Iranian Journal of Operations Research
Vol. 13, No. 2, 2022, pp. 96-120
DOI:

Factors Affecting Demand Predict to Reduce Bullwhip Effect in Supply Chain

Milad Rezaeefard[1], Nazanin Pilevari[2*], Farshad Faezy Razi[3], Reza Radfar[4]

Demand planning based on demand data in the supply chain includes the most significant steps in production planning. Therefore, the supply chain's correct demand forecasting may reduce this effect, known as the bullwhip effect or uncertainty concerning customer demand, thus reducing companies' and organizations' costs and surplus activities. Therefore, this article examined the statistical population characteristics to test the hypotheses through the path analysis drawn using descriptive statistics and FCM(fuzzy cognitive map) method. Then, the model strength was investigated using structural equation modeling (SEM) in AMOS software, and structural equations were presented. This article selected the Aftab oil factory as a case study. The findings of this study emphasized that demand management performance is highly essential for industries. Companies can design the sector independently as a demand management sector for evaluating customer demands at different levels of the supply chain. According to the fit of the main model, CFI and NFI indices are equal to 0.99 and 0.97, respectively, which are close to the optimal fit threshold. RMSEA and SRMR indices are equal to 0.01 and 0.01, respectively, both showing a relatively good fit of the model.

Keywords: *Supply Chain, Customer Demands, FCM 0ethod, Bullwhip Effect, Surplus Activities, Structural Equation Modeling*

Manuscript was received on 10/11/2022, revised on 03/06/2023 and accepted for publication on 05/30/2023.

[1] PhD Student of Industrial Management, Department of Industrial Management, Faculty of management and economics, Science and Research Branch, Islamic Azad University, Tehran,Iran.
Email: milad.rezaeifard@yahoo.com
*Corresponding author:
[2] Associate Professor of Industrial Management, West Tehran Branch, Islamic Azad university, Visitor Professor of Science and Research Branch, Tehran, Iran. Email: nazanin.pilevari@gmail.com
[3] Associate professor of Industrial Management, Semnan Branch, Islamic Azad University, Semnan, Iran.
Email: f.faezi@semnanian.ac.ir
[4] Professor of Industrial Management, Science and Research Branch, Islamic Azad University, Tehran, Iran. Email: reza.radfar@uwe.ac.uk

1. Introduction

Over recent decades, supply chain management has been extensively researched.This field significantly evolved between 1970 and 2000 with the advancement of communication technologies and the fading of strict geographical borders, which had exposed most businesses to more competitive environments, and even made them realize that operational or financiasuperiority was not enough to win competitions and attract or retain more customers(Moradi et al., [16]).

Over the past two decades, managers have witnessed change and turning points in technological advances, the globalization of markets, and economic and political stabilization. Furthermore, the increased number of global competitors has urged organizations to rapidly improve their internal processes to remain competitive. Thus, companies have had to focus on their market strategies, advanced engineering, excellent design, and strong support to retain their customers over the years (Ashfaq et al., [1]). Manufacturing organizations were forced to increase flexibility and actionability in modified products and processes, and even develop new products to respond to the customers' changed requirements (Van Nguyen et al., [31]). Today's competitive global market requires to act based on the customer's demand in terms of quality, speed, and fast service. Therefore, such pressures on companies have enabled them to fulfill everything. Besides, all these movements act as vital information to strongly affect the supply chain (Lima-Junior and Carpinetti, [13]). No business can perform supply chain activities on its own, and all these companies look for more profits, increased market share, and reduced production costs. A supply chain involves one or more separate entities connected by the flows like financial, information, and materials(Song et al., [27]). The ideal for companies and organizations is full coordination in this chain. Changes in customer demand include problems for all organizations leading to uncertainty in the amount of production and purchase of raw materials and in general the supply chain (Murray et al., [17]). In addition, in the global competition market, the importance of SCM is increasing daily. Maximizing the profit and minimizing the cost are the main factors which play important roles in the supply chain. Furthermore, it is important to make the model optimal for both consumers and the manufacturer(Uddin et al., [30]) The supply chain is defined as a system for converting raw materials, transportation of products, and purchases between different levels of supplier and customer (Sajedi et al., [23]) (Fu et al., [5]). The most efficient solution to this complicated problem is customer demand forecasting at a sufficient time before its occurrence, especially when production affects stocks. Thus, supply chain forecasting is the first step in production planning (Li et al., [12]). Forecasting is an inevitable part of decision-making, with many decisions based on forecasting unknown future events (Nandra et al., [18]). Demand forecasting refers to future customer demand for a given product forecast which can be conducted based on historical production data. Demand forecasting plays a significant role in supply chain decision-making. In addition, it represents an essential step for activity planning in response to customer demand (Hofmann and Rutschmann, [7]). All forecasting methods include general needs, including appropriate inputs constituting the information to be extracted, interpreted, or forecasted from demand behaviors (Kara et al., [10]). Recently, time-based forecasting and metaheuristic algorithms have been the safest and most reliable methods of all forecasting methods. Accordingly, this article investigates the demand forecasting implementation methods using metaheuristic algorithms. Moreover, this paper examines how this model reduces the bullwhip effect on the supply chain.

The significance and inevitability of sustainable development concerning the strong dependence of industries on their surrounding environment necessitate the issue of demand forecasting in supply chain planning. So far, no research has been conducted to identify indicators and reduce the bullwhip effect through research methods in soft operations.

1.1. The bullwhip effect

The unmanaged supply chain is utterly unstable followed by the frequent problem of the bullwhip effect. This effect causes a fluctuation in the supply chain, the main cause of which is changes in the demand rate. Additionally, the network can fluctuate significantly(Schwieterman et al.,[25]). Every organization in the supply chain attempts to solve the problem from their point of view, known as the bullwhip effect considered by all industries with effects including increasing costs and service level weakness (Taghikhah et al., [29]).

1.2. Litreature review

Ietto et al., [8] in an article titled "Demand Forecasting" tried to predict demand using online information generated by users and based on finding key points in past research. They concluded that their findings differ from previous studies. In this study, they found that predictive criteria such as exponential distribution have better performance in the case of online information.

Sarkar et al., [28] tried to predict the demand of the air transport industry using the hybrid approach of ARIMA and support vector regression. The hybrid model proposed in this study can be used for future management capacities and target planning. The time series in this study has been analyzed by S. Arima. In the following, four hybrid models are used to predict future statistical indicators in this industry. The study results indicate that the research model shows better results than other methods.

Pereira and Frazzon, [19] examined the success factor affecting demand management and distribution management with a customer-centric approach. This article considered the customer as the main element of the supply chain. Additionally, each industry had correctly defined distribution and demand management. Also, the supply chain management type had a special effect on distribution and demand management. The flexible managers were more successful and effective in supply chain performance. Jiang [9] and Rahmani and Yavari[21] presented a model for customer demand forecasting for cabins in transport companies. The results showed that forecasting by using the time series modelling method presents the best results with the least error in MAD, MSE and MAPE. Rabbani et al., [20] developed distribution chain supply and demand management solutions for entrepreneurial systems in Pakistan. They defined four models in detail. In addition, they expressed the supply chain management structure in detail and conducted the management strategies in each entrepreneurial institution. they concluded the following:

1. There is a real relationship between committed suppliers and final products and services.
2. Entrepreneurs can be useful suppliers for offering the final products and services
3. High-efficiency work can attract customers.
4. Demand management can affect all levels and has a real relationship with the goodwill and reputation of entrepreneurs (Ritech, [22]).

Brintrup et al., [3] developed a production model for developing supply chain independence in demand management analysis and interpretation. They draw a model in which new inventories were imported with new demands. They presented a useful relationship between the buyer, who is the demander, and demand management. Furthermore, they considered the lowest cost of sending the end products and services to the end customer and created policies that maintain efficiency and optimal time. Further, they addressed flexibility as the key to the success of demand management in the supply chain.

Salmela et al., [24] examined manufacturing engineering in the automotive industry with a demand management approach to BTO engineering in Britain. They distributed questionnaires among 180 buyers in the automotive industry. They emphasized that their demand for buying cars is based on their income and also created segmentation units for constructing different cars according to their income. Mirmohammadi and Sahraeian [15] designed a network for distributing customer demand in the network and determining the number of products for displacement. They further measured its performance using the ANOVA. The results indicated that the returned products at medium quality lead to lower costs and higher social benefits and the NSGA II exploration method is efficient because it creates job opportunities and leads to lower economic and environmental costs (Salmela and Huiskonen, [24]). Liu et al., [14] conducted a study on entrepreneurial enterprises about how demand for services and final goods is reflected in China. They concluded that customer orientation is the result of using customers' feedback and the point that they should be flexible.

