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An Interaction Investigation of the Contributing Factors of the Bullwhip Effect Using a Bi-Level Social Network Analysis Approach

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ABSTRACT The bullwhip effect refers to the phenomenon of the increase in demand variability from supply chain downstream members to upstream members. This effect is critically important for the different sectors involved in a supply chain and is one of the main causes of inefficiency, material waste, and low sustainability in supply chain management. In order to help minimize the bullwhip effect and achieve sustainable development in a supply chain, this study identifies the influential factors of the bullwhip effect in a supply chain and the interactive relationships among them. A bi-level bullwhip effect analysis model was established to evaluate the causes of the bullwhip effect at different levels by using a social network analysis approach. Furthermore, to help achieve efficient and sustainable development, the implications of mitigating the impacts of the bullwhip effect in a supply chain were explored based on the results of the inter-relationships analysis among the contributing factors of the bullwhip effect.

INDEX TERMS Supply chain management, sustainable development, bullwhip effect, social network analysis, graph theory, information distortion.

I. INTRODUCTION

Globalization has complicated the supply chain of manufacturing with the involvement of various stakeholders and multiple influential factors. Suppliers and retailers have observed that, as the variation of product demand increases, there is a considerable fluctuation of inventory and back-order levels across the supply chain [1]. Consequently, the demand uncertainty and variability increase from downstream members to upstream members in the supply chain, which is called the bullwhip effect (BWE). This effect causes tremendous waste in supply chains due to higher inventory holding costs, manufacturing costs, and lower customer service level [2], which are the major causes of inefficiencies in supply chain management [3]. Moreover, sustainability within the supply chain has become one of the areas receiving considerable

interest [4]. For example, blockchain technology has been applied to achieve a sustainable supply chain [5].

Many studies have been carried out to identify the contributing factors of the BWE and the related approaches to reduce its impact on supply chains. By establishing a supply chain model, the influence of demand forecasting and order lead time on the BWE has been quantified [6], in addition to which the impact of distribution system on the BWE has been presented [7]. As pointed out by Wang *et al.* [8], information sharing has a positive impact on the BWE, while the relationship between market competitions and the BWE has been discussed [9]. And the impact of the market ripple effect on the BWE was also highlighted [10]. Moreover, network data envelopment analysis (NDEA), which is an advanced approach of network data analysis, has been applied to measure the intensity of the BWE by simulating a two-stage supply chain [11]. However, there are still two challenges:

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- (1) There is a need for the theoretical model to evaluate the interactive relationships among the BWE contributing factors and the relationships between the BWE contributing factors and other factors (parameters) involved in a supply chain, such as inventory level, to better understand the causes of the BWE.
- (2) There is a need for a practical approach to measure the centrality of contributing factors in a network constructed by supply chain factors and improve sustainability in supply chains.

To address these issues, this study established a novel theoretical process to visualize and analyze BWE contributing factors and their relationships based on social network analysis (SNA) and graph theory. A social network consists of a finite set or sets of nodes and focuses on relationships among social entities [12]. The network of nodes is linked by relationship ties which can take many forms such as friendship, and impact [13]. Therefore, it can be utilized to study the causes of BWE by focusing on interactive relationships.

Besides the introduction section, the theoretical bi-level SNA model is presented in section 2; subsequently, the supply chain of Zara is illustrated by utilizing this new approach in section 3, which is followed by the result and discussion in section 4; finally, the managerial implications, validation, and a conclusion are given in sections 5 to 7.

II. THEORETICAL BI-LEVEL SNA MODEL OF BULLWHIP EFFECT ANALYSIS

In this section, the previous studies about the social networks and the four BWE contributing factors related to the case study of Zara are discussed firstly; then, the bi-level SNA approach is introduced in part C; lastly, centrality metrics and link prediction metrics are given in part D and E.

A. SOCIAL NETWORKS AND GRAPH THEORY

A social network is the pattern of friendships, advice, communication, or support that exists among the members of a social system with the computational foundation of graph theory, which is the study of mathematical structures used to model pairwise relations between objects. [14]. Social networks have been applied to study opinion leadership [15], public procurement ecosystem [16], as well as sustainable human resource management [17]. Besides that, SNA has played a key role to obtain the optimal condition of ultra-precision machining [18].

In the research area of the sustainable supply chain, the importance of social networks has been highlighted by Tachizawa and Wong [19]. Moreover, Lu *et al.* [20] have shown how to evaluate the uncertainty in a complex environment using social networks. And a theoretical model has been built to explain the sustainability in the supply chains based on graph theory and social networks [21]. Besides that, SNA also has been utilized for the study of the polysilicon trade network [22]. However, there is no study to apply the SNA method to evaluate the inter-relationships among the causes

of the BWE. And the theoretical bi-level SNA model has not been developed in previous studies.

B. CONTRIBUTING FACTORS OF THE BULLWHIP EFFECT

Based on a literature review, the four most critical BWE contributing factors relevant to the case study of Zara were identified as follows:

- (1) **Lead Time** refers to the time interval between the order placing and shipment receiving, which is the main factor that varies and affects all members within a supply chain [23]. With longer lead times, a small change in the estimate of demand variability implies a significant change in safety stock and reorder level, which can lead to a significant change in order variability. It has been pointed out that the reduction of lead time is effective to mitigate the BWE and minimize material waste [24].
- (2) **Decen./Centralized System** can be a system of information, manufacturing, or distribution. As using aggregate demand forecasting could lead to lower demand uncertainