Journal of System Management (JSM)
Online ISSN: 2538-1571, Print ISSN: 2322-2301
Doi: 10.30495/JSM.2022.1966147.1691
9(1), 2023, pp. 97-117

Received: 22/09/2022
Accepted: 15/12/2022

RESEARCH ARTICLE **Open Access**

Analyzing the Drivers of Bullwhip Effect in Pharmaceutical Industry's Supply Chain

Parvaneh Tavakol [1], Bijan Nahavandi [2]*, Mahdi Homayounfar [3]

Abstract
The purpose of this study is to evaluate the drivers of bullwhip effect in supply chain of the pharmaceutical industry. This research is descriptive in terms of method and applied in terms of purpose. Conducting the research, first, based on the reviewing the literature on bullwhip effect in the supply chain, affecting drivers were extracted and were sent to 15 experts in form of a questionnaire. Then, using the fuzzy Delphi method, the final affecting criteria on bullwhip effect in the supply chain of the pharmaceutical industry were identified. Finally, in order to examine the relationships between the 13 basic drivers, another questionnaire was designed and asked the experts to fill it, where based on their answers and using DEMATEL and fuzzy cognitive map methods, critical drivers were determined. FCMapper software was used to conduct fuzzy cognitive map method and MATLAB was used for the DEMATEL method. In terms of centrality index in fuzzy cognitive map method, structured inventory control process, delivery time, inventory storage of chain elements, inventory policy and product return rate are 5 criteria of critical importance. In addition, the indicators of the number of echelons, forecasting (method) error and up-to-date demand forecast are in the eleventh to thirteenth ranks. Based on the results of DEMATEL method, inventory policy, price fluctuations, inventory storage of chain elements, structured inventory control process, differences with the desired inventory and information transparency were identified as the main drivers of bullwhip effect in the supply chain of the pharmaceutical industry.
Keywords: *Supply Chain, Bullwhip Effect, Inventory Fluctuation, Fuzzy Cognitive Map, DEMATEL, Delphi*

Introduction

Since the first time when Harris presented the economic order quantity (EOQ) model to determine the order size, the world has experienced an increasing progress in the inventory management system, and until today, nearly a century has passed since the formulation of this model, the importance of improvement in effectiveness of these systems remained a problem (Nodoust & Mirzazadeh, 2015; Salahshouri et al., 2019). The effectiveness of the inventory management system is usually affected by demand variability, especially at upstream levels (Kumara et al., 2020). Researches have shown that demand variability is strengthened upstream the supply chain, which increases supply chain costs and disruptions in providing services to end customers (Pastor et al., 2019).

1. PhD Candidate, Department of Industrial Management, Bandar-e- Anzali International Branch, Islamic Azad University, Bandar-e-Anzali, Iran
2*. Assistant Professor, Department of Industrial Management, Science and Research Branch, Islamic Azad University, Tehran, Iran (Corresponding Author: bijan.nahavandi@srbiau.ac.ir)
3. Assistant Professor, Department of Industrial Management, Rasht Branch, Islamic Azad University, Rasht, Iran

For the first time, Forrester (1961) observed by analyzing a supply chain how a small change in type of the customer demand can be strengthened and make big changes in distribution, production and replenishment processes (Fu et al., 2015). This effect is known as the Forrester effect, which is one of the indicators of ineffectiveness in supply chain management. According to Forrester's theory, this reinforcement occurs due to the presence of non-zero delivery time as well as the inappropriate estimation of demand (caused by the lack of timely information feedback among the levels of the chain) (Najafi et al., 2018). Further, Lee et al (1997) studied the propagation of demand variability and its driving factors and referred to this phenomenon as the bullwhip effect. In general, the bullwhip effect creates an atmosphere of instability in the production and distribution systems, which significantly reduces their operational and financial performance (Dominguez et al., 2018). The bullwhip effect, during which the supply chain amplifies changes in consumer orders by getting closer to the upper echelons of the chain, is a field of interest in operations management due to its costly consequences in production and distribution systems (Pont et al., 2020).

Since Lee et al. (1997) called Forrester's effect as bullwhip effect, many researchers have studied this topic. It has become a valuable field of research in the last two decades, which has been reviewed in the researches of Wang and Disney (2016), Pastor et al. (2019) and etc. from the theoretical and experimental perspective. This phenomenon emerges through the interaction of behavioral and operational components. Behavioral causes of the bullwhip effect arise from the fact that managerial decisions are not always perfectly rational. Instead, decision makers usually react to changes in demand (Ponte et al., 2020). Lee et al. (1997) stated that bullwhip effect is related to four main factors: demand signal processing, order batching, rationing game and price changes. In their paper, these four causes are deeply analyzed and identified as the main drivers of demand change propagation. When examining demand signal processing, many contributions have shown that the use of local information at each level of the supply chains leads to the propagation of variance in the upstream levels of the chain. This reinforcement is affected by the forecasting method used at each level of the chain (Yuan and Zhou, 2016; Ma and Bao, 2017), the inventory policy (Cheng, 2009; Braz et al., 2018) and delivery time (both in terms of length of time (Chen et al., 2000) and its variability (Dak et al., 2018). Smaller order batches also reduce the bullwhip effect (Holland and Soodi, 2004; Hossein and Drake, 2011), so that some researchers have proven that the bullwhip effect can be reduced by using batches equal to the average amount of demand (Potter and Disney, 2006). When demand exceeds production capacity/available inventory, rationing policies will use to allocate capacity/inventory to downstream orders. Once downstream decision makers understand the rationing criteria, they may increase their order to ensure the capacity/inventory they need. This behavior is known as the rationing game and leads to increased demand changes along the supply chain (Pastor et al., 2019).

According to the statistics published in the first 5 months of 2019, pharmaceutical products are the seventh major imported group and Iran has imported pharmaceutical products from more than 50 countries in the world, which European countries, especially Germany, allocated the highest number of pharmaceutical imports to them. In the group of pharmaceutical products, pharmaceutical supplements, have the largest share in imports. According to official statistics, in 2016, the worth of Iran’s medicine export was 60 million dollars. The country's import value in the same year was 1500 million dollars. During the years 2001 to 2017, Iran has faced a 28%

decrease in the value of medicine production and a 13% increase in the value of medicine import. Considering the 20% population growth, it can be concluded that the domestic producers have not been successful in developing the pharmaceutical industry at the same time as the country's population increases, and a large part of the country's pharmaceutical needs has been met through medicine imports. Considering that pharmaceutical and related costs in Iran include about 30% of the total cost of health care and nearly 50% of the cost of outpatient health care, it is of main importance in the country's health system. Historical studies show that during the past few decades, despite problems such as imposed war and economic sanctions, providing the medicine needed by the society has always been one of the main concerns of the country. In addition, the covid-19 pandemic, which can be seen intensifying and waning in 6 peaks of the disease, in some time periods, Iran has faced with a surplus or shortage of the medicine. So, the need to know and study the drivers that affect the inventory management system in the pharmaceutical system, in order to reduce demand fluctuations and medicine amplifications, is one of the main concerns of the policy makers of health sector. Obviously, the importance of bullwhip effect drivers under crisis conditions, such as pandemics and sanctions, is different from normal conditions. Since the problem is not considered previously in the literature under contextual conditions and due to the lack of structured knowledge on inventory management systems behavior in crisis, this study goes beyond the previous works by developing a systematic methodology including a hybrid graph theory-based methods to analyze bullwhip effect drivers in crisis condition and by considering feedback structure among them.

In this research, a hybrid approach based on fuzzy cognitive map and DEMATEL has been used to analyze the drivers in the pharmaceutical industry. By creating a feedback network between identified drivers, these techniques make it possible to better analyze the interactions and relationships in the system. As a result, the basic problems of inventory variance and bullwhip effect will be studied more precisely and will be reduced with appropriate measures. The main question of the current research is that what are the main drivers of the bullwhip effect in the pharmaceutical supply chain and what are their roles in creating the bullwhip effect?

2. Literature Review

In many supply chains, demand information is usually distorts. Distortion of information flow is considered as a source of bullwhip effect. This effect occurs when a downstream member, regardless of its actual demands, make an order with a high variance and this demand distortion propagates to the upstream members (Dominguez et al., 2015; Goudarzi and Farzipour Saen, 2020). Lee et al. (1997) stated that the intensity of bullwhip effect is related to four main factors: demand signal processing, order baching, rationing game and price fluctuations. In their paper, these causes are deeply analyzed and identified as the main drivers of demand change propagation. When examining demand signal processing, many contributions have shown that the use of local information at each level of supply chains leads to the propagation of variance in the upstream levels of the chain. This reinforcement is affected by the forecasting method used at each level of the chain (Yuan and Zhu, 2016; Ma and Bao, 2017), the inventory policy (Cheng, 2009; Braz et al., 2018) and delivery time, both in terms of length of time (Chen et al., 2000) and its variability (Dak et al., 2008).

