demand can be prepared in a timely and cooperation with the supplier company can be maintained properly so that the company can avoid losing sales and customers. This study aims to propose a model to predict the sales quantity (multi-products) by adopting the Recency-Frequency-Monetary (RFM) concept and Fuzzy Analytic Hierarchy Process (FAHP) method. The measurement of sales prediction accuracy in this study using a standard measurement of Mean Absolute Percentage Error (MAPE), which is the most important criteria in analyzing the accuracy of the prediction. The results indicate that the average MAPE value of the model was high (3.22%), so this model can be referred to as a sales prediction model.

Keywords: sales prediction model, multi-products, RFM, FAHP

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1. Introduction

Predicting the number of sales is an activity to estimate the amount of sales of the product by the manufacturer or distributor for a time period and area specific marketing. Predicting sales is also part of the functions of management as one of the contributors to the success of a company. Due to the company's failure to provide the product may have negative implications on the level of service to the consumer so that will reduce the competitiveness of the company. As a result, corporate profits will be reduced, because the consumer will choose the company that can meet their needs.

Predicting the number of sales is not a simple recharging, but the management and control of scientific and effective way to improve enterprise management and market penetration capacity, optimization of customer service, fast and coordinated as well as economic benefits for the company.

Predicting excessive or inaccurate sales can lead to inventory-related cost issues, resulting in inefficient investment. Therefore, it takes an economic model that can be used to predict the number of sales in order that inventory costs become more efficient, service to consumers could be improved and provide a significant competitive advantage for the company.

To answer these problems, this study will propose to construct a model that can predict the sales quantity by adopting the RFM concept.

Recency, frequency and monetary (RFM) were a powerful and well-known concept in database marketing, and were widely used to measure the value of customers based on their prior purchasing history. The RFM concept had also been successfully integrated into the mining process in the past few years [1-3], giving rise to the idea that the RFM concept also can be applied to predict sales based on prior sales history.

In previous studies, the number of sales could be predicted by using a variety of methods, such as the neural network [4-6], model predictive control [7-8], ABC analysis [9-10], support vector machines [11] or data mining [12-15].

While, generally the RFM model was applied to analyze customer behavior [3], [16-18] so that it could identify valuable customers in a company. Particularly, direct marketing had a long history in using the RFM model.

There are several studies have discussed the different versions of RFM analysis and by introducing additional variables. For example, RFV (Recency, Frequency, Value) version was proposed to choose the number of segments and the time frame used in such a way as to maximize the results of direct marketing campaigns [19].

King [20] suggested that when the focus is on citizen segmentation, RFM model should be changed to RFC (recency, frequency and cost) version, as cost is direct financial cost, in providing services to the citizen and indirect quality of life costs to citizen or those affected by the citizen's actions.

Another version, Maskan [21] and Hu et al. [22] in Weighted RFM (WRFM) version, each R, F, M value was multiplied by a weight value, wR, wF and wM according to its relative importance to make intuitive judgments about ranking ordering. LRFM (length, recency, frequency, and monetary) version was proposed by adopting self-organizing maps (SOM) technique for a children dental clinic in Taiwan to segment the patients [23].

Hosseini et al. [24] proposed a procedure according to the expanded RFM model by adding one additional parameter, period of product activity, to classify customer product loyalty under B2B concept. The findings showed that the developed methodology for CRM produces better results than other commonly used models.

Yeh I-C et al [25] expanded RFM model to RFMTC version by adding two parameters, namely: time of the first purchase and churn probability. Using Bernoulli sequence in probability theory, they developed a formula that can estimate the probability of the customer purchasing again, and the expected value of the total number of times that the customer will purchase in the future. Adding these two parameters has provided more predictive accuracy than RFM model.

Meanwhile, the benefits that can be gained from this study are: (1) can be an alternative model to predict the multi-products sale in the future, which is the basis for useful input for management to look at the future sales prospects, so that management can predict the economic benefit the company in the future; (2) may contribute to the development of predictive systems multi-product sales by using a new approach.

2. Research Method

The study integrates RFM concept and FAHP method to predict sales quantity. Figure 1 illustrates the IPO (Input, Process and Output) diagram of the proposed model. The model consists of seven major parts: the opinion of experts, FAHP method, adoption of RFM concept (the scoring of criteria, the scaling of criteria), original database, data pre-processing, and sales quantity prediction with their evaluation processes. Each part of the approach is applied one after another. The output of each part becomes the input of the next part(s).