See-To and Ngai [26] conducted a study to create a two-stage model in the supply chain with a demand-oriented approach. This study attempted to investigate the existing problems in the telecommunication, post, and telegraph industries. The work should be distributed in these industries without intermediaries. Profitability can be distributed in this way and reach the distributor and additional intermediaries in the supply chain can be eliminated, creating an environmental and physical exchange between the first distributor (manufacturer) and the end customer.

Ashfaq et al., [1] examined various existing policies such as inventory in hand, total inventory, and inventory-slave policy in a two-tier chain with a fixed usage pattern and showed that existing policies are in the hands of an unstable policy, while the other two policies remain stable. They also examined the effect of these two policies on ordering and existing changes.

Nandra et al., [18]) studied price fluctuations in the bullwhip effect in the supply chain, and the rate of price change in addition to its whipping fluctuations. This paper presented a mathematical model to investigate the effect of the price change speed due to the whip (in the supply chain) using the Lyapunov coefficient. The results of the coefficient showed the bullwhip effect affects the speed of fluctuations and the price comes to be evaluated.

Supply chain management looks at the supply chain and the organizations within it as a whole. This management provides a systematic way to manage the various activities required to coordinate the flow of products and services to provide better services to the end customer(Gong et al.,. [6]). The work creates the possibility of conflict between them. Efficient supply chain management requires a simultaneous improvement in the level of customer service and the efficiency of the internal activities of the member companies of the chain. A high level of customer service means a high rate of supply of orders, a high rate of timely delivery, and a low rate of return products from customers. In contrast, internal efficiency for supply chain organizations means that these organizations have a favorable rate of return on investment. Managers have found ways to reduce their operating and sales costs. Today, with the increasing development of management methods, supply chain management, and logistics are recognized as the basis of business. Various techniques in supply chain management have been proposed to prevent problems caused by the increasing expansion of goods and services exchanges in different dimensions and angles. Studies have shown that companies that integrate their processes with the advancement of information technology are more responsive to market changes and have more flexibility. In its simplest form, a supply chain consists of a company and its customers and suppliers. This set is a basic group of members that creates a simple supply chain. There are three other types of members in extended supply chains. The first is that at the beginning of these supply chains, the supplier or the initial supplier, and the second is that at the end of the chain, the customer or the end customer. Finally, there is a whole category of companies that serve each other in these chains. These companies offer services such as logistics, finance, marketing, and information technology.

Many studies have addressed supply chains, and this shows the importance of the subject and the competition between the supply chain, which itself consists of several companies. Some important cases in previous studies include trying to reduce the bullwhip effect in the supply chain, which is possible by predicting the correct amount of customer demand. Also sharing information in the supply chain can reduce the bullwhip effect. Supply chain management is the other important factor in this relationship. These studies have shown that the management of the supply chain is a combination of science and art. Important elements are effective in the efficiency of the supply chain, and the integration between these elements has a tremendous impact on their effectiveness and efficiency.

Most previous studies have mainly forecast customer demand based on time series models, such as moving average, exponential smoothing, and Box-Jenkins method (ARIMA), and causal models, such as regression analysis, and econometric models. In this article, we are looking to improve the accuracy of the model prediction and reduce the error in the previous models to help make accurate and very close-to-reality predictions and also reduce the bullwhip effect in the supply chain.

2. Method

This article investigates the bullwhip effect in the multi-product supply chain. Thus, first the almost ideal demand system was used to calculate the demand equations for estimating demand variance and use the moving average method and retailer demand at the expected time to calculate the forecasted orders and also calculate the bullwhip effect. In general, most of the studies on the bullwhip effect have addressed single products companies. This paper examines the bullwhip effect on several products companies by estimating the product demand equations.

In a three-level supply chain, the bullwhip effect is (Fanoodi et al.,[4]):

$$BE = \frac{Var(Q_t)}{Var(D_t)} \tag{1}$$

($Var\ Q_t$) :Variance of distribution center orders to the manufacturer

($Var\ D_t$): Retailer demand variance

Canela and Siansimino proposed another equation as follows:

$$OVR = \frac{Var(Q)/\mu_Q}{Var(D)/\mu_D} \tag{2}$$

In fact, OVR indicates order instability in the supply chain.

$V(Q)$ and μ_Q show the variance and average order of the distribution center and $Var(Q)$ and μ_D indicate the variance and the average retailer demand.

If the value of the mentioned equation is equal to or less than one, the bullwhip effect is removed from the supply chain and it occurs when demand and order fluctuations are close to each other.

It should be noted that in this section, the almost ideal demand equation system was used for estimating retailer demand variance which was in the dominator of the bullwhip effect.

In order to calculate the variance of orders, which was in the numerator of the bullwhip effect, the moving average method was used to forecast the expected demand in the order calculation formula, as explained below.

There are two main methods for ordering two products including the order period method and the order point method. In this article, the ordering method up to level r was used to obtain the amount of order of the distribution center from the manufacturer. The retailer is assumed to use the order policy up to level r, being based on the order period.

This ordering method is standard in many production systems. It is assumed that the inventory system is managed at the beginning of each period and the amount of order which the distribution center gives to the manufacturer should be such to meet the retail demand. The amount of order from the distribution center to the manufacturer is as follows (Baryannis et al.,[2]):

$$\begin{aligned} y_t &= \hat{D}_t^L + z\hat{\delta}_t^L \\ q_t &= y_t - y_{t-1} + D_t = \left(\hat{D}_t^L - \hat{D}_{t-1}^L\right) + z\left(\hat{\delta}_t^L - \hat{\delta}_{t-1}^L\right) + D_{t-1} = \\ &\frac{L}{N}\left(\sum_{i=1}^{N} D_{t-i} - \sum_{i=2}^{N-1} D_{t-i}\right) + z\sqrt{L}\left(\hat{\delta}_t - \hat{\delta}_{t-1}\right) + D_{t-1} = \frac{L}{N}\left(D_{t-1} - \right. \\ &\left. D_{t-N-1}\right) + z\sqrt{L}\left(\hat{\delta}_t - \hat{\delta}_{t-1}\right) + D_{t-1} \end{aligned} \tag{3}$$

Thus

$$q_t = \left(1 + \frac{L}{N}\right) D_{t-1} + \left(-\frac{L}{N}\right) D_{t-N-1} + z\sqrt{L}\left(\hat{\delta}_t - \hat{\delta}_{t-1}\right) \tag{4}$$

In which y_t and $1-y$ represent the values of optimal inventory level at periods t and 1-t in the center. In addition, q_t indicates the order of the distribution center from the manufacturer. Z is obtained based on the level of service to the buyer from standard normal table, being considered at 99% in this study.

In order to obtain the variance of orders from distribution center to the supplier, variance should be taken from both sides of Eq. 4. Therefore, based on Eq. 4:

$$\begin{aligned} &Var(q_t) = Var\left(\left(1 + \frac{L}{N}\right) D_{t-1} + \left(-\frac{L}{N}\right) D_{t-N-1} + z\sqrt{L}\left(\hat{\delta}_t - \hat{\delta}_{t-1}\right)\right) = \\ &\left(1 + \frac{L}{N}\right)^2 Var(D_{t-1}) + \left(-\frac{L}{N}\right)^2 Var(D_{t-N-1}) + Z^2 L Var\left(\hat{\delta}_t - \hat{\delta}_{t-1}\right) + \\ &\left(1 + \frac{L}{N}\right)\left(-\frac{L}{N}\right) Cov(D_{t-1}, D_{t-N-1}) + 2\sqrt{L}\left(1 + \frac{L}{N}\right) Cov\left(D_{t-N-1}, \hat{\delta}_t - \right. \\ &\left. \hat{\delta}_{t-1}\right) + 2Z\sqrt{L}\left(-\frac{L}{N}\right) Cov\left(D_{t-1}, \hat{\delta}_t - \hat{\delta}_{t-1}\right) \end{aligned} \tag{5}$$

In which, according to Chen et al., it is assumed:

$$\begin{aligned} &Cov(D_{t-1}, D_{t-N-1}) = 0, \quad Cov\left(D_{t-1}, \hat{\delta}_t\right) = 0 \;\; \forall I = 0, 1, \ldots, N \\ &Var\left(\hat{\delta}_t - \hat{\delta}_{t-1}\right) = Var\left(\hat{\delta}_t\right) + Var\left(\hat{\delta}_{t-1}\right) - 2Cov\left(\hat{\delta}_t, \hat{\delta}_{t-1}\right), Cov\left(\hat{\delta}_t, \hat{\delta}_{t-1}\right) \\ &\qquad = 0 \end{aligned} \tag{6}$$

Thus, we have:

$$\begin{aligned} Var(q_t) = \left(1 + \frac{L}{N}\right)^2 Var(D_{t-1}) + \left(-\frac{L}{N}\right)^2 Var(D_{t-N-1}) + z^2 L\left(Var\left(\hat{\delta}_t\right)\right. \\ \left. + Var\left(\hat{\delta}_{t-1}\right)\right) \end{aligned} \tag{7}$$

The expected time (delivery) is one of the factors affecting the bullwhip effect in the supply chain. There are two types of waiting time in a three-level supply chain network: one between the supplier and the distribution center, $L1$ and the other between the retailer and the distribution center. $L2$. This problem is indicated in the Figure 1(Kilimci et al., [11]).

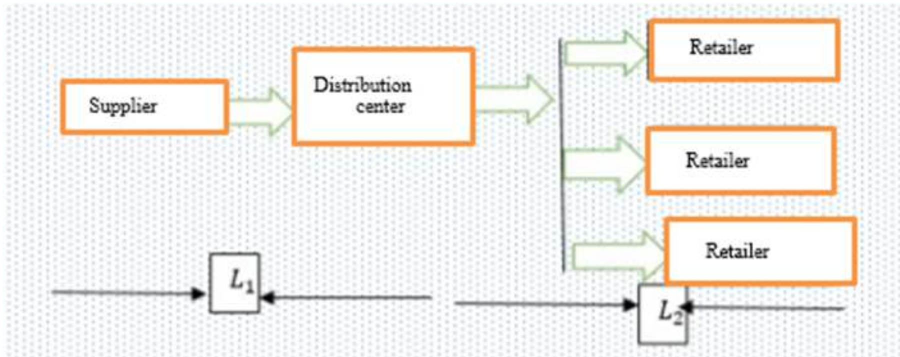

Figure 1. Three-level supply chain.

This was a theoretical-practical paper; so, it required library and field studies. Thus, many articles, books, and dissertations were reviewed.

The researchers referred to many universities and libraries in person to collect data. Numerous studies have been reviewed in the model selection stage, with explained the reasons for their selection. Further, the results were reviewed by experts in each model stage to evaluate the validity of the model. Then, the expert's opinions were required for identifying and selecting the critical factors for achieving strategic goals (in a real example). Thus, some questionnaires were designed and distributed among them, following checking their validity and reliability. Sometimes, the experts were interviewed for better data collection. The output of the validity and reliability stages of the questionnaire entered the model. The relationships between causal factors and relations were identified to determine their direct or inverse effects on each other. Each relationship was given a weight, indicating the extent of the relationship. In the next step, the fuzzy perceptual mapping of success factors was drawn in education. FCMapper software was used for drawing the fuzzy perceptual mapping. After that, the success critical factors were identified followed by analyzing the factors and scenarios. The effect of critical factors on the goals was indicated by drawing the final graph of fuzzy perceptual mapping. Ultimately, the necessary strategies of the organization were designed with the help of the obtained mapping to achieve the determined goals and scenarios.

2.1. Reliability of data collection tool

This reliability test shows the logical consistency of the respondents' answers to all questions in one measure or the whole questionnaire. As the alpha is closer to 100%, the questionnaire is more reliable. It should be noted that the alpha coefficient of less than 60% is normally considered weak, the range of 70% is considered acceptable and more than 80% is considered good. However, as the reliability is closer to one, it is better (Hofmann and Rutschmann, [7]), and the validity of the questionnaire (test) will decrease. If no actual score is given to the questions and the subject's answers are completely unrelated to each other, the alpha tends to be zero. If all of the questions are reliable and indicate a result, the alpha coefficient is one (Kara et al., [10]).

$$\rho_\chi = \frac{k}{k-1}[1-\frac{\sum S_k^2}{S_t^2}] \tag{8}$$

In this formula, k represents the number of questions, and S_t^2 indicates the total score of each subject.

Table 1. Results of Cronbach's alpha.

Variable	Cronbach's alpha
Demand segmentation	0.918
Demand forecasting	0.976
Sales and operations planning	0.986
Demand management support	0.990
Demand management performance	0.989
Supply chain performance	0.921

Based on the provided information on the calculated alpha coefficient and the conclusion rule about the validity of the questionnaire, the whole questionnaire and Cronbach's alpha coefficient for each studied component are valid and sufficient. However, the conducted studies recognized none of the questions of the questionnaire as inappropriate.

2.2. Data analysis.

2.2.1. Normality of data

❖ Test objective

First the statistical distribution of the tested variable should be ensured to select the appropriate test for analyzing the hypotheses. The Kolmogorov Smirnov (k-s) was used for checking the normality of data. The null hypothesis in this test is the normal distribution of the variable. If the significance level of the test is lower than 0.05, the null hypothesis is rejected and it is concluded that the distribution of the desired variable is not normal.

Table 2. Normality of data.

Variable	Number	Z value	Significance level	Bullwhip effect (BE)
Demand segmentation	384	3.015	0.010	2.504
Demand forecasting	384	1.485	0.007	2.503
Sales and operations planning	384	2.414	0.000	2.507
Demand management support	384	2.007	0.003	2.632
Demand management performance	384	3.203	0.000	2.531
Supply chain performance	384	3.338	0.012	2.555

Considering the significance level column, it is concluded that none of the variables have a normal distribution. This article used the correlation coefficient test for evaluating for the correlation between independent variables and dependent variables. Thus, the Pearson correlation coefficient is used in case of normal population, while the Spearman correlation coefficient is adopted un case of abnormal population. The Spearman correlation coefficient was used in this paper due to that none of the variables were normal.

2.3 Identify factors affecting customer demand forecasting in supply chain to reduce bullwhip effect by fuzzy perceptual mapping

At this stage, the factors affecting the customer demand forecasting in the supply chain are modeled to reduce the bullwhip effect by fuzzy perceptual mapping. The research experts identified and weighed the causal relationships between the factors in each customer demand forecasting after determining the effective factors in the previous stages. The factors effects on each other in form of fuzzy linguistic variables (very small, small, middle, big and very big)

entered the fuzzy system by fuzzy triangular numbers and turned into definite numbers in the range -1 and 1 by defuzzification method.
The closer the number is to -1 or 1, the higher the effectiveness of the two factors on each other. As the number is closer to zero, the factors affect each other more weakly. Figure 2 displays the membership functions of linguistic variables and Table 6 shows the used linguistic variables.

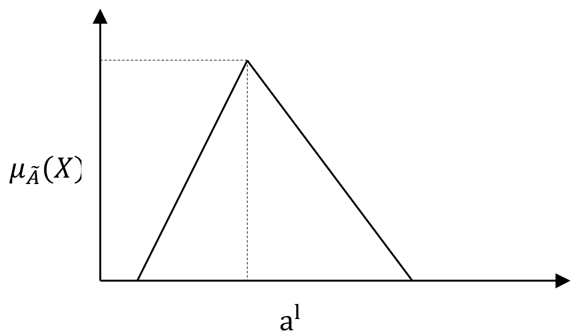

Figure 2. The shape of a triangular fuzzy number

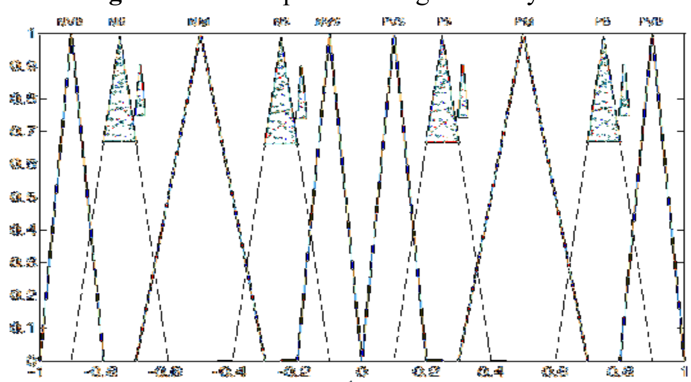

Figure 3. Membership functions of linguistic variable.

Table 3. Linguistic variables used in the fuzzification process.

Fuzzy number	Linguistic variable
(0.8,0.9,1)	Positive very big (PVB)
(0.6,0.75,0.9)	Positive big (PB)
(0.3,0.5,0.7)	positive middle (PM)
(0.1,0.25,0.4)	Positive small (PS)
(0,0.1,0.2)	Positive very small (PVS)
(-0.2,-0.1,0)	Negative very small (NVS)
(-0.4,-0.25,-0.1)	Negative small (NS)
(-0.7,-0.5,-0.3)	Negative middle (NM)
(-0.9,-0.75,-0.6)	Negative big (NB)
(-1,-0.9,-0.8)	Negative very big (NVB)

In this article, the maximum mean method was used for defuzzification, so that the average was taken from the center of the obtained fuzzy numbers. For example, if nine experts answer the question on the effect of the factor Ci to Cj as the linguistic variables "very big", "very big", "big", " big ", " big ", "very big ", "middle", and “big”, it means that the opinion of five experts is "big", three experts "very big", and one expert “middle”. In this case, the fuzzy numbers were considered equal equivalent to the averaged linguistic variables and placed in the relation matrix of FCMapper software. After the implementation, a fuzzy perceptual mapping model was drawn to be analyzed and used by managers and experts. Then, the stages of drawing a fuzzy perceptual mapping model in the field of customer demand in the supply chain were described .

2.4. Model factors affecting customer demand forecasting in supply chain to reduce bullwhip effect by fuzzy perceptual mapping.

This graph shows the long-term final goal of customer demand forecasting in a rhombus and the outputs affecting the long-term goal in a circle. The factors affecting outputs were divided into six groups of "demand segmentation", "demand forecasting", "sales and operations planning", "demand management support", "demand management performance" and "supply chain performance". Figure 5 shows the fuzzy perceptual mapping of customer demand forecasting in general. In this figure, the concepts which are in a field are indicated as a general symbol. Due to the large number of causal relationships between the concepts and mass fuzzy perceptual mapping, Figure 5 keeps the relationships with a weight more than 0.7 and redraws the fuzzy perceptual mapping of customer demand forecasting. Figure 6 displays the fuzzy perceptual mapping of customer demand forecasting with the relations weighing more than 0.7. In this figure, the variables are drawn at the same size and the centrality approach is not used in the drawing due to the elimination of many relations. This fuzzy perceptual mapping indicates more significant relations more clearly.
In this fuzzy perceptual mapping, the relationships weight is based on the experts opinion.

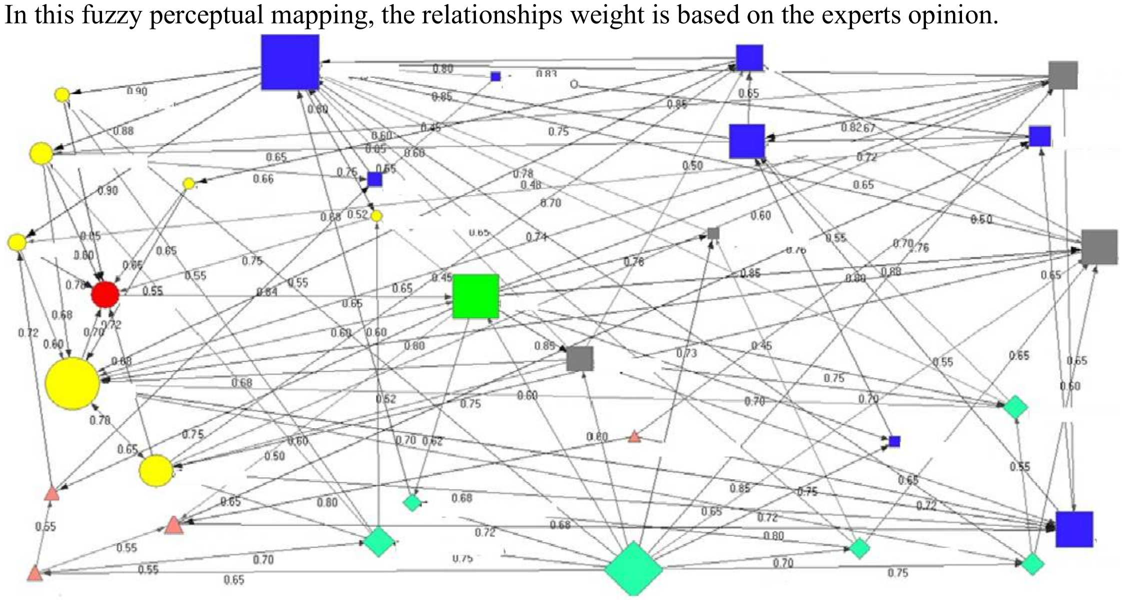

Figure 4. Fuzzy perceptual mapping of customer demand forecasting with the experts opinion.

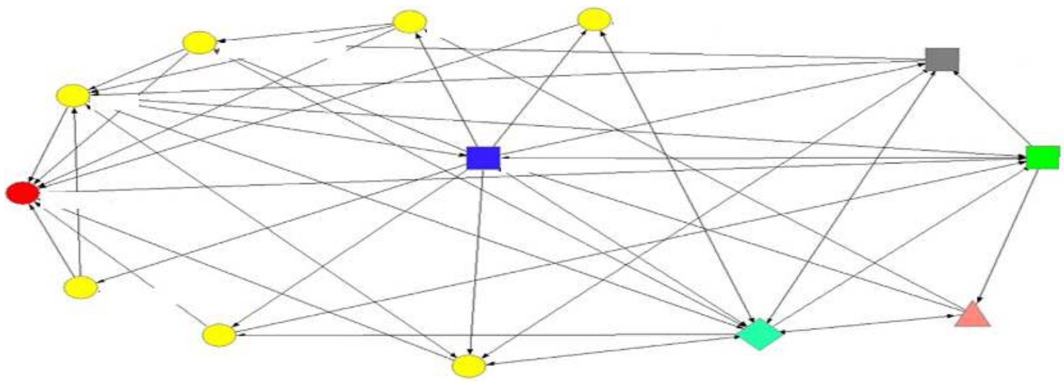

Figure 5. General classified fuzzy perceptual mapping of customer demand forecasting.

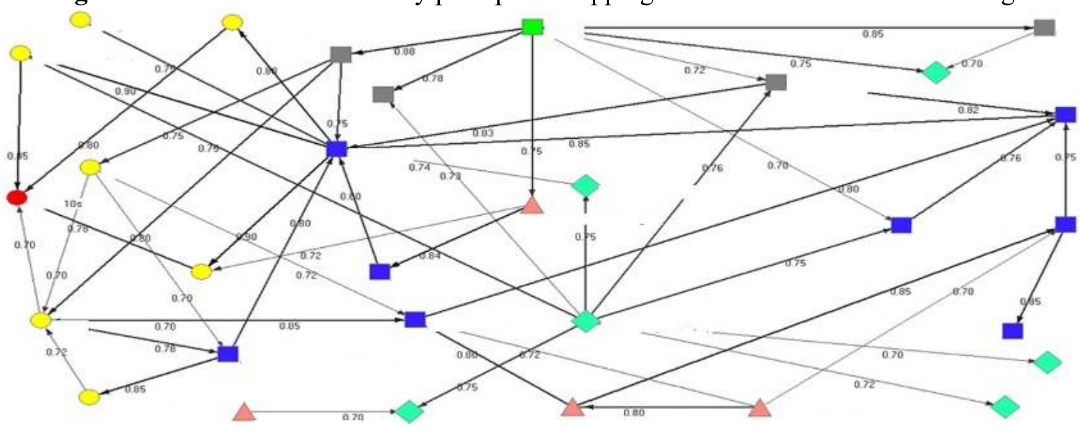

Figure 6. Fuzzy perceptual mapping of customer demand forecasting by experts with weights more than 0.7.

3. Discussion

3.1. Testing hypotheses

This questionnaire attempts to examine if there is a correlation between independent variables and dependent variables and if the relationship is positive or negative.

Hypothesis 1: There is a direct significant relationship between demand management and supply chain performance.

For this purpose, Spearman correlation coefficient is used due to the abnormality of data. If the significance level is higher than 0.05, there is no statistically significant relationship (positive or negative) between the variables.

As indicated in the table below, the correlation coefficient between these two variables is 0.756 and the significance level is 0.000 which is lower than 0.05. Thus, there is a significant relationship between these two variables and demand management is related to supply chain performance because the correlation coefficient is positive. This is a direct significant relationship. Thus, the hypothesis is confirmed.

Table 4. Demand management correlation coefficient with supply chain performance

Supply chain performance	correlation coefficient	0.756
	significance level	0.000
	number	384
	Bullwhip effect (BE)	2.509

Hypothesis 2: There is a direct significant relationship between forecasting and demand management.
Spearman correlation coefficient is used due to the abnormality of data. If the significance level is higher than 0.05, there is no statistically significant relationship between the variables.
As indicated in the table below, the correlation coefficient between these two variables is 0.699 and the significance level is 0.000 which is lower than 0.05. Thus, there is a significant relationship between these two variables and forecasting is related to demand management because the correlation coefficient is positive. This is a direct significant relationship. Thus, the hypothesis is confirmed.

Table 5. Prediction factor correlation coefficient with demand management

Forecasting	correlation coefficient	0.699
	significance level	0.000
	Number	384
	Bullwhip effect (BE)	2.523

Hypothesis 3: There is a direct significant relationship between segmentation and demand management.
For this purpose, Spearman correlation coefficient is used due to the abnormality of data. If the significance level is higher than 0.05, there is no statistically significant relationship (positive or negative) between the variables.
As indicated in the table below, the correlation coefficient between these two variables is 0.711 and the significance level is 0.000 which is lower than 0.05. Thus, there is a significant relationship between these two variables and segmentation is related to demand management because the correlation coefficient is positive. This is a direct significant relationship. Thus, the hypothesis is confirmed.

Table 6. Segmentation factor correlation coefficient with demand management

Segmentation	correlation coefficient	0.711
	Significance level	0.000
	number	384
	Bullwhip effect (BE)	2.567

Hypothesis 4: There is a direct significant relationship between sales planning and executive operations with demand management.
For this purpose, Spearman correlation coefficient is used due to the abnormality of data. If the significance level is higher than 0.05, there is no statistically significant relationship (positive or negative) between the variables.
As indicated in the table below, the correlation coefficient between these two variables is 0.614 and the significance level is 0.000 which is less than 0.05. Thus, there is a significant relationship between these two variables and sales planning and executive operations is related to demand management, because the correlation coefficient is positive. This is a direct significant relationship. Thus, the hypothesis is confirmed.

Table 7. Sales planning factor and executive operations correlation coefficient with demand management

Sales planning and executive operations	correlation coefficient	0.614
	significance level	0.000
	number	384
	Bullwhip effect(BE)	2.549

Hypothesis 5: There is a direct significant relationship between management support and demand management.
For this purpose, Spearman correlation coefficient is used due to the abnormality of data. If the significance level is higher than 0.05, there is no statistically significant relationship (positive or negative) between the variables.
As indicated in the table below, the correlation coefficient between these two variables is 0.701 and the significance level is 0.000 which is less than 0.05. Thus, there is a significant relationship between these two variables, with management support related to demand management because the correlation coefficient is positive. This is a direct and significant relationship. Thus, the hypothesis is confirmed.

Table 8. Management support factor correlation coefficient with demand management

Management support	correlation coefficient	0.701
	significance level	0.000
	number	384
	Bullwhip effect (BE)	2.601

Table 9. Correlation coefficient, variables

	segmentation	forecasting	Planning and sales	Management support	Demand management	supply chain
segmentation	1	0.859	0.798	0.689	0.617	0.821
forecasting		1	0.820	0.678	0.701	0.744
Planning and sales			1	0.728	0.632	0.653
Management support				1	0.693	0.756
Demand management performance					1	0.748
Supply chain performance						1

Table 12 shows that the variables are positively correlated to each other.

3.1.1. Collinearity test of relationship between variables and regression model fitting

First, the linearity of the relationship between each of the independent variables with the dependent variable is tested and then the best regression model is fitted in a stepwise way.

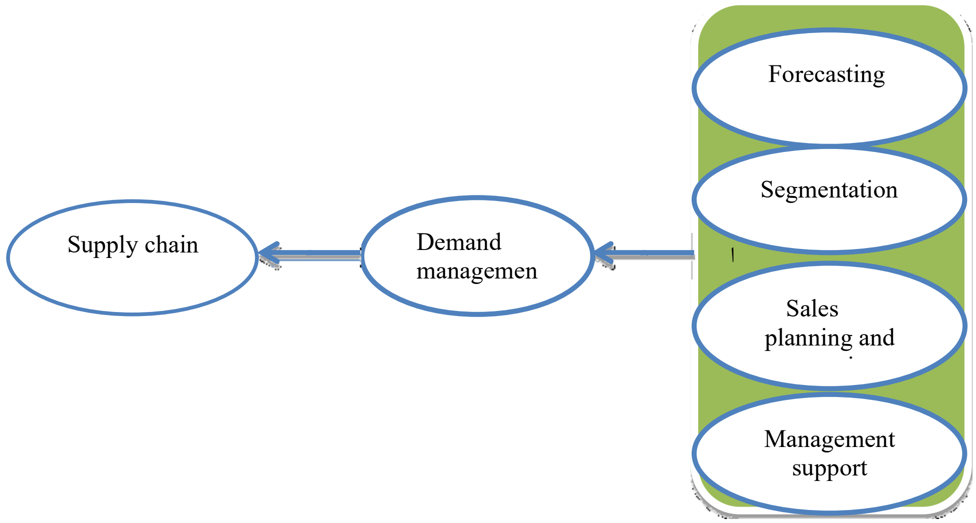

Figure 7. Step by step fitting regression model

Based on the following outputs:

Table 10. Test the alignment of the relationship between variables and the fit of the regression model

Dependent Variable						
	Model summary					Estimated parameter
	R Square	Fisher statistics	Degree of freedom 1	Degree of freedom 2	significance level	b1
Linearity test	0.565	829.182	1	383	0.000	1.752

Since the significance level is 0.000, the linearity of the relationship between supply chain performance and demand management is confirmed .

Based on the following outputs:

Table 11. The relationship between supply chain performance and demand management

Dependent Variable						
	Model summary					Estimated parameter
	R Square	Fisher statistics	Degree of freedom 1	Degree of freedom 2	significance level	b1
Linearity test	0.584	789.304	1	383	0.000	0.971

Since the significance level is 0.000, the linearity of the relationship between demand forecasting and demand management is confirmed.

Based on the following outputs:

Table 12. The relationship between demand forecasting and demand management

Dependent Variable						
	Model summary					Estimated parameter
	R Square	Fisher statistics	Degree of freedom 1	Degree of freedom 2	significance level	b1
Linearity test	0.556	741.283	1	383	0.000	0.900

Since the significance level is 0.000, the linearity of the relationship between segmentation and demand management is confirmed.

Based on the following outputs:

Table 13. The relationship between segmentation and demand management

Dependent Variable						
	Model summary					Estimated parameter
	R Square	Fisher statistics	Degree of freedom 1	Degree of freedom 2	significance level	b1
Linearity test	0.568	760.103	1	383	0.000	1.444

Since the significance level is 0.000, the linearity between sales planning and executive operations and demand management is confirmed .
Based on the following outputs:

Table14. The relationship between sales planning and executive operations and demand management

Dependent Variable						
	Model summary					Estimated parameter
	R Square	Fisher statistics	Degree of freedom 1	Degree of freedom 2	significance level	b1
Linearity test	0.590	854.394	1	383	0.000	1.575

Since the significance level is 0.000, the linearity of the relationship between management support and demand management is confirmed .

3.2. The proposed fitted model

We let SPSS fit or propose the best regression model using the stepwise regression method. In the stepwise method, the first predictor variable is analyzed according to the highest coefficient of zero-order correlation with the criterion variable.
After that, other predictor variables are included in the analysis in terms of partial correlation and semi-partial coefficients.
In this method, all of the variables which have been entered the equation are checked as the last input variable after entering the new variable of partial or semi-partial correlation coefficient. If the model loses its significance after entering the new variable, it is removed from the equation. In general, the order of entering variables is not based on the selection of the researcher in the stepwise method.

Table 15. Proposed fitted model

Model Summary[g]				
Model	R	R Square	Modified R	Estimation of standard error deviation
1	0.466a	0.317	0.315	5.50800
2	0.491b	0.341	0.337	5.43250
3	0.512c	0.362	0.356	5.36331
4	0.522d	0.373	0.365	5.33024

Based on the table above, the R square (correlation coefficient) of model 4 is more than the others, thus the model is more appropriate. It should be noted that the numerical correlation coefficient is between zero and one, and as it is closer to one, the model is more appropriate.

Thus, the fitted model can be written as follows.

$$Y = A - 0.182X_1 - 0.22X_2 - 0.193X_3 - 0.275X_4$$

In which A represents a fixed regression coefficient.

❖ Path analysis of model 1

the error rate is 1.53 and the regression coefficient between segmentation and demand management is 0.89. In addition, 5.95 and 4.63 represent the explained variance of forecasting and supply chain, respectively.

❖ Structural equation

If segmentation is indicated with X_1, the regression model fitted to the data is as follows.

$$Y = A - 0.89X_1$$

For this model, the chi-square statistic is 171.659and degree of freedom is 13, and significance level is 0.000. Since the significance level is less than 0.05, it is concluded that the regression model between the dependent and independent variables is significant and appropriate.

Table 16. Indicators of structural equations of segmentation

Index (internal and external)	Standard load factor	CR
Segmentation		8.486
S1	0.78	
S2	0.95	

As can be indicated in the above figure and table, the load factor for all items is more the threshold of 0.5. The acceptable threshold for composite reliability (CR) which is normally considered as 0.6, which is higher than the significance threshold for the latent variable.

❖ Fitting model 1

In order to estimate the model from the maximum probability method and evaluate the model fit from chi-square (2χ) indices, the chi-square ratio index to degree of freedom, comparative fit index (CFI), normal fit index (NFI), root mean square error of approximation (RMSEA), and standardized root mean square residual (SRMR) were used.

Table 17. Fit indicators of model number 1

Fit index	Value	Standard values
Chi square on degree of freedom	171.695	
CFI	0.94	More than 0.9
NFI	0.923	More than 0.9
RMSEA	0.06	Less than 0.1 It is highly desirable if it is less than 0.05. It is desirable if it is 0.08-0.08.
SRMR	0.09	Less than 0.1 It is highly desirable if it is less than 0.05. It is desirable if it is 0.08-0.08.
GFI	0.91	More than 0.9 (some suggest the values more than 0.8)
AGFI	0.9	More than 0.9 (some suggest the values more than 0.8)

If the CFI and NFI indices are more than 0.90, the model fit is concluded to be appropriate. In addition, if the RMSEA and SRMR indices are less than 0.05, it shows a highly desirable and appropriate fit while a value less than 0.08 indicates a desirable and appropriate fit.
As can be observed, the CFI and NFI indices equal 0.94 and 0.923, respectively, all of which are above the desirable fit threshold. The RMSEA and SRMR indices are 0.06 and 0.09, respectively, both of which indicate the appropriate fit of the model.

❖ Path analysis of model 2

In Figure 14, the error rate is 3.25 and the regression coefficient between forecasting and demand management is -0.773. In addition, 8.12 and 4.63 indicate the explained variance of forecasting and the supply chain, respectively.

❖ Structural equation

If we show the service predictor variable with X_1, the regression model fitted to the data is as follows.
$\mathrm{Y} = \mathrm{A} - 0.667\mathrm{X}_2$
For this model, the chi-square statistic is 194.612 and the degree of freedom is 13 and the significance level is considered as 0.000. Since the significance level is less than 0.05, it is concluded that the regression model between the dependent and independent variables is significant and appropriate.

Table ١٨. Predictive structural equation indices

Index (internal and external)	Standard load factor	CR
Forecasting		6.987
S3	0.645	
S4	0.88	

As can be observed in the above figure and table, the load factor for all items is above the threshold 0.5 and the acceptable threshold for composite reliability (CR) is normally considered as 0.6. This value is significant for the latent variable above the threshold.

❖ Fitting model 2

In order to estimate, the maximum probability method was used and in order to evaluate the model fit, chi-square indices ($\chi 2$), chi-square ratio index on degree of freedom, comparative fit index (CFI), normal fit index (NFI), root mean square error of approximation, and standardized root mean residual (SRMR) were used .

Table 19. Fit indicators of model number 2

AGFI	GFI	SRMR	RMSEA	NFI	CFI	Chi square on degree of freedom	Fit index
0/924	0/92	0/05	0/014	0.90	0.931	194.612	value

As can be observed, the CFI and NFI are 0.931 and 0.90, respectively, all of which are higher than the desired fit threshold. The RMSEA and SRMR are 0.014 and 0.05, respectively, both of which indicate an appropriate fit of the model.

❖ Path analysis of model 3

In Figure 15, 1.54 represents the error rate and -0.96 indicates the regression coefficient between the sales planning variable, executive operations, and demand management. In addition, 4.1 and 4.63 show the explained variance of the sales planning variable and supply chain, respectively.

Structural equation

If we show sales planning and executive operations with X_3, the regression model fitted to the data is as follows.

$$\mathrm{Y} = \mathrm{A} - 0.96\mathrm{X}_3$$

For this model, the chi-square statistic is 245.395 and the significance level is considered as 0.000. Since the significance level is less than 0.05, it is concluded that the regression model between the dependent and independent variables is significant and appropriate.

Measuring the model structure reliability is one of the indicators for evaluating the accuracy of the model.

Table 20. Indicators Sales planning and executive operations based on structural equations

Index (internal and external)	Standard load factor	CR
Sales planning		5.87
S5	0.85	
S6	0.82	
S7	0.86	

As can be observed in the above figure and Table 23, the load factor for all items is above the threshold 0.5 and the acceptable threshold for composite reliability (CR) is normally considered as 0.6. This value is significant for the latent variable above the threshold.

❖ Fitting model 3

Table 21. Fit indicators of model number 3

AGFI	GFI	SRMR	RMSEA	NFI	CFI	Chi square on degree of freedom	Fit index
0/90	0/90	0/067	0/018	0/924	0/91	245/395	value

As can be observed, the CFI and NFI are 0.91 and 0.924, respectively, all of which are higher than the desired fit threshold. The RMSEA and SRMR are 0.018 and 0.067, respectively, both of which indicate an appropriate fit of the model.

❖ Path analysis of model 4

In Figure 16, 1.25 indicates the error rate and -0.9 shows the regression coefficient between forecasting and demand management. In addition, 5.54 and 4.63 show the explained variance of management support and supply chain, respectively.

❖ Structural equation

If we indicate management stability with $X_{۴}$, the regression model fitted to the data is as follows.

$$Y = A - 0.9X_4$$

For this model, the chi-square statistic is 198.114 and the significance level is considered as 0.000. Since the significance level is less than 0.05, it is concluded that the regression model between the dependent and independent variables is significant and appropriate.

Measuring the model structure reliability is one of the indicators for evaluating the accuracy of the model .

Table 22. Indicators of management stability with structural equation

Index (internal and external)	Standard load factor	CR
Management stability		6.32
S8	0.87	
S9	0.67	

As can be observed in the above figure and table, the load factor for all items is above the threshold 0.5 and the acceptable threshold for composite reliability (CR) is normally considered as 0.6. This value is significant for the latent variable above the threshold.

❖ Fitting model 4

Table 23. Fit indicators of model number 4

AGFI	GFI	SRMR	RMSEA	NFI	CFI	Chi square on degree of freedom	Fit index
0/82	0/91	0/018	0/024	0/90	0/96	198/114	value

As can be observed, the CFI and NFI are 0.96 and 0.9, respectively, all of which are higher than the desired fit threshold. The RMSEA and SRMR are 0.024 and 0.018, respectively, both of which indicate an appropriate fit of the model.

❖ Path analysis of the proposed model

the load factors are defined as before and 2.47 shows the error rate.

❖ Structural equation

If we indicate forecasting with $X_{۱}$, segmentation with $X_{۲}$, support management with $X_{۳}$, and sales planning and executive operations with $X_{۴}$, the regression fitting model will be as follows:

$$Y = A - 0.89X_1 - 0.773X_2 - 0.9X_3 - 0.96X_4$$

For this model, the chi-square statistic is 1230.64 with degree of freedom as 719 and the significance level is considered as 0.000. Since the significance level is less than 0.05, it is concluded that the fitted regression model between the dependent and independent variables is significant and appropriate.

❖ Fitting the proposed model

Table 24. Indicators of fit of the proposed model

AGFI	GFI	SRMR	RMSEA	NFI	CFI	Chi square on degree of freedom	Fit index
0/99	0/98	0/015	0/010	0/90	0/93	1230/64	value

Since all of the indicators support the main research model, this model is highly powerful and is acceptable as an appropriate model.

❖ Path analysis of the proposed model

In Figure 18, the load factors are defined as before and show an error rate of 3.12.

❖ Structural equation

If we show forecasting with $X_۱$, segmentation with X_2 , support management with $X_۳$, and sales planning and executive operations with $X_۴$

$Y = A - 0.89X_1 - 0.773X_2 - 0.9X_3 - 0.96X_4$

For this model, the chi-square statistic is 2896.3 and the significance level is considered as 0.000. Since the significance level is less than 0.05, it is concluded that the fitted regression model between the dependent and independent variables is significant and appropriate.

❖ Fitting the primary model

Table 25. General model fit indicators

AGFI	GFI	SRMR	RMSEA	NFI	CFI	Chi square on degree of freedom	Fit index
0/833	0/833	0/01	0/01	0/97	0/99	2896/3	value

As can be observed, the CFI and NFI are 0.99 and 0.97, respectively, all of which are higher than the desired fit threshold. The RMSEA and SRMR are 0.01 and 0.01, respectively, both of which indicate the relatively appropriate fit of the model.

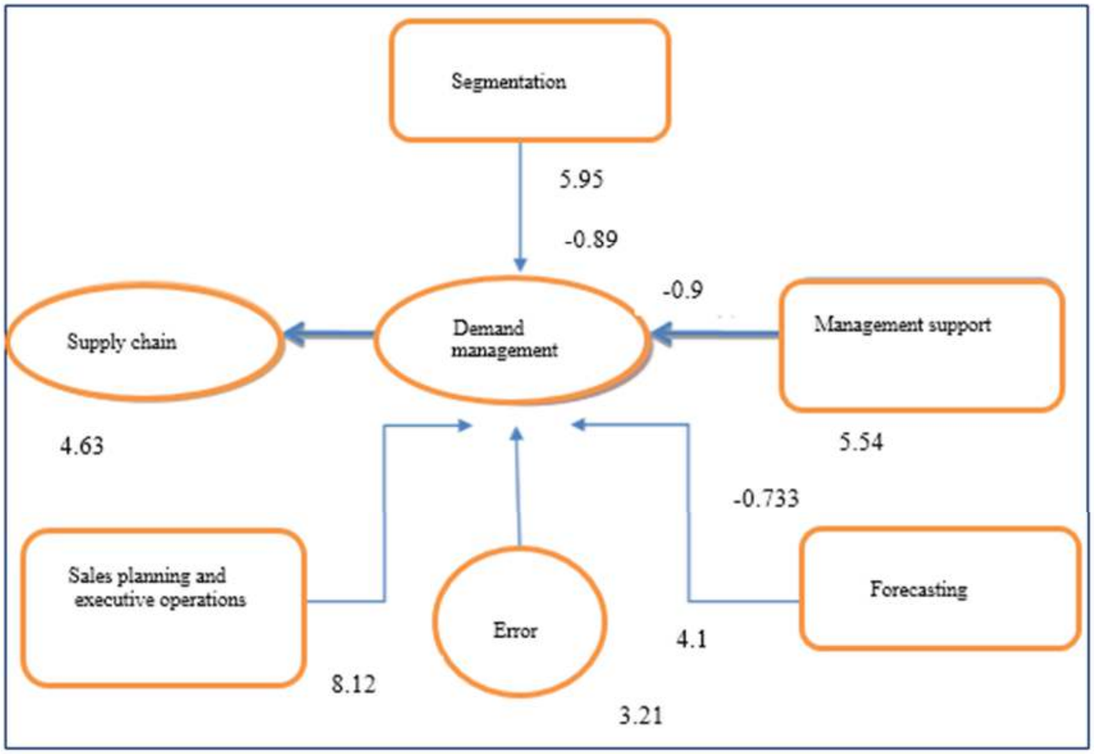

Figure 8. Path analysis of the main model

❖ Comparing the secondary model with the primary model

In order to compare the secondary model with the primary model, the chi-square test was used. If the significance level of the test is less than 0.05, it is concluded that the primary model is better.

Table 26. Indicators comparing the sub-model with the general model

	Chi-square statistics	Significance level	NFI	IFI	RFI
Comparing two models	489.582	0.06	0.912	0.919	0.916

Since the significance level is more than 0.05, it is concluded that there is no significant difference between the two models .

Table 27. Path coefficients in the structural model.

Path	Path coefficient	Significance	Result
Segmentation → demand management → supply chain	-0.89	<0.05p	Accepted
Forecasting → demand management → supply chain	-0.773	<0.05p	Accepted
Sales planning → demand management → supply chain	-0.96	<0.05p	Accepted
Management support → supply chain	0.9	<0.05p	Accepted

3.3. Discussion and conclusion

Identifying each company's demand properly and responding to these demands quickly is the key to success. Lack of appropriate forecasting of demand in business interactions can result in capital loss and increased inventory costs. In addition, it was concluded that a significant relationship exists between forecasting and demand management performance. Contrary to some researchers who considered forecasting to be directly related just to supply chain, this result indicates that its relationship is indirect through the demand management performance. On the other hand, a direct and significant relationship exists between segmentation and demand management performance. At the meantime, different studied factors have the most effect. There is a direct and significant relationship between sales planning and executive operations with demand management. Nevertheless, this factor has the least effect on demand management among the studied factors. Furthermore, there is a direct and significant relationship between management support and demand management. Management support in planning has been investigated in many studies. However, it has had little status among the supply chain studies. The results of this study have some explicit suggestions for the actors in the field of supply chain. The findings of this study emphasize that demand management is significant for industries. Aftab oil factory can design sector independently as demand management sector to review customer demands at different levels of the supply chain. If demand is received from various levels of supply chain, importing a lot of load on the demand management sector, demand management can be divided into upstream and downstream demand managements. Aftab oil factory can design products and product packages based on the amount of customers 'income or based on other customers' characteristics. However, this requires an accurate analysis of the information obtained from customer databases before designing products. Aftab oil plant should first achieve a comprehensive understanding of different population groups based on the analysis of the records and using the professional insights they have obtained. The customers who have accompanied Aftab oil company for a long time should be identified. Understanding the needs of such old customers is relatively easy. By introducing some useful services to old customers, they can be turned into some incentives to encourage other customers for establishing long-term relationships with Aftab oil factory.

3.4. Practical suggestions

Using a sales terminal (POS) throughout the supply chain, this action can alert all levels of the chain equally to changes in customer demand and plan accordingly.

- Use the Internet to inform and share demand and current inventory information with all suppliers.
- Use inventory management by the seller, to monitor and manage the inventory of downstream members by the manufacturer. To decide in each period how much inventory to send to themselves and how much inventory to downstream members.

Use the "daily price reduction" policy to prevent price fluctuations that affect consumption rates.

- Conditional gradual payments by the manufacturer to retailers based on the amount of goods sold to end customers (ie when the retailer can buy more if he sells more product)

Use of information systems such as ERP and CRM.

- Informe customers about the lack of inventory and supply of products, to prevent quotas. It can have an effect on the occurrence of bullwhip effect or reduce it.

In the supply chain, with traditional communications, each actor (each company or member of the chain) is responsible for controlling their inventory and the activities of ordering, distributing and other activities related to their products, in other words, companies are responsible for inventory. The companies are responsible for inventory, distribution and ordering of goods and do not interfere in similar activities related to their suppliers and retailers, which causes one of the most important problems and basic concepts. For all actors in the supply chain with traditional communications (such as retailers, distributors, manufacturers, and suppliers of raw materials), these actors are more likely to ask, "How much should we order now?" Or suppliers to supply) order to be able to meet the demand of customers of a category of supply chain (direct customers

of your company who trade directly with them). This can be a problem of inventory control / production of the company in the supply chain system with traditional communications.
- Due to the higher efficiency of three particle mass models, artificial intelligence networks, and neural network algorithm trained with scale gradient algorithm and bat algorithm compared to previous models in the field of edible oil consumption prediction, it is recommended to use these three powerful techniques on forecasting the amount of consumption used in the direction of the government's macro-planning.

-Governments can enter the forecast of future years of price, gross domestic and foreign production, population, import, export, and consumption of other oil products made by reliable organizations in these three techniques to benefit from the future forecast of each.

3.5. Contribution

• using the bullwhip effect in customer demand forecasting in supply chain
• customer demand forecasting in supply chain using the FCM method.

Refrences

[1] Ashfaq, S., Tang, Y., & Maqbool, R. (2020), A study on the CAPM and its extensions in perceptive of Pakistani asset management organisations. *International Journal of Services Operations and Informatics*, 10(3), 207-221.

[2] Baryannis, G., Dani, S., & Antoniou, G. (2019), Predicting supply chain risks using machine learning: The trade-off between performance and interpretability*, Future Generation Computer Systems*, Vol. 101, pp. 993-1004.

[3] Brintrup, A., Pak, J., Ratiney, D., Pearce, T., Wichmann, P., Woodall, P., & McFarlane, D. (2020), Supply chain data analytics for predicting supplier disruptions: A case study in complex asset manufacturing , *International Journal of Production Research*, Vol. 58, No. 11, pp. 3330-3341.

[4] Fanoodi, B., Malmir, B., & Jahantigh, F.F. (2019), Reducing demand uncertainty in the platelet supply chain through artificial neural networks and ARIMA models, *Computers in Biology and Medicine*, Vol. 113, p. 103415.

[5] Fu, W., Chien, C.F., & Lin, Z.H. (2018), A hybrid forecasting framework with neural network and time-series method for intermittent demand in semiconductor supply chain. In*: IFIP International Conference on Advances in Production Management Systems* (pp. 65-72). Springer, Cham.

[6] Gong, M., Gao, Y., Koh, L., Sutcliffe, C., & Cullen, J. (2019), The role of customer awareness in promoting firm sustainability and sustainable supply chain management, *International Journal of Production Economics*, Vol. 217, pp. 88-96.

[7] Hofmann, E. and Rutschmann, E., (2018), Big data analytics and demand forecasting in supply chains: a conceptual analysis', *The International Journal of Logistics Management*, Vol. 29, No. 2, pp. 739-766.

[8] Ietto, B., & Orsini, V. (2023), Managing Inventory Level and Bullwhip Effect in Multi Stage Supply Chains with Perishable Goods: A New Distributed Model Predictive Control Approach. In: *International Conference on Operations Research and Enterprise Systems*, (ICORES 2023), (pp. 229-236).

[9] Jiang, W., (2019), An intelligent supply chain information collaboration model based on Internet of Things and big data, *IEEE Access*, Vol. 7, pp. 58324-58335.

[10] Kara, M.E., Fırat, S.Ü.O., & Ghadge, A. (2020), A data mining-based framework for supply chain risk management, *Computers & Industrial Engineering*, Vol. 139, p. 105570.

[11] Kilimci, Z.H., Akyuz, A.O., Uysal, M., Akyokus, S., Uysal, M.O., Atak Bulbul, B., & Ekmis, M.A. (2019), An improved demand forecasting model using deep learning approach and proposed decision integration strategy for supply chain, *Complexity*, Vol. 2019, No. 7, pp. 1-15.

[12] Li, L., Chi, T., Hao, T., Yu, T. (2018), Customer demand analysis of the electronic commerce supply chain using Big Data, *Annals of Operations Research*, Vol. 268, No. 1-2, pp. 113-128.

[13] Lima-Junior, F.R. & Carpinetti, L.C.R. (2019), Predicting supply chain performance based on SCOR® metrics and multilayer perceptron neural networks, *International Journal of Production Economics*, Vol. 212, pp. 19-38.

[14] Liu, W., Wang, S., Zhu, D., Wang, D., & Shen, X. (2018), Order allocation of logistics service supply chain with fairness concern and demand updating: model analysis and empirical examination, *Annals of Operations Research*, Vol. 268, No. 1-2, pp. 177-213.

[15] Mirmohammadi, S.H., Sahraeia, R. (2018), A Novel Sustainable Closed-loop Supply Chain Network Design by Considering Routing and Quality of Products, *International journal of Engineering*, Vol. 31, No. 11, pp. 1918-1928.

[16] Moradi, M., Rabbani, M., Babaei Meybodi, M., & Taghi Honari, M. (2022),Development of a Hybrid Model for the Evaluation of Sustainable Supply Chains using Dynamic Network Data Envelopment Analysis, *Iranian Journal of Operations Research*,12(2),1-13.

[17] Murray, P.W., Agard, B., & Barajas, M.A. (2018), Forecast of individual customer's demand from a large and noisy dataset, *Computers & Industrial Engineering*, Vol. 118, pp. 33-43.

[18] Nandra, R., Marak, K. R., Kaur, R., Dey, B. K., & Majumder, A. (2021), Establishing relation between production rate and product quality in a single-vendor multi-buyer supply chain model. *International Journal of Services Operations and Informatics*, 11(2-3), 315-331.

[19] Pereira, M.M. and Frazzon, E.M. (2020), A data-driven approach to adaptive synchronization of demand and supply in omni-channel retail supply chains, *International Journal of Information Management*. https:. . doi.org. 10.1016. j.ijinfomgt.2020.102165

[20] Rabbani, M., Hosseini-Mokhallesun, S.A.A., Ordibazar, A.H., & Farrokhi-Asl, H. (2020), A hybrid robust possibilistic approach for a sustainable supply chain location-allocation network design, *International Journal of Systems Science: Operations & Logistics*, Vol. 7, No. 1, pp. 60-75.

[21] Rahmani, K., & Yavari, M. (2019), Pricing policies for a dual-channel green supply chain under demand disruptions', *Computers & Industrial Engineering*, Vol. 127, pp. 493-510.

[22] Ritech, A. (2020), Scheduling and short-term demand forecasting in an on-demand ride service industry. *International Journal of Services and Operations Management.* https:. . doi.org. 10.1155. 2015. 682390

[23] Sajedi, S., Sarfaraz, A.H., Bamdad, S., & Khalili-Damghani, K. (2020), Designing a Sustainable Reverse Logistics Network Considering the Conditional Value at Risk and

Uncertainty of Demand under Different Quality and Market Scenarios', *International journal of Engineering*, Vol. 33, No. 11, pp. 2252-2271.

[24] Salmela, E., & Huiskonen, J. (2019), Co-innovation toolbox for demand-supply chain synchronization, *International Journal of Operations & Production Management*, Vol. 39, No. 3, pp. 211-224.

[25] Schwieterman, M.A., Goldsby, T.J., & Croxton, K.L. (2018), Customer and supplier portfolios: can credit risks be managed through supply chain relationships?, *Journal of Business Logistics*, Vol. 39, No. 2, pp. 123-137.

[26] See-To, E.W., & Ngai, E.W. (2018), Customer reviews for demand distribution and sales nowcasting: a big data approach, *Annals of Operations Research*, Vol. 270, Nos. 1-2, pp. 415-431.

[27] Song, J.M., Chen, W., & Lei, L. (2018), Supply chain flexibility and operations optimisation under demand uncertainty: a case in disaster relief, *International Journal of Production Research*, Vol. 56, No. 10, pp. 3699-3713.

[28] Sarkar, M., Dey, B. K., Ganguly, B., Saxena, N., Yadav, D., & Sarkar, B. (2023), The impact of information sharing and bullwhip effects on improving consumer services in dual-channel retailing. *Journal of Retailing and Consumer Services*, 73, 103307.

[29] Taghikhah, F., Voinov, A., & Shukla, N. (2019), Extending the supply chain to address sustainability, *Journal of Cleaner Production*, Vol. 229, pp. 652-666.

[30] Uddin, M. F., Mondal, M., Hussain, K. A., (2014), Comparison and Supply Chain Optimization for Vendor-Buyer Coordination System, *Iranian Journal of Operations Research*, 5(1)64-81.

[31] Van Nguyen, T., Zhou, L., Chong, A.Y.L., Li, B., & Pu, X. (2020), Predicting customer demand for remanufactured products: A data-mining approach', *European Journal of Operational Research*, Vol. 281, No. 3, pp. 543-558.