In many supply chains, defining a minimum order batching to upstream levels in order to use economy of scale and reduce setup and transportation costs is a common practice. However, as Li et al. (1997) stated, order batching amplifies demand changes towards upstream in the supply chain, and the result of these changes is that manufacturers often face more orders in some periods and less orders in others. A smaller batch size reduces the bullwhip effect (Holland and Soudi, 2004; Hussain and Derrick, 2011) and some researchers have proven that the bullwhip effect can be reduced by using batches equal to the average amount of demand (Potter et al. Disney, 2006). When demand exceeds production capacity/available inventory, rationing policies are used to allocate capacity/inventory to downstream orders. Once downstream decision makers understand the rationing criteria, they may increase their order to ensure their required capacity/inventory. This behavior is known as the rationing game and leads to increased demand fluctuations along the supply chain (Pastor et al., 2017).

A poor demand forecast can also reduce the availability of products, change the customer's demand and affect the working capital. In addition, deviation in demand forecasting is also a fundamental cause of bullwhip effect and can lead to inefficiencies, excess inventory, warehouses, and backorders (Kumara et al., 2020). The variety of orders is also one of the main problems of operations managers in inventory management. In fact, both forecasting and inventory processes become more difficult when demand is variable. In addition, product diversity leads to uncertainty, higher inventory, and lower service levels. In many supply chains, demand changes at upstream levels are not caused by changes in consumer demand, but have endogenous causes in the supply chain. In fact, replenishment orders tend to change more upstream in the supply chain, and increased variability leads to higher operating costs (Pastor et al., 2019). Another main reason for demand propagation is price fluctuations. In fact, when consumers are price sensitive, their demand will change according to discounts and promotions. Therefore, the effect of price promotions/discounts at each level of the supply chain, especially before and after promotional periods (Trapero and Pedregal, 2016), reinforces demand changes at upstream levels (Zhang and Burke, 2011; Reiner et al. Fichtinger, 2009). Sharing the promotions information and discount policies have been shown to be effective solutions to eliminate price bullwhip (Gavirenni, 2006). By examining the studies conducted in the field of bullwhip effect in the supply chain, a list of bullwhip effect drivers is given in Table (1):

Table 1

Drivers of Bullwhip Effect in Supply Chain

Driver	**References**
Purchase Cost	Lee et al. (1997), Zotteri (2013), Nodoust and Mirzazadeh (2015), Pastore et al. (2019)
Order Batching	Lee et al. (1997), Chen et al. (2000), Holland and Sodhi (2004), Hussain and Drake (2011), Li et al. (2014), Braz et al. (2018), Pastore et al. (2019), Zhu et al. (2020)
Inventory Class	Narayanan and Raman (2004), Zotteri (2013), Pastore et al. (2019), Dominguez et al. (2020)
Lead Time	Chen et al. (2000), Li et al. (2014), Matamoros et al. (2011), Zhao et al. (2018), Pastore et al. (2019), Gaalman et al. (2019), Ponte et al. (2020a), Zhu et al. (2020), Dominguez et al. (2020), Ponte et al. (2020b)
Product Type	Zotteri (2013), Pastore et al. (2019)
Promotions	Lee et al. (1997), Gavirneni (2006), Reiner & Fichtinger (2009), Zhang and Burke (2011), Pastore et al. (2019)
Type of Information	Braz et al. (2018), Ojha et al. (2019)

Driver	**References**
Information Distortion	Braz et al. (2018), Zhao et al. (2018), Ojha et al. (2019), Jiang and Ke (2019), Zhou et al. (2019), Goodarzi and Farzipoor Saen (2020), Ponte et al. (2020b)
Information Transparency	Ponte et al. (2020a), Dominguez et al. (2020)
Structured Inventory Control Process	Chong (2013), Braz et al. (2018), Zhao and Zhu (2018)
Return Rate	Corum et al. (2014), Dominguez et al. (2015), Cannella et al. (2016), Zhu et al. (2017), Braz et al. (2018), Zhao et al. (2018), Ponte et al. (2020a), Dominguez et al. (2020)
Inventory Policy	Cheng (2009); Braz et al. (2018), Dominguez et al. (2020)
Safety Stock	Zhao et al. (2018), Pastore et al. (2019)
Demand Quantity	Li et al. (2014), Zhao et al. (2018), Ponte et al. (2020b)
Distribution Rate	Corum et al. (2014), Dominguez et al. (2015), Cannella et al. (2016), Zhao et al. (2018)
Transportation System	Zhao et al. (2018)
Customer Demand Change	Li et al. (2014), Haines et al. (2017), Zhao et al. (2018), Pastore et al. (2019)
Order Backlog	Nodoust and Mirzazadeh (2015), Haines et al. (2017), Zhao et al. (2018), Ponte et al. (2020b)
Inventory Arrival Rate	Haines et al. (2017), Zhao et al. (2018)
Number of Echelons	Braz et al. (2018), Pastore et al. (2019)
Rationing	Li et al. (2014), Braz et al. (2018)
Shortage Game	Li et al. (2014), Braz et al. (2018); Zhu et al. (2020)
Price Fluctuations	Lee et al. (1997), Chen et al. (2000), Li et al. (2014), Li (2013), Trapero and Pedregal (2016), Braz et al. (2018), Zhu et al. (2020), Ponte et al. (2020b)
Demand Forecast Updating	Lee et al. (1997), Li (2013), Zhu et al. (2020)
Forecasting Error	Metters (1997), Chen et al. (2000), Li (2013), Braz et al. (2018), Ponte et al. (2020b)
Difference with Desired Inventory (Inventory Gap)	Lee et al. (1997), Li (2013), Yuan and Zhu (2016), Ma and Bao (2017), Braz et al. (2018)
Monopoly of Marketing Channel	Li (2013), Gupta e al. (2019)
Stability of Supplier's Quality	Li (2013), Gupta e al. (2019)
Quantity Discount	Gavirneni (2006), Trapero and Pedregal (2016), Ponte et al. (2020b), Zhu et al. (2020)
Investment Accelerator Effect	Wang and Disney (2016), Zhu et al. (2020)

Regarding the bullwhip effect in supply chain, several researches have been conducted, such as: Mirab Samiee et al. (2020) investigated the role of demand forecasting accuracy on the amount of the bullwhip effect-related cost, taking an intervened demand process with stochastic perturbations into account. They conducted a simulation study on a two-echelon supply chain to investigate the association between forecasting accuracy and the bullwhip effect-related cost. Zhu et al. (2020) investigated affecting factors on bullwhip effect in the oil and gas supply chain using case study evidence from six companies in North America. Regarding the factors that drive or mitigate the bullwhip effect in different types of companies in the oil and gas supply chain, seven propositions are developed and several additional findings are obtained. Pastore et al. (2020) studied a two-echelon single-product supply chain with final demand distributed according to a known AR

(1) process but with unknown parameters. The results show that the bullwhip effect is affected by unknown parameters and is influenced by the frequency with which parameter estimates are updated.

Goodarzi, and Farzipoor Saen (2020) proposed a novel mathematical approach, a new network data envelopment analysis model, to measure relative bullwhip effect of non-serial supply chain networks and their divisions. Since bullwhip effect is undesirable, worst-practice frontier approach is considered to calculate bullwhip effect of non-serial SCNs. To better understand the Bullwhip Effect in closed-loop systems, Ponte et al. (2020a) obtained expressions for the order and inventory variance amplification in four archetypes that differ in the structure of information transparency. They proved the existence of an optimal return rate, and derived its expression in the four closed-loop supply chain archetypes. The optimal rate is dependent on the node’s cost structure, the lead times, and the variability of demand. Dominguez et al. (2020) analyzed the bullwhip effect and inventory performance of a multi-echelon closed loop supply chain with variable remanufacturing lead times under different scenarios of return rate and information transparency in the remanufacturing process. The results showed that ignoring such variability generally leads to an overestimation of the dynamic performance. They observed that enabling information transparency generally reduces order and inventory variability, but it may have negative effects on average inventory if the duration of the remanufacturing process is highly variable.