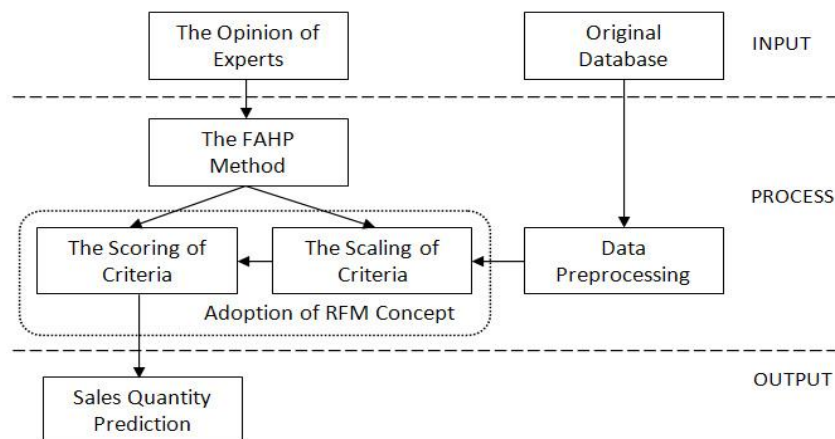


Figure 1. IPO (Input, Process, Output) diagram of the proposed model

The detailed process of each part is expressed as follows:

2.1. The Opinion of Experts

This step is the step of taking the opinion of the experts who are directly involved with the sales process in the company. Capturing the opinion of these experts is conducted using questionnaires. The questionnaire contains criteria that affect the company's sales system. The results of this questionnaire processing are classification criteria that influence the sales process.

The criteria are derived from the results of this questionnaire will be the basis of further questionnaire development for pairwise comparisons matrix between the criteria for each criterion. Further questionnaire would be given also to the experts in advance, so that the values obtain pairwise comparisons for each of the criteria. The values of pairwise comparisons will be normalized and will be analyzed by the Fuzzy Analytic Hierarchy Process (FAHP) method. The FAHP method is adopted to minimize subjectivity of the expert's assessment matrix [26].

2.2. The Method of Fuzzy Analytic Hierarchy Process (FAHP)

The FAHP method was the insertion of fuzzy theory into AHP method developed by Thomas L. Saaty (2008) in the 1970s [27].

The FAHP method was a further analysis of AHP to overcome uncertainty and ambiguity in human decision to the next level [28]. The FAHP method was designed to solve complex problems involving multiple criteria.

An advantage of the FAHP is that it is designed to handle situations in which the subjective judgments of individuals constitute an important part of the decision process. FAHP method is used to determine model variables and its weight.

The FAHP method using Triangular Fuzzy Number (TFN) for pair wise comparison of criteria and alternatives made through linguistic variables [27]. TFN and linguistic variables are corresponding to the Saaty scale shown in Table 1 [29].

Table 1. Definition and Function of TFN [29]

Saaty Scale	Fuzzy Num.	Definition	Membership Function
1	~ 1	Equally important	(1, 1, 3)
3	~ 3	Moderately more important	(1, 3, 5)
5	~ 5	Strongly more important	(3, 5, 7)
7	~ 7	Very strongly more important	(5, 7, 9)
9	~ 9	Extremely more important	(7, 9, 11)
2, 4, 6, 8		Intermediate Values	(1, 2, 3), (3, 4, 5), (5, 6, 7), (7, 8, 9)

TFN in Table 1 denoted by $M = \{l, m, u\}$, where M is the set of fuzzy numbers, whereas l , m and u , respectively declared the smallest possible value, the value of the closest, and the greatest possible value. The value of l , m , and u could also be determined by the decision itself [15].

Scale pairwise comparisons could apply TFN, having the consistency of the hierarchical model has been tested in advance by calculating the value of Consistency Ratio (CR) by Equation (1), and its value should be less than 10%. If the value is more than 10%, then the assessment procedure has to be repeated and improved to increase consistency.

$$CR = \frac{CI}{RI} \quad (1)$$

Where CR is the Consistency Ratio, CI is the Consistency Index; RI is the Random Index for each matrix has order n .

Consistency Index (CI) of the matrix pairs could be calculated with the Equation (2).

$$CI = \frac{\lambda_{\max} - n}{n - 1} \quad (2)$$

Where CI is Consistency Index, λ_{\max} is the largest eigenvalue of the matrix has order n , and n represents the number of elements compared/order of the matrix.

In the FAHP method, if $X = \{x_1, x_2, x_i, \dots, x_n\}$ represents a set of objects and $G = \{g_1, g_2, g_j, \dots, g_m\}$ represents the set of goals and there were a number of criteria that would m used for analysis are obtained $M_{gi}^1, M_{gi}^2, M_{gi}^j, \dots, M_{gi}^m, i = 1, 2, \dots, n$, where the whole $M_{gi}^j (j=1,2,\dots,n)$ is the TFN [30].

The main steps in the FAHP method as follows [30]:

- Step 1** : Calculate the value of fuzzy synthetic extent (S_i) using criteria to i ;
Step 2 : Calculate the degree of possibility of $S_2 = (l_2, m_2, u_2) \geq S_1 = (l_1, m_1, u_1)$, comparison between S_1 and S_2 requires the value of $V(S_2 \geq S_1)$ dan $V(S_1 \geq S_2)$;
Step 3 : Compare the degree of possibility among criteria fuzzy numbers $M_i (i = 1, 2, \dots, k)$;
Step 4 : Compute the vector W' , then it is normalized, so that obtained normalized weight vector as shown in Equation (3). Finally, sort the weight W in descending.

$$W = (d(A_1), d(A_2), \dots, d(A_k))^T \quad (3)$$

Where W is not a fuzzy number for each comparison matrix.

2.3. Original Database and Data Pre-processing

Data preparation is one of the most important and often time-consuming aspects of data mining projects. Data pre-processing step is needed to make knowledge discovery easier and correctly. Data pre-processing such as reduction in dimensionality reduction, normalization, feature selection, data transformation, and concept hierarch generation significantly could improve the model. In fact, a further increasing the prediction accuracy and saving in elapsed time.

In this step, the following operations should be made [31]:

1. Dimensionality Reduction: Unnecessary attributes should be deleted, such as attributes that have only a few values (the others are null) or have only single value;
2. Filling: Missing values should be filled in using an appropriate approach;
3. Handling: Outliers and inaccurate values should be handled and removed from the dataset;
4. Transformation: Data should be transformed into an appropriate format.

A result of data pre-processing step is the sales transaction dataset.

2.4. The Concept of Recency-Frequency-Monetary (RFM)

The concept of RFM was introduced by Bult and Wansbeek (1995) and has proven very effective [32] when applied to marketing databases, and to measure customer behavior in accordance with their previous purchase history. They define RFM terms as follows:

Recency (R) is the time interval between the last and the current transaction, where many direct marketers believe that most-recent purchasers are more likely to purchase again than less-recent purchasers. The lower the time interval, then the higher is the recency value of customer.

Frequency (F) is number of purchases made within a certain period. This value is used based on the assumption that customers with more purchases are more likely to buy products than customers with fewer purchases. The higher the amount of purchases in the interval, then the higher is the frequency value.

Monetary (M) refers to the amount of money spent during a certain period. The higher the total money spends in the interval, then the higher the monetary value [12-13]. The three behavioral attributes, Recency, Frequency, and Monetary are simple method, in that they could be easily computed for any database according the purchase history, and are easy to understand, also very powerful in their predictive ability [13].

By adoption of the RFM concept is as a base using three criteria. Three criteria with the greatest weight (α, β and γ), which is the calculation results using the FAHP method would be defined the scaling.

2.5. The Scaling of Criteria

In this step, the RFM concept is applied by defining the scaling of the selected criteria. This process is divided into three parts as follows [3]: (1) Sort the data of the three selected criteria in descending or ascending, (2) Partition the three criteria respectively into 5 equal parts and each part was equal to 20% of all. The five parts are assigned 5, 4, 3, 2 and 1 score that refer to the transaction dataset. The top 20% part is assigned as 5, while the next 20% part is assigned as 4 and so forth. For example, the '5' refers to the most frequency of products sold per month, while '1' refers to the least frequency of products sold per month, (3) Repeat the previous sub-processes (1 and 2) for each criteria individually.

In summary, the main result of this process is to define the scaling of the three selected criteria for scoring.

2.6. The Scoring of Criteria

The real purpose of the scoring of criteria is to project customer behavior. In this study, the scoring of criteria is to project how many scores of each criterion (refer to scaling table) for each product.

The score of each product should be calculated as follows: product score = (criteria-1 weight x criteria-1 score) + (criteria-2 weight x criteria-2 score) + (criteria-3 weight x criteria-3 score).

Further, the score of each product could be defined as Equation (4), where α , β and γ show FAHP weight of each criterion, and V_1 , V_2 , V_3 are the score of the criteria derived from the table of scaling. The product score would be a multiplier factor of the products to be predicted its products quantity [14].

$$\text{Product score} = \alpha .V_1 + \beta .V_2 + \gamma .V_3 \quad (4)$$

2.7. Sales Quantity Prediction

The prediction of sales quantity for the next month could be generated by multiplying the product quantity with the product score of this month. Thus, the sales data in this month become the basis for predicting sales of each product in the coming month by taking into account external factors (product score).

2.8. Measurement of Results Prediction

In fact, there is no prediction has an accuracy rate of 100%, because every prediction certainly contain errors. Therefore, to determine the prediction method that has a high degree of accuracy, it is necessary to calculate the error rate in the prediction. The smaller of error margin is generated, the better the prediction method. Calculation of the prediction error is also the calculation accuracy in the measurement [33].

The general standard of measurement used prediction error is the mean absolute error (MAE) for accuracy, and the mean absolute percentage error (MAPE) to the percentage of accuracy [10], [34].

$$\text{MAE} = \frac{1}{n} \sum_{t=1}^n |A_t - F_t| \quad (5)$$

Where A_t is actual value at the time to t , F_t is predicted value at time to t , and n is lots of data.

$$\text{MAPE} = \frac{1}{n} \sum_{t=1}^n \left| \frac{A_t - F_t}{A_t} \right| \quad (6)$$

Where A_t is actual value at the time to t , F_t is predicted value at time to t , and n is lots of data.

MAPE is used a great deal by both academicians and practitioners and it is the only measure appropriate for evaluating budget forecasts and similar variables whose outcome depended upon the proportional size of errors relative to the actual data [35].

MAPE is also often useful for purposes of reporting, because it is expressed in generic percentage terms that would be understandable to a wide range of users. MAPE value is used to analyze process performance prediction as shown in Table 2 [36].

Table 2. MAPE Value for Prediction Evaluation [36]

MAPE Value	Prediction Accuracy
MAPE ≤ 10%	High
10% < MAPE ≤ 20%	Good
20% < MAPE ≤ 50%	Reasonable
MAPE > 50%	Low

3. Results and Analysis

This section presents a case study that shows how the model proposed in this study applied to the real world by using real data from a pharmacy. All steps of the proposed model are expressed in details as follows:

3.1. Data Description

The dataset used in this empirical study was imported from a database of pharmacy-X consisting of the products table included 6,877 items in 2 types of products, the sales orders table included 127,047 transactions, the sales orders detail table included 399,738 transactions, and the products quantity sold included 3,956,683 products from January to December 2015. The average of sales orders per month was 10,587, the average of products quantity sold per month was 329,724, and the average of sales orders size per month was Rp 1.223.481.963.

3.2. Experts Opinion

We invited five experts who were responsible for the sales process in the pharmacy; the pharmaceutical analyst (FA), manager of the stock (MS) and the administration of the stock (AS) to determine the important criteria influencing the sales process. All five experts were asked to create and choose the criteria that influence the sales process.

After all of the criteria were obtained and only the criteria selected by an expert or null were eliminated, it would be obtained the recapitulation as shown in Table 3. These criteria would be the basis of making a further questionnaire about pairwise comparison matrix for each criterion, and then be processed using FAHP method.

Table 3. Recapitulation Criteria

No	Criteria	Experts				
		FA1	MS1	AS1	MS2	AS2
<i>Factors associated with Products</i>						
1	Monetary – K ₁	x	x	x	x	X
2	Lead time – K ₂	x	-	x	-	-
3	Quantity – K ₄	x	x	x	-	X
4	Season – K ₈	x	x	x	-	X
<i>Factors associated with Operator</i>						
5	Services to customer – K ₁₂	-	x	x	-	-
6	Check of stock – K ₁₃	x	-	x	-	-
7	Discount – K ₁₇	x	x	x	-	-
8	Management polish – K ₁₉	x	x	-	-	-
9	Speculation – K ₂₀	x	-	x	x	-
<i>Factors associated with Process</i>						
10	Frequency – K ₁₅	x	x	x	x	X

Where :

- FA1 : Pharmaceutical analyst at the pharmacy-X x : selected
- MS1 : Stock Manager at the pharmacy-X - : not selected
- AS1 : Stock Staff at the pharmacy-X
- MS2 : Stock Manager at the pharmacy-Y
- AS2 : Stock Staff at the pharmacy-Y

3.3. The FAHP Method

The entire value of the resulting pairwise comparisons would be normalized before checking the value of CR (Consistency Ratio) by Equation (1), where the value of RI (Random Index) was 1.49.

After the entire value of $CR < 10\%$, then the value of pairwise comparisons could be expressed with Triangular Fuzzy Number.

The initial step in FAHP method was to define the value of fuzzy synthetic extents (S_i) with criteria i through the fuzzy addition operation. Then, the operating results of this fuzzy addition were calculated the inverse to be (0.003, 0.006, 0.011) for FA1, (0.003, 0.005, 0.010) for MS1, and (0.003, 0.006, 0.010) for AS1.

The next step was to calculate the contingency degree of two TFN, so that obtained the value of the contingency degree.

Assuming $d(S_i) = \min V(S_i \geq S_k)$ for $k = 1, 2, \dots, k; k \neq i$, so that the values of the weight vector obtained, and then the values of the weight vector normalized using Equation (3). The results of the ranking based on the weight values could be indicated in Table 4, where the weights of MQF were (0.154, 0.153, 0.142).

Once the weights were normalized, it would be obtained (0.343, 0.341, 0.316) as (α, β, γ) .

Table 4. Ranking Criteria Based on Weight

Weight	Criteria	Description	Value	Rank
W_1	K_1	Monetary	0.154	1
W_2	K_2	Lead time	0.097	6
W_3	K_4	Quantity	0.153	2
W_4	K_8	Season	0.100	5
W_5	K_{11}	Services	0.066	9
W_6	K_{13}	Check of stock	0.103	4
W_7	K_{15}	Frequency	0.142	3
W_8	K_{17}	Discount	0.078	8
W_9	K_{19}	Management	0.087	7
W_{10}	K_{20}	Speculation	0.019	10

3.4. Data Pre-processing

Dataset used in this case study was provided by a pharmacy and collected through its database within one year period (from January to December 2015). The complete dataset included 6,877 items product in 2 types of products, 127,047 sales orders, and 399,738 sales orders detail. The sales orders included many columns such as no receipt, ordering date, customer id, sales type, doctor id, product type, status, no invoice, timestamp. While, sales orders detail table included no receipt, product id, quantity, net price, gross price, discount, expire date, tax, dose, storage id, and doctor fee; product table included attributes such as barcode, product name, factory id, category, composition, unit, price, and minimum stock.

Data pre-processing step to fill missing values and makes dimensionally reduction, transformation, concept hierarchy generation, and normalization.

The attributes were derived from the tables of sales master and sales detail, unnecessary such as customer id, doctor id, invoice number, etc. were clearly unfit to be used in the transaction dataset will be discarded. Thus, only five attributes, namely ordering date, product id, monetary, quantity and frequency that would be used to build a sales transaction dataset.

Monetary attribute filled with multiplication of quantity and selling price for each product per month. Quantity attribute was the total of sales quantity per product per month, and frequency attributes transformed of the number of sales orders per product per month.

This study would take a historical data that includes 399,738 sales transactions using MQF criteria, and strip away any unused data. The partial data of pharmacy-X dataset was shown in Table 5.

Table 5. The Partial Data of Pharmacy-X Dataset

Month	Product Id	Monetary	Quantity	Frequency
1	AI-0024	14,545	47	5
1	AI-0025	118,166	292	16
...
12	AI-0190	62,952,465	22,333	664
12	AI-0853	1,974,474	46,402	248

3.5. MQF Scaling

By adoption of the RFM concept, this study produced three criteria consisting of monetary (M), quantity (Q), and frequency (F) as attributes. Monetary represents the total of sales transactions per month in millions of rupiah, Quantity was the number of products sold per month, and Frequency was the amount of products sold per month.

Each attribute would be divided into five parts. For quantity and frequency, the '5' refers to the most attributes, while '1' refers to the least attributes, but for monetary, on the contrary.

From the transactions dataset, obtained that the most value for quantity in month was 20,419 and the least value for quantity in month was 0. The most value for frequency in month was 1,726 and the least value for frequency in month was 0. The most value for monetary in month was 0 and the least value for monetary in month was 24,510,046; so that the scaling of MQF attributes in dataset of pharmacy-X as shown in Table 6.

Table 6. The Scaling of MQF Attribute

Score	Monetary (in thousands)	Quantity	Frequency
5	Under 4,902	Over 16,335	Over 1,381
4	4,902–9,804	12,251 – 16,335	1,036 – 1,381
3	9,804–4,706	8,168 – 12,251	690 – 1,0336
2	14,706–19,608	4,084 – 8,168	345 – 690
1	Over 19,608	Under 4,084	Under 345

3.6. MQF Scoring

The data partial scoring of MQF attributes based on Table 5 and Table 6 for each pharmaceutical product per month as shown in Table 7.

Table 7. The Scoring of MQF Attributes for Pharmacy-X Dataset

Month	Product Id	M	Q	F	Score
1	AI-0024	5	1	1	2.372
1	AI-0025	5	1	1	2.372
...
12	AI-0190	1	4	2	2.339
12	AI-0853	5	4	1	3.395

3.7. Testing and Evaluation

Testing was conducted as follows: (a) predicting sales quantity of each pharmaceutical product per month; (b) to calculate the difference between the predictive sales data and actual data to obtain the values of MAE and MAPE using Equation (5) and (6); and (c) to calculate the percentage of the average error of MAE and MAPE, in order to obtain the calculation results as shown in Figure 2.

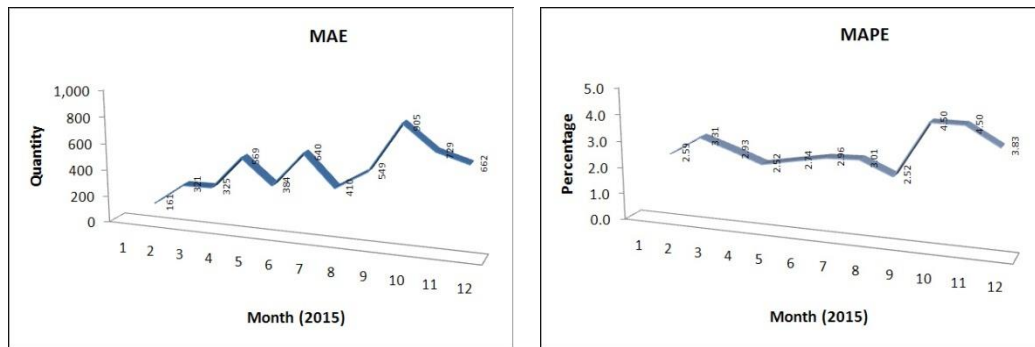


Figure 2. Calculation Results Mean Prediction Error of Pharmaceutical Product

Figure 2 illustrates that the average of the mean absolute error (MAE) for the prediction of the sales quantity was 514.06 and the average of the mean absolute percentage error (MAPE) for the prediction of the sales quantity was 3.22%. Referring to Table 2, the prediction accuracy for the model was high, because the value of $MAPE \leq 10\%$, so the results of this evaluation could contribute to the development of sales prediction system of pharmaceutical products in pharmacy.

4. Conclusion

These results indicated that mean absolute percentage error (MAPE) for the prediction of the sales quantity was high (3.22%). This means that the model can be used to predict the sales quantity of pharmaceutical products in pharmacy, so it can be an alternative solution to improve the efficiency of inventory management in pharmacy. Further research can compare different prediction methods such as artificial intelligence and so on to get the most accurate method to predict the sales quantity, especially with data patterns such as case study in this research. Because, in general, we expect that the proposed model can become a generalization is not a specialization for all datasets.

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