Pastore et al. (2020) studied bullwhip effect in a European automotive spare parts chain to explain how demand variability propagates in different groups of products. They considered more than 30,000 products, characterized by different technical characteristics, demand classes and planning parameters and concluded that the considered supply chain is affected by the bullwhip effect. Their findings indicates that bullwhip effect is larger for fast moving products rather than for slow movers. Hence, dealers tend to decouple supply and demand and, when they are given incentives to forward-buy, they may prefer to forward-buy fast moving items. Kadivar and Akbarpour Shirazi (2018) investigated the measure of the bullwhip effect in three different supply-chains; (I) with a central warehouse, (II) with a cross-docking system, and (III) without any distribution systems. These three different supply chains are subsequently analyzed to discover which supply chain helps reduce the bullwhip effect more. It was found that factors such as lead time, market share of each retailer, autoregressive coefficient and moving average parameter contribute to the selection of the most effective distribution system. Ma and Bao (2018) investigated the energy-efficient air conditioning supply chain, which is composed of one supplier (MIDEA) and two retailers. They measured the impact of retail prices variability in the two-echelon supply chain on the bullwhip effect. The order-up-to inventory policy and the moving average forecasting method are respectively employed by the two retailers. The results indicate that it’s inadvisable to conduct large fluctuation on price. Besides, demand dates that are more historical may actually reduce the bullwhip effect. We also find that the bullwhip effect will be bigger when the competition becomes fiercer, and there's a necessity for retailers to take measures to reduce the influence of competitors' prices.

Braz et al. (2018) compared the causes and mitigating factors of the bullwhip effect in forward supply chains and closed-loop supply chains. To this end, they employed a systematic literature review that combines bibliometric and content analyses. They found that the primary mitigating factor is related to increasing the product return rate. they suggest that closing a supply chain can reduce the bullwhip effect, which could lead to positive impacts in the environmental performance. Wang and Disney (2016) provided a review of the bullwhip literature which adopts empirical, experimental and analytical methodologies. Findings from empirical and experimental research are compared with analytical and simulation results. They also considered assumptions and approximations for modelling the bullwhip effect in terms of demand, forecast, delay, replenishment policy, and coordination strategy. Finally, the recent research trends and future research directions concerned with supply chain structure, product type, price, competition and sustainability are identified in their work. Fu et al. (2015) derived equivalently the expression of bullwhip metric via control-theoretic approach by applying discrete Fourier transform and (inverse) z-transform when the demand signal is stationary stochastic. A four-echelon supply chain is formulated and its dynamical features are analyzed to give the discrete model.

On the other hand, Najafi et al. (2018) studied the problem of optimal combination of forecasting to reduce the Bullwhip Effect in a Four-level Supply Chain when demand is variable. For this purpose, a Four-level Supply Chain has been considered. Moving average, exponential smoothing, linear regression and multilayer perceptron artificial neural network can be considered for predicting in each level. First, the desired supply chain is simulated for this means. The different combinations of aforementioned Forecasting Methods are calculated. BaniHashemi and Haji Molana (2016) proposed a linear four-level supply chain including store, retailer, wholesaler and factory, and used moving average to predict the demand. They considered nine different scenarios including demand changes (low, medium, high) and precautionary (low, moderate, high). The findings showed that when using moving average method to predict the demands, any increase in the customers' demand change swing will result in the decrease of the bullwhip effect on the whole chain. In addition, if the demand changes are considered as constant and fixed, any increase in precautionary saving in each part of the supply chain will increase the bullwhip effect on the whole chain.

3. Research Methodology

This research is descriptive-survey in terms of method and practical in terms of purpose. From the methodological point of view, this research has a mixed methodology. To conduct the research, based on the literature review and studying the scientific papers related to the bullwhip effect in supply chain, its drivers were extracted and sent to the experts in the form of a questionnaire. The experts include academic experts in supply chain and inventory management field of study and pharmaceutical industry managers of Barkat pharmaceutical company who have the following features: (1) at least 15 years of work experience, (2) at least 5 years of experience in managerial positions, (3) receiving the master's degree or higher in the fields of industrial management or industrial engineering, and (4) familiarity with the risks of inventory management and the concept of bullwhip effect. According to the mentioned features, 5 academic and 9 industry experts were identified as the research experts. It should be noted that during the interview with the experts, they were asked to introduce other experts to the researchers, and finally the number of industry experts increased to 10 experts. In this research, first a Delphi questionnaire was designed based on the drivers identified from the literature review and was sent to the experts in 3 rounds. After analyzing the answers using fuzzy Delphi method, 13 more important drivers affecting the bullwhip effect with the score of ≥ 0.7, were selected as the main drivers. Finally, in order to investigate the relationships between the main drivers, another questionnaire was designed and sent to the research experts. According to the answers and applying fuzzy cognitive map and DEMATEL methods, these drivers were structured and the critical ones were identified. The software used to implement fuzzy cognitive map technique was FC-Mapper and the graph drawing software was Visio 2016. For implementation of DEMATEL method, MATLAB 21 software was used. In the following, the applied methods for data analysis are described.

Fuzzy Delphi

fuzzy Delphi method introduced by Ishikawa et al. (1993) is a method derived from the traditional Delphi method and fuzzy set theory. According to Noorderhaben's study, fuzzy Delphi solves the ambiguities in experts' opinions to a large extent (Homayounfar et al., 2018; Tamjidyamcholo and Toloie Eshlaghy, 2022). In the first step of the research, fuzzy Delphi method will use for screening the drivers identified from the literature review. In the next step, a questionnaire including collected factors will be sent to the experts to determine the importance of each factor based on linguistic values (Table 2). After collecting the questionnaires, the results of the first round were sent to the experts in the form of a questionnaire so that they modify their judgments after reviewing the results of the initial stage, if it is needed. After collecting and analyzing the experts' judgments in the second round, the average difference was checked, if this difference is less than 0.2, consensus is achieved and the fuzzy Delphi steps will be completed. Otherwise, the analysis of the results of this round will also be sent to the experts, again. This process will continue until the experts achieve to the consensus in their judgments. If the experts decide to add a factor during these rounds, this factor will be added to the questionnaire in the next round and opinions about this factor will be asked. At the end, in order to confirm the final factors, the average score of each factor should be compared with the threshold value (0.7). For this purpose, first the triangular fuzzy numbers of experts' judgments should be replaced with linguistic values and then their fuzzy average should be calculated to compute the average of the n respondents' judgments. Table (2) illustrates the utilized scale for transforming linguistic values into triangular fuzzy numbers.

Table 2
Linguistic values and their equivalent fuzzy numbers

Fuzzy Value	**Verbal Word**
(7, 9, 9)	Very High
(5, 7, 9)	High
(3, 5, 7)	Medium
(1, 3, 5)	Low
(1, 1, 3)	Very Low

Fuzzy Cognitive Map

Fuzzy Cognitive Map (FCM) was first introduced by Axelrod in the 1970s to present is an extended version of the mapping that is used to model the complex chain of causal relationships and displays the strength of the causal relationships with a number in the range [-1 1]. In this method, like normal mapping, positive numbers indicate a direct relationship and negative numbers indicate a reverse relationship between phenomena. Koso is the first person who added fuzzy logic to cognitive map with the aim of using qualitative knowledge (Koso, 1986). Rodriguez-Repiso et al. (2007) used four matrices with the title, initial matrix, fuzzy matrix, relationship strength matrix and final matrix to form a fuzzy mapping.

Initial Matrix. The initial matrix is a n×m matrix, where n represents the number of factors and m the number of the experts interviewed to obtain data. Each element Oij of the matrix represents the importance of factor j from the perspective of expert i within the pre-defined scale. The elements $O_{i1}. O_{i2}. \dots . O_{im}$ are the components of the vector V_i belonging to row i (Rodriguez-Repiso et al, 2007).

Fuzzified Matrix. The numerical vectors V_i are transferred into fuzzy sets, where each element of the fuzzy set represents the degree of membership of component Oij of vector Vi to the own vector Vi. The numerical vectors are converted into fuzzy sets with values within the interval [0 1] in the following way.

$$X_i(O_{ij}) = \frac{O_{ij} - \mathrm{Min}(O_{iq})}{\mathrm{Max}(O_{iq}) - \mathrm{Min}(O_{iq})} \quad (1)$$

Direct estimation of the values in the interval [0 1] may determine the membership values in a way that could not be reflect the real world and are not logically justified. In such cases, upper and/or lower threshold values should be defined by the experts. Therefore, if V_i is the numerical vector of m elements related to the concept i and O_{ij} (j = 1, 2… m) are the components of vector V_i, the values of the upper and lower thresholds (α_u and α_l, respectively) are as follows:

$$\forall j = 1.2.\ldots.m \qquad O_{ij}(O_{ij} \geq \alpha_u) \rightarrow X_i(O_{ij}) = 1 \quad (2)$$

$$\forall j = 1.2.\ldots.m \qquad O_{ij}(O_{ij} \leq \alpha_l) \rightarrow X_i(O_{ij}) = 0 \quad (3)$$

Using the above procedure, numerical vectors are converted into fuzzy sets. In addition, a probable deviation of ± 20% between the experts is considered. In other words, if an expert considers the importance of a factor more than 80, it becomes 1 in the fuzzy matrix of success. Likewise, if it is below 20, it will be zero in this matrix.

Strength of Relationship Matrix. The strength of relationship matrix is a n×n matrix which its rows and columns are the under-consideration factors and each element in the matrix indicates the relationship between factor i and factor j. Also, the elements of this matrix S_{ij} lies in the interval [-1 1]. Actually, three possible relations between two concepts i and j are definable:

If Sij>0, there is a direct or positive relationship between factors i and j. In other words, as factor i increases, factor j also increases or vice versa.

If Sij<0, there is an inverse or negative relationship between factors i and j. This means that as factor i increases, factor j decreases or vice versa.

If Sij=0, there is no relationship between factors i and j.

According to V1 and V2, which are vectors related to factors 1 and 2, and X1 (Vj) and X2 (Vj), which are the membership values of factor j in V1 and V2, these vectors have direct relationship (Sij>0) if X1 (Vj) is similar to X2 (Vj) for all or most of the elements of two vectors. The vectors V1 and V2 have a reverse relationship (Sij<0) if X1 (Vj) is similar to (1-X2 (Vj)) for All or most of the elements of two vectors. For vectors that have direct or inverse relationship with each other, the distance dj between the j-th element of vectors V1 and V2 is calculated from equations 4 and 5, respectively.

$$d_j = |X_1(V_j) - X_2(V_j)| \quad (4)$$

$$d_j = |X_1(V_j) - (1 - X_2(V_j))| \quad (5)$$

The average distance between vectors V1 and V2 is equal to AD:

$$AD = \frac{\sum_{j=1}^{m} |d_j|}{m} \quad (6)$$

Closedness or similarity calculation between two vectors is also measurable through equation 7.

$$S = 1 - AD \quad (7)$$

Final Index. When the strength of relationship matrix is completed, some of the data included in it might be misleading data. Not all key success factors presented in the matrix are related and there is not always a causal relationship between them. In order to analyze the data and convert the strength of relationship matrix into the final matrix, it must be noted that strength of relationship matrix includes only those fuzzy elements that represent the causal relationships between the factors.

Graphical Representation of Fuzzy Cognitive Mapping (FCM): The graphical representation of the final matrix draws a targeted fuzzy map for key success factors. In the final representation, each arrow connects the factors, and has a weight ($\pm w_{ij}$) that indicates the intensity or strength of the direct or inverse causal relationship between the two factors (Rodriguez-Repiso et al., 2007).

DEMATEL Method

DEMATEL is a graph theory-based method, was first put forward by American scientist in Science and Human Affairs Program (SHAP) between 1972 and 1976 to resolve the complicated and intertwined problem group (Wu, 2012). This structural modeling approach adopts the form of a directed graph, a causal-effect diagram, to present the interdependence relationships and the values of influential effect between factors (Yadegari et al., 2021). Through analysis of visual relationship of levels among system factors, all elements are divided into causal group and effected group and this can help researchers better understand the structural relationship between system elements, and find ways to solve complicate system problems (Zhou et al., 2011). At first, DEMATEL method focused primarily on the fragmented and even contradictory phenomenon to find a reasonable solution. With further research, this method has been widely applied in more and more areas.

However, this effective structural modeling tool has not yet been used in the field of export barriers, this paper will employ DEMATEL method to classify barriers influencing honey export and to identify the most important barriers. The steps of DEMATEL method based on Gabus and Fontela (1972) are as follows:

Finding out the factors influencing the under-examination system. A large number of literature reviews is required to search and collect relevant information in this phase.

Generating the initial direct-relation matrix form a committee of experts, and acquire the assessments about direct affect between each pair of elements. Converting the linguistic assessments into crisp values, we obtain the direct-relation matrix A = [aij], where A is a n×n non-negative matrix, aij indicates the direct impact of factor i on factor j. When i = j the diagonal elements is zero (aij = 0).

Normalizing the initial direct-relation matrix (D) through Eq. (8). All elements in matrix D are complying with$0 \leq d_{ij} \leq 1$, and all principal diagonal elements are equal to 0.

$$D = \frac{1}{\max \sum_{j=1}^{n} a_{ij}} \cdot A \qquad (8)$$

Acquiring the total-relation matrix T using the Eq. (9) in which I is a n×n identical matrix. The element tij indicates the indirect effects that factor i have on factor j, so the matrix T can reflect the total relationship between each pair of system factors.

$$T = D\,(I - D)^{-1} \qquad (9)$$

Calculating the sum of rows and columns in matrix T through equations (10) and (11). The sum of row i (ri) represents all direct and indirect influence given by factor i to all other factors, and so ri can be called the degree of influential impact. Similarly, the sum of column j (cj) can be called as the degree of influenced impact, since cj summarizes both direct and indirect impacts received by factor j from all other factors:

$$r_i = \sum_{j=1}^{n} t_{ij} \qquad (10)$$

$$c_j = \sum_{i=1}^{n} t_{ij} \qquad (11)$$

Naturally, when i = j, the indicator ri + ci can represent all effects received by factor i. On the contrary, ri - ci shows the net effect that factor i has on the whole system. Specifically, if the value of ri - ci is positive, the factor i is a net cause, exposing net causal effect on the system. When ri - ci is negative, the factor is a net result clustered into effect group.

Constructing cause-effect relationship diagram based on ri + cj and ri - cj. A cause-effect diagram can be drawn by mapping the dataset of (ri + cj, ri - cj).

4. Research Findings

4.1. Screening the drivers of Bullwhip effect

In the first round of fuzzy Delphi method, experts primarily assessed the drivers of bullwhip effect extracted from the literature review where 29 drivers were selected as the more important drivers. Next, in order to calculate the importance of the drivers, a questionnaire in the first round of the Delphi method was sent to the experts asked them to determine the importance of the drivers. After analyzing the results, the questionnaire of the second round of Delphi was sent to the experts with the average score of each driver in first round. Analyzing the results of the second-round questionnaires showed that in 6 drivers, the difference between the average of the experts' judgments in the first and second round is more than 0.2. Therefore, the third round Delphi questionnaire was sent to the experts with the average score of each driver in the second round. Because the difference of the drivers in the second and third round was less than 0.2, a consensus has been took place and 13 drivers with the average score of greater than 0.7. These 13 drivers were identified as the basic drivers of bullwhip effect in the pharmaceutical industry. The results of the third round of fuzzy Delphi can be seen in table (3).

Table 3

The results of the fuzzy Delphi Method

Approve/ Reject	Difference	Average	Very High	High	Mean	Low	Very Low	Verbal Value
			(7,9,9)	(5,7,9)	(3,5,7)	(1,3,5)	(1,1,3)	Driver
Reject	0.122	5.256	2	3	6	3	1	Purchasing Cost
Reject	0.133	6.155	4	5	2	4	0	Order Batching
Reject	0.133	5.533	2	6	3	2	2	Inventory Category
Accept	0	7.833	9	4	2	0	0	Lead Time
Reject	0.133	5.267	2	4	5	2	2	Type of Product
Reject	0.133	3.956	0	2	5	6	2	Advertisement
Reject	0.122	5.122	2	3	5	4	1	Type of Information
Accept	0	8.344	11	4	0	0	0	Information Distortion
Accept	0.011	7.078	5	6	4	0	0	Information Transparency
Accept	0.110	7.722	7	7	1	0	0	Structured Inventory Control Process
Accept	0.133	7.078	6	6	2	0	1	Return Rate
Reject	0.133	6.433	3	5	7	0	0	Inventory Policy
Accept	0	7.078	5	6	4	0	0	Safety Stock
Reject	0.133	5.656	3	4	5	1	2	Demand Quantity
Reject	0.133	4.622	1	3	6	2	3	Distribution Rate
Reject	0.133	3.956	0	2	5	6	2	Transportation System
Accept	0.133	7.322	8	4	2	5	1	Customer Demand Change
Accept	0	7.055	7	3	4	1	5	Order Backlog
Reject	0.133	6.700	3	7	5	0	5	Inventory Arrival Rate
Accept	0.133	7.078	5	7	2	1	5	Number of Echelons

Approve/ Reject	Difference	Average	Very High	High	Mean	Low	Very Low	Verbal Value
			(7,9,9)	(5,7,9)	(3,5,7)	(1,3,5)	(1,1,3)	Driver
Reject	0	4.878	0	4	7	3	1	Rationing
Reject	0	3.956	0	2	5	6	2	Shortage Game
Accept	0.133	7.600	6	8	1	5	5	Price Fluctuations
Accept	0.011	7.222	4	9	2	0	5	Up to date Demand Forecasting
Accept	0.133	8.222	10	5	5	5	5	Forecasting Error
Accept	0	7.089	4	8	3	5	5	Inventory Gap
Reject	0.133	5.789	2	6	4	2	1	Monopoly of Marketing Channel
Reject	0.133	6.178	3	5	6	0	1	Stability of Supplier's Quality
Reject	0.011	4.989	2	1	8	3	1	Discount

Based on the results, indicators of lead time, information disruption, information transparency, structured inventory control process, return rate, safety stock, demand changes, inventory policy, number of echelons, price fluctuations, up-to-date forecasting, forecasting error and inventory gap were selected as main factors for implementation of the second phase of the research.

4.2. Evaluation of bullwhip effect drivers using fuzzy cognitive map

At this stage, fuzzy cognitive map is used in order to modelling the internal relationships and calculate the influence of 13 drivers extracted by fuzzy Delphi method. In this way, based on the evaluation of 15 experts from 13 drivers, an initial 15 x 13 matrix was formed. In the initial matrix, rows include 13 drivers as: lead time (C1), information disruption (C2), information transparency (C3), structured inventory control process (C4), return rate (C5), safety stock (C6), changes in customer demand (C7), inventory policy (C8), number of echelons (C9), price fluctuations (C10), up to date forecasting (C11), forecasting error (C12) and inventory gap (C13), and the columns of this matrix include the answers of 15 experts regarding the drivers based on the 5 point scale. In the next step, the fuzzified matrix was obtained and then the strength matrix of the relationships was calculated. Table (4) shows the elements of the relationships power matrix. In this matrix, the relationships of the all 13 drivers have been shown, which calculated using equations 1 to 6 are. For example, S1,7 = 0.85 indicates a strong relationship between two drivers of price fluctuation and return rate.

Table 4
Strength of Relationship Matrix

C13	C12	C11	C10	C9	C8	C7	C6	C5	C4	C3	C2	C1	Driver
0.80	0.73	0.57	0.77	0.78	0.80	0.85	0.67	0.77	0.77	0.77	0.67	0	C1
0.60	0.53	0.57	0.63	0.62	0.71	0.72	0.60	0.77	0.77	0.57	0	0.67	C2
0.77	0.63	0.67	0.80	0.72	0.77	0.72	0.70	0.67	0.80	0	0.57	0.77	C3
0.77	0.63	0.73	0.80	0.77	0.90	0.85	0.77	0.83	0	0.80	0.77	0.77	C4
0.67	0.70	0.70	0.77	0.84	0.81	0.78	0.67	0	0.83	0.67	0.77	0.77	C5
0.80	0.53	0.70	0.63	0.67	0.80	0.68	0	0.67	0.77	0.70	0.60	0.67	C6
0.72	0.72	0.65	0.78	0.78	0.84	0	0.68	0.78	0.85	0.72	0.72	0.85	C7
0.73	0.69	0.70	0.72	0.78	0	0.84	0.80	0.81	0.90	0.77	0.71	0.80	C8

C13	C12	C11	C10	C9	C8	C7	C6	C5	C4	C3	C2	C1	Driver
0.71	0.73	0.72	0.79	0	0.78	0.78	0.67	0.84	0.77	0.72	0.62	0.78	C9
0.70	0.70	0.73	0	0.79	0.72	0.78	0.63	0.77	0.80	0.80	0.63	0.77	C10
0.77	0.63	0	0.73	0.72	0.70	0.65	0.70	0.70	0.73	0.67	0.57	0.57	C11
0.53	0	0.63	0.70	0.73	0.69	0.72	0.53	0.70	0.63	0.63	0.53	0.73	C12
0	0.53	0.77	0.70	0.71	0.73	0.72	0.80	0.67	0.77	0.77	0.60	0.80	C13

Finally, after analyzing the data, the strength of relationship matrix (SRMS) was converted into the final matrix (FMS). In this regard, by receiving the judgments of the experts, the cause-and-effect relationships between the drivers were structured. Then neutral relationships between drivers were removed and the causal direction of relationships was also determined. The results are shown in table (5).

Table 5
Final Matrix

C13	C12	C11	C10	C9	C8	C7	C6	C5	C4	C3	C2	C1	Driver
0.80	0	0	0	0	0.80	0.85	0.67	0.77	0.77	0	0	0	C1
0.60	0.53	0.57	0.63	0	0.71	0.72	0.60	0	0.77	0.57	0	0.67	C2
0.77	0.63	0.67	0.80	0	0.77	0.72	0.70	0.67	0.80	0	0.57	0	C3
0.77	0.63	0	0	0	0	0.85	0.77	0.83	0	0.80	0	0	C4
0.67	0	0	0.77	0	0.81	0.78	0.67	0	0.83	0	0	0	C5
0.80	0	0	0.63	0	0.80	0.68	0	0	0.77	0	0	0.67	C6
0.72	0.72	0.65	0.78	0	0.84	0	0.68	0.78	0	0	0	0	C7
0.73	0	0.70	0.72	0	0	0.84	0.80	0	0.90	0.77	0	0.80	C8
0	0	0	0	0	0.78	0	0	0	0.77	0.72	0.62	0.78	C9
0.70	0	0.73	0	0.79	0.72	0.78	0.63	0.77	0.80	0.80	0.63	0.77	C10
0	0.63	0	0.73	0	0.70	0	0.70	0.70	0.73	0	0	0	C11
0.53	0	0	0	0	0.69	0	0.53	0.70	0.63	0	0.53	0	C12
0	0	0	0	0	0.73	0	0.80	0	0.77	0	0	0	C13

In addition, the fuzzy cognitive map diagram drawn using FCMapper 6 software is shown in Figure 2. In this map, the size of the squares is proportional to the influential measure of each driver. The graph structure indicates that the map has 13 nodes (drivers), all of which are central nodes.

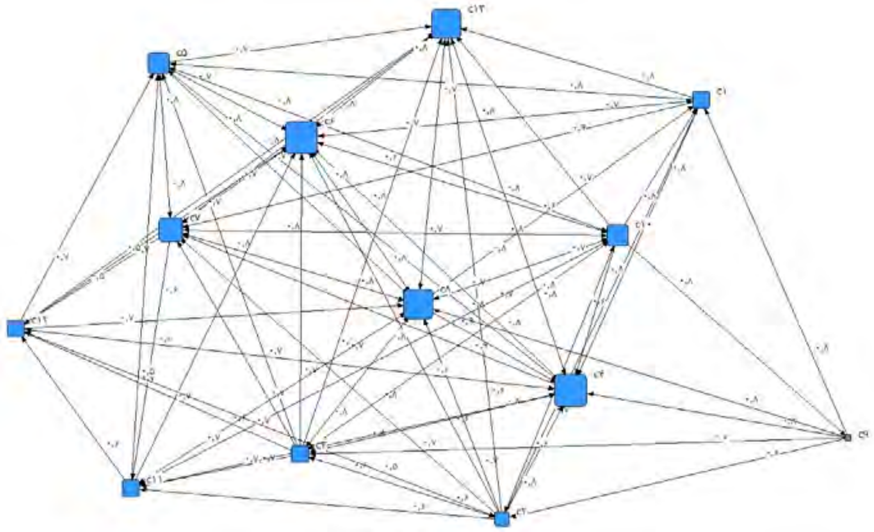

Figure 1. *Fuzzy Cognitive Map of Bullwhip Effect Drivers*

Among the other outputs of fuzzy cognitive map; the influential, to be influenced and centrality indicators could be mentioned, which are determined in table (6). In this table, the drivers are ranked in descending order based on the centrality index. Higher influential values indicate the more influence of drivers in the system, which is obtained from the sum of the absolute values of the influence of this driver on the other drivers. In addition, “to be influenced” index shows the degree of influence of all drivers on this driver. The large values of the “to be influenced” for each driver indicate that it strongly influenced by the changes of the drivers that affect it. This indicator is also the sum of the absolute values of the influence of other drivers on given driver. For example, the influential and to be influences indexes of the structured inventory control is computed as follows:

$OUT\ (C4) = 0.80 + 0.77 + 0.90 + 0.80 + 0.84 + 0.72 + 0.70 + 0.73 = 6.26$

$IN\ (C4) = 0.71 + 0.77 + 0.81 + 0.80 + 0.84 + 0.78 + 0.72 + 0.70 + 0.69 + 0.73 = 7.55$

The centrality index includes the sum of influential and to be influenced indexes, and its value shows the degree of interaction of the driver with the other drivers. Therefore, during the analysis of fuzzy cognitive map, this indicator should be considered carefully by decision makers. The centrality index for the structured process of inventory control is calculated as follows:

$C(C4) = 6.26 + 7.55 = 13.81$

Although in figure (1) the inferentiality of each driver on other drivers is specified, but the most important index of importance is the centrality. Therefore, in terms of the centrality index, the structured inventory control process, lead time, safety stock, inventory policy and return rate are 5 essential drivers of the system which have more effect on bullwhip effect. As can be seen in Table 6, among all drivers, the first, third and fourth driver belong to the inventory management system.

Table 6

Ranking of the Bullwhip Effect Drivers Based on Centrality Index

Centrality	To be Influenced	Influentially	Driver
14.611	8.350	6.261	C8
13.200	5.072	8.128	C10
13.183	8.533	4.650	C4
11.900	7.550	4.350	C6
11.394	6.222	5.172	C7
10.739	3.656	7.083	C3
9.745	5.217	4.528	C5

Centrality	To be Influenced	Influentially	Driver
9.383	7.083	2.300	C13
8.717	2.356	6.361	C2
8.368	3.678	4.690	C1
7.517	3.317	4.200	C11
6.772	3.150	3.622	C12
4.456	0.789	3.667	C9

As can be seen in Table 6, the structured process of inventory control ranks fourth and second in terms of influential and to be influenced, however, it ranks first in terms of the centrality index and is considered as the most important drivers of the bullwhip effect. Lead time is ranked first in terms of influential and seventh in terms of to be influenced, however, based on the centrality index, this driver is ranked as second one. The safety stock of the supply chain echelons also ranks sixth in terms of influential and ranks first in terms of to be influenced. But, according to the centrality index, it took the third place among all drivers of bullwhip effect. Inventory policy and return rate are ranked as 8th and 5th drivers in terms of inferentiality and 2nd and 5th in terms of to be influenced. According to the centrality index, these drivers are in the fourth and fifth place.

4.3. Evaluation of bullwhip effect drivers using DEMATEL method

In this section, after determining the most important drivers of the bullwhip effect using fuzzy Delphi, DEMATEL method in used to determine the critical drivers among all. For this purpose, the relation cells which show the casual relationships between the drivers (were previously determined by the experts), became the basis for determining the intensity of the relationships. In this way, the experts were asked to determine the effect of each of the factors placed in the rows on the factors of the columns (in the relation cells). based on the scale of table (7).

Table 7

Scoring Scale in DEMATEL Method

Very High		High		Medium		Low		Very Low		Influence
10	9	8	7	6	5	4	3	2	1	Score

In order to use the experts' judgments in determination of the critical drivers, the group direct relationships matrix was formed by combining the individual matrixes through geometric mean, where, the result is presented in Table 8. After normalization of the group direct relationships matrix, the intensity matrix of total relationships (direct and indirect) was formed. Sum of the numerical values of the drivers placed in the rows (Ri) indicates their influentially and sum of the numerical values of drivers placed in the columns (Ci) indicates its "to be influenced" index.

Table 8

Group Direct Relationships Matrix

C13	C12	C11	C10	C9	C8	C7	C6	C5	C4	C3	C2	C1	Driver
3.855	0	0	0	0	6.568	8.194	3.859	2.747	5.286	0	0	0	C1
5.585	6.554	6.429	5.505	0	5.571	3.850	2.286	0	6.860	7.296	0	3.238	C2
5.340	5.714	4.312	7.144	0	7.444	7.569	3.374	3.587	8.662	0	6.122	0	C3
8.286	3.436	0	0	0	0	2.858	5.701	4.145	0	4.224	0	0	C4
5.482	0	0	4.286	0	5.530	4.145	4.632	0	7.199	0	0	0	C5
7.098	0	0	5.715	0	3.502	3.357	0	0	4.660	0	0	6.490	C6
4.714	4.132	4.333	6.580	0	6.848	0	4.714	3.108	0	0	0	0	C7

C13	C12	C11	C10	C9	C8	C7	C6	C5	C4	C3	C2	C1	Driver
8.115	0	3.338	8.563	0	0	3.198	8.286	0	9.143	2.628	0	6.315	C8
0	0	0	4.280	0	5.855	0	0	0	5.983	4.410	4.429	8.286	C9
3.454	0	5.047	0	0	9.228	7.225	7.860	6.186	5.139	3.200	3.140	5.714	C10
0	4.177	0	3.375	0	6.754	0	6.440	4.202	5.213	0	0	0	C11
8.991	0	0	0	0	7.335	0	5.568	2.875	6.119	0	4.696	0	C12
0	0	0	0	0	6.108	0	6.544	0	6.325	0	0	0	C13

Table (9) shows the amount of influentially (Ri), to be influenced (Ci), sum of influentially and to be influenced (Ri + Ci) and difference of influentially and to be influenced (Ri-Ci) of each driver. Depending on whether the value of Ri-Ci is positive or negative, indicators are divided into two groups of cause and effect (Zhou et al., 2011). The cause group with a positive Ri-Ci value includes: information disruption, information transparency, return rate, number of chain levels, price fluctuations, up-to-date forecasting and forecasting error. On the other hand, lead time, structured inventory control process, safety stock, demand change, inventory policy and inventory gap are in the effect group, because their Ri-Ci value is negative.

Table 9
Evaluation of Critical Indexes

Status	R-C	R+C	C	R	Driver
-	-0.076	4.240	2.158	2.082	C1
Critical	1.535	4.554	1.510	3.045	C2
Critical +	1.521	5.142	1.761	3.382	C3
Critical +	-1.560	5.569	3.656	2.005	C4
-	0.112	4.153	2.020	2.133	C5
Critical +	-1.439	5.651	3.545	2.106	C6
-	-0.207	4.882	2.544	2.338	C7
Critical +	-0.666	6.221	3.443	2.777	C8
-	1/377	3.377	1	2.377	C9
Critical +	0.394	5.761	2.684	3.078	C10
-	0.288	3.975	1.844	2.131	C11
-	0.427	4.101	1.837	2.264	C12
Critical +	-1.805	5.178	3.492	2.686	C13

Among all factors of the cause group, information transparency has the highest Ri-Ci, which means that information transparency affects the whole system more than other factors. In addition, Table (9) shows that the effect of information transparency is equal to 3.382, which places it in the first rank of causal factors. Therefore, information transparency is a critical driver in the system. The factors that have the next highest Ri-Ci are price fluctuations and information disruption. The influence values of these factors are equal to 3.078 and 3.045, respectively, which indicate their great effect on the whole system. Therefore, price fluctuations and information disruption are considered as critical factors. The Ri-Ci score of the return rate, number of echelons, up-to-date forecasting and forecasting error is also positive which put them in the cause group, however, their effect on other factors is moderate and compared to other factors of the group, they are not considered critical.

Among the factors of the effect group: the structured process of inventory control has a value of Ci equal to 3.656, which has the first rank among the factors of this group. So, the structured process of inventory control is chosen as the critical factor in terms of to be influenced. In addition, the factor with second score among the factors of effect group is the safety stock of chain elements. Considering the high “to be influenced” score of this driver (3.545) compared to other drivers, the safety stock could be considered as a critical driver in the system. The inventory gap also has a high Ci score (3.492) compared to other drivers. Therefore, in terms of to be influenced, this driver is also considered as a critical driver. Finally, the inventory policy with an “to be influenced” score of 3.443 has a significant difference with other drivers. Therefore, it is selected as the fourth critical drivers in the effect group. According to the Ci index, other drivers of the effect group are not considered critical.

Among the 13 under consideration drivers, inventory policy has the highest value (6.221) of Ri + Ci. The indicators of price fluctuations (5.761), safety stock (5.671), structured inventory control process (5.569), inventory gap (5.178) and information transparency (5.142) respectively have the highest score in Ri + Ci. This shows that they are critical in making bullwhip effect. It should be noted that information transparency and price fluctuations were previously identified as critical from the influential index. On the other hand, structured process of inventory control, safety stock, inventory policy and inventory gap in terms to be influenced, also were determined critical previously.

5. Conclusion

In this study, two graph theory-based methods, i.e., fuzzy cognitive map and DEMATEL, have been used to identify the critical drivers of bullwhip effect in the supply chain of the pharmaceutical industry. The applied methods provide a systematic approach to analyze the system components. In order to determine the importance of the critical drivers affecting on bullwhip effect, after reviewing the literature, some important drivers were identified. Then, by receiving experts' judgments and using fuzzy Delphi, more importance drivers were determined. Since, the output of the Delphi method specifies the importance of the bullwhip effect drivers individually and nevertheless of their feedback structures, it’s a suitable basis for ranking drivers. According to the assumption of drivers’ independency, information distortion, forecasting error, lead time, structured inventory control process and price fluctuations are among the most important drivers, respectively. Based on the output of the fuzzy cognitive map method, as the first method which considers indirect effects in ranking drivers, structured process of inventory control, lead time, safety stock, inventory policy, product return rate and information disruption placed in the first to sixth ranks of the affecting drivers on bullwhip effect in terms of the centrality factor. On the other hand, based on DEMATEL as a popular and approved method with feedback structure, inventory policy, price fluctuations, safety stock, structured process of inventory control, inventory gap and information transparency are among the most important drivers.

From a practical point of view, the findings suggest management strategies to reduce or even eliminate the bullwhip effect in pharmaceutical supply chains. It’s clear that the structured process of inventory control, safety stock and inventory policy are among the critical drivers in both methods. Therefore, concentrating on these drivers and making strategies for their improvement, it is possible to reduce the bullwhip effect as one of the most important risks in the supply chain. Since choosing the proper inventory policy is the main mitigation strategy to reduce the bullwhip effect. Although the effective inventory policy is difficult to meet, it depends to senior management's views to the role of inventory and the expertise of supply chain and logistics professionals to structure a decision-making process for an inventory policy.

Safety stock, also plays an essential role in the supply chain and helps businesses avoid stock-outs and meet demand. But it should be noted that the safety stock is a part of inventory and zero stock is not recommended in any of the supply chains. However, to avoid having too much safety stock, top managers should adjust safety stock uniformly. As market creates complex scenarios, rigid methods are incapable of adjusting the safety stock to a demand that's different and extremely variable. In this situation, taking into account the main variables are essential. for adjustment of safety stock levels to cover risks without going overboard it's recommended to use new technologies related to big data in logistics. The other way to avoid having too much safety stock is improving processes and elements that are controllable. Concentrating on demand forecasting methods while continue to operate with high levels of safety stock is a pitfall. It's much more effective to focus on improvement of controllable endogenous variables such as cutting internal lead times helps reduce cycles, limit wasted time and eliminate reworks. Using the warehouse management software to control the stock levels is another way to avoid too much safety stock. This software can ensure appropriate levels of safety stock: neither too high nor too low.

For future research, it is suggested that the effect of bullwhip should be investigated in terms of the drivers used in the research and at different levels of a multi-echelon supply chain. Also, the drivers of the bullwhip effect based on weight determination methods should also be investigated and the results should be compared with the current research. Finally, by using the simulation of the system's behavior and studying the effects of changes in the basic drivers on the behavior of the bullwhip effect, proper policies would be developed to reduce this phenomenon.

References

Banihashemi, S.A., & Haji Molana, S.M. (2017). Analyzing Bullwhip Effect Sensitivity in a Four-level Supply Chain Using Average Moving Method to Forecast the Demand. Industrial Management Journal, 9(1), 43-58. 10.22059/imj.2017.223681.1007173

Braz, A.C., Mello, A.M., de Vasconcelos Gomes, L.A., & Nascimento, P.T. (2018). The bullwhip effect in closed-loop supply chains: A systematic literature review. Journal of Cleaner Production, 202, 376-389. doi.org/10.1016/j.jclepro.2018.08.042

Cannella, S., Bruccoleri, M., & Framinan, J.M. (2016). Closed loop supply chains: What reverse logistics factors influence performance? International Journal of Production Economics, 175, 35-49. doi.org/10.1016/j.ijpe.2016.01.012

Chang, A.Y., Yu, H.F., Yang, T.H. (2013). A study of the key factors contributing to the bullwhip effect in the supply chain of the retail industry. Journal of Industrial and Production Engineering, 30(7), 433-442. doi.org/10.1080/21681015.2013.849767

Chen F., Drezner, Z., Ryan, J., K., Simchi-Levi, D. (2000). Quantifying the Bullwhip Effect in a Simple Supply Chain: The Impact of Forecasting. Management Science, 46 (3), 436-443. doi:0025-1909/00/4603/0436505.00

Cheng, L.C. (2009). Impact of inventory policy consistency on the three-stage supply chain performance. Journal of Academy of Business and Economics, 9 (4), 33-53. doi:10.1016/j.cie.2008.02.002

Corum, A., Vayvay, Ö., Bayraktar, E., (2014). The impact of remanufacturing on total inventory cost and order variance. Journal of Cleaner Production, 85, 442-452. doi.org/10.1016/j.jclepro.2014.06.024

Dominguez, R., Cannella, S., Barbosa-Povoa, A.P., Framinan, J.M. (2018). OVAP: A strategy to implement partial information sharing among supply chain retailers. Transportation Research Part E: Logistics and Transportation Review. 110, 122–136. doi.org/10.1016/j.tre.2017.12.016

Dominguez R., Cannella S., Framinan, J.M. (2015). On returns and network configuration in supply chain dynamics. Transportation Research Part E: Logistics and Transportation Review, 73, 152-167. doi.org/10.1016/j.tre.2014.11.008

Tai, P.D., Hien Duc, T.T., Buddhakulsomsiri, J. (2018). Measure of bullwhip effect in supply chain with price-sensitive and correlated demand. Computers & Industrial Engineering, 127, 408-419. doi.org/10.1016/j.cie.2018.10.027

Forrester, J.W. (1961) Industrial Dynamics, New York, MIT Press.

Fu, D., Ionescu, C., Aghezzaf, E.H., De Keyser, R. (2015). Quantifying and mitigating the bullwhip effect in a benchmark supply chain system by an extended prediction self-adaptive control ordering policy. Computers & Industrial Engineering, 81, 46–57. doi.org/10.1016/j.cie.2014.12.024

Gabus, A., Fontela, E. (1972). World problems, an invitation to further thought within the frame work of DEMATEL. Battelle Geneva Research Center, Geneva, Switzerland.

Gavirneni, S. (2006). Price fluctuations, information sharing, and supply chain performance European Journal of Operational Research, 174, 1651-1663. doi.org/10.1016/j.ejor.2005.04.037

Goodarzi, M., Farzipoor Saen, R. (2020). How to measure bullwhip effect by network data envelopment analysis? Computers & Industrial Engineering, 139, 105431. doi.org/10.1016/j.cie.2018.09.046

Haines, R., Hough, J., Haines, D. (2017). A Metacognitive Perspective on Decision Making in Supply Chains: Revisiting the Behavioral Causes of the Bullwhip Effect. International Journal of Production Economics, 184, 7-20. doi.org/10.1016/j.ijpe.2016.11.006

Holland, W., Sodhi, M.S. (2004). Quantifying the effect of batch size and order errors on the bullwhip effect using simulation. International Journal of Logistics Research and Applications, 7 (3), 251-261. doi:10.1080/13675560412331298518

Homayounfar, M., Goudarzvand chegini, M., Daneshvar, A. (2018). Prioritization of Green Supply Chain Suppliers Using a hybrid Fuzzy Multi-Criteria Decision-Making approach. Journal of Operational Research and Its Applications, 15(2), 41-6. doi: 20.1001.1.22517286.2018.15.2.5.9

Hussain, M., Drake, P.R. (2011). Analysis of the bullwhip effect with order batching in multi-echelon supply chains. International Journal of Physical Distribution & Logistics, 41 (8), 797-814.doi:10.1108/09600031111185248

Ishikawa, A., Amagasa, M., Shiga, T., Tomizawa, G., Tatsuta, R., Mieno, H. (1993). The max–min Delphi method and fuzzy Delphi method via fuzzy integration. Fuzzy Sets and Systems, 55, 241–253. doi.org/10.1016/0165-0114(93)90251-C

Jiang, Q., Ke, G. (2019). Information Sharing and Bullwhip Effect in Smart Destination Network system. Ad Hoc Networks, 87 (1), 17-25. doi.org/10.1016/0165-0114(93)90251-C

Kadivar, M., Akbarpour Shirazi, M. (2018). Analyzing the Behavior of the Bullwhip Effect considering Different Distribution Systems. Applied Mathematical Modelling, 59, 319-340. doi.org/10.1016/j.apm.2018.01.028

Kelle, P., Milne, A. (1999). The effect of (s, S) ordering policy on the supply chain. International Journal of Production Economics, 59, 113–122. doi.org/10.1016/S0925-5273(98)00232-1

Koso, B. (1986). Fuzzy cognitive maps. International Journal of Man-Machine Studies, 24, 65-75. doi.org/10.1016/S0020-7373(86)80040-2

Kumara, A., Shankarb, R., Aljohani, N.R. (2020). A big data driven framework for demand-driven forecasting with effects of marketing-mix variables. Industrial Marketing Management, 90, 493-507. doi.org/10.1016/j.indmarman.2019.05.003

Lee, H.L., Padmanabhan, V., Whang, S. (1997). Information distortion in a supply chain: The bullwhip effect. Management Science, 43, 546–558. doi:10.1287/mnsc.1040.0266

Lee, S., Klassen, R.D., Furlan, A., Vinelli, A. (2014). The green bullwhip effect: Transferring environmental requirements along a supply chain. International Journal of Production Economics, 156, 39-51. doi.org/10.1016/j.ijpe.2014.05.010

Li, C. (2013). Controlling the bullwhip effect in a supply chain system with constrained information flows. Applied Mathematical Modelling, 4, 1897-1909. doi.org/10.1016/j.apm.2012.04.020

Li Q., Disney S.M., Gaalman G. (2014). Avoiding the bullwhip effect using Damped Trend forecasting and the Order-Up-To replenishment policy. International Journal of Production Economics, 149, 3-16. doi.org/10.1016/j.ijpe.2013.11.010

Ma, J., Bao, B. (2017). Research on bullwhip effect in energy-efficient air conditioning supply chain. Journal of Cleaner Production, 143, 854-865. doi.org/10.1016/j.jclepro.2016.12.035

Metters, R. (1997). Quantifying the bullwhip effect in supply chains. Journal of Operations Management, 15, 89–100. doi.org/10.1016/S0272-6963(96)00098-8

Mirab Samiee, Z., Rostamzadeh, M., Fatahi Valilai, O. (2020). An Analysis of the BWE-Associated Costs: The issue of Demand Forecasting Accuracy. IFAC, 53 (2), 10836-10842. doi.org/10.1016/j.ifacol.2020.12.2870

Mostafaee, K., Azar, A., Moghbel, A. (2018). Identification and Analysis of Operational Risks: A Fuzzy Cognitive Map Approach. Journal of Asset Management and Financing, 6(4), 1-18. [In Persian] 20.1001.1.23831170.1397.6.4.2.9

Najafi, M., Daneshmand-Mehr, M., Sadeghian, R. (2019). The Impact of Forecasting Methods Combination for Reducing Bullwhip Effect in a Four-level Supply Chain under Variable Demand. Journal of Operational Research in Its Applications, 16(3), 89-109. 20.1001.1.22517286.2019.16.3.4.7

Narayanan, V.G., Raman, A. (2004). Aligning incentives in supply chains. Harvard business review, 82(11), 94-102.

Nodoust, S., & Mirzazadeh, A. (2015). An Uncertain Time Horizon Inventory Management Model with Partial Backlogging Considering Deterioration Cost. Journal of System Management, 3(3), 67-83.

Ojha, D., Sahin, F., Shockley, J., Sridharan, S.V. (2019). Is there a performance tradeoff in managing order fulfillment and the bullwhip effect in supply chains? The role of information sharing and information type. International Journal of Production Economics, 208, 529-543. doi.org/10.1016/j.ijpe.2018.12.021

Pastore, E., Alfieri, A., Zotteri, G., Boylan, J.E. (2020). The impact of demand parameter uncertainty on the bullwhip effect. European Journal of Operational Research, 283 (1), 94-107. doi.org/10.1016/j.ejor.2019.10.031

Pastore, E., Alfieri, A., Zotteri, G. (2019). An empirical investigation on the antecedents of the bullwhip effect: Evidence from the spare parts industry. International Journal of Production Economics, 209, 121-133. doi.org/10.1016/j.ijpe.2017.08.029

Ponte, B., Framinan, J.M., Cannella, S., Dominguez, R. (2020). Quantifying the Bullwhip Effect in closed-loop supply chains: The interplay of information transparencies, return rates, and lead times. International Journal Production Economics, 230, 107798. doi.org/10.1016/j.ijpe.2020.107798

Potter, A., Disney, S.M. (2006). Bullwhip and batching: An exploration. International Journal of Production Economics, 104 (2), 408-418. doi.org/10.1016/j.ijpe.2004.10.018

Reiner, G., Fichtinger, J. (2009). Demand forecasting for supply processes in consideration of pricing and market information. International Journal of Production Economics, 118(1), 55-62. doi.org/10.1016/j.eswa.2006.01.032

Rodríguez Repiso, L., Setchi, R., Salmeron, J. (2007). Modelling IT projects success with Fuzzy Cognitive Maps. Expert Systems with Applications, 32, 543-559. doi.org/10.1016/j.eswa.2006.01.032

TamjidYamcholo, A., & Toloie Eshlaghy, A. (2022). Subjectivity Reduction of Qualitative Approach in Information Security Risk Analysis. Journal of System Management, 8(1), 145-166. doi: 10.30495/jsm.2022.1945866.1578

Trapero, J.R., Pedregal, D.J. (2016). A novel time-varying bullwhip effect metric: An application to promotional sales. International Journal of Production Economics, 182, 465–471. doi.org/10.1016/j.ijpe.2016.10.004

Wang, X., Disney, S.M. (2016). The bullwhip effect: Progress, trends and directions. European Journal of Operation Research, 250 (3), 691–701. doi.org/10.1016/j.ejor.2015.07.022

Wu, W.W. (2012). Segmenting critical factors for successful knowledge management implementation using the fuzzy DEMATEL method. Applied Soft Computing, 12(1), 527-535. doi.org/10.1016/j.asoc.2011.08.008

Yadegari Taheri, T., Vakil Alroaia, Y., Faezi Razi, F., Heydariyeh, S.A. (2021). Identification and Prioritization of Organizational Intelligence Criteria in Production Cooperatives of Iran. Journal of System Management, 7 (4), 205-227. doi: 10.30495/jsm.2021.1942062.1531

Yuan, X.G., Zhu, N. (2016). Bullwhip Effect Analysis in Two-Level Supply Chain Distribution Network Using Different Demand Forecasting Technology. Asia-Pacific Journal of Operational Research, 33(3), 1650016. doi.org/10.1142/S0217595916500160

Zhang, X., Burke, G.J. (2011). Analysis of compound bullwhip effect causes. European Journal of Operational Research, 210(3), 514-526. doi.org/10.1016/j.ejor.2010.09.030

Zhao, Y., Cao, Y., Li, H., Wang, S., Liu, Y., Li, Y., Zhang, Y. (2018). Bullwhip effect mitigation of green supply chain optimization in electronics industry. Journal of Cleaner Production, 180, 888-912. doi.org/10.1016/j.jclepro.2018.01.134

Zhao, S., Zhu, Q. (2018). A risk-averse marketing strategy and its effect on coordination activities in a remanufacturing supply chain under market fluctuation. Journal of Cleaner production, 171, 1290-1299. doi.org/10.1016/j.jclepro.2017.10.107

Zhou, L., Naim, M.M., Disney, S.M. (2017). The impact of product returns and remanufacturing uncertainties on the dynamic performance of a multi-echelon. International Journal of Production Economics, 183, 487-502. doi.org/10.1016/j.ijpe.2016.07.021

Zhou, Q., Huang, W., Zhang, Y. (2011). Identifying critical success factors in emergency management using a fuzzy DEMATEL method. Safety science, 49 (2), 243-252. doi.org/10.1016/j.ssci.2010.08.005

Zhu, T., Balakrishnan, J., da Silveira, G.J.C. (2020). Bullwhip Effect in the Oil and Gas Supply Chain: A Multiple-case Study. International Journal of Production Economics, 224, 107548. doi.org/10.1016/j.ijpe.2019.107548

Zotteri, G. (2013). An empirical investigation on causes and effects of the Bullwhip-effect: Evidence from the personal care sector. International Journal of Production Economics, 143 (2), 489-498. doi.org/10.1016/j.ijpe.2012.06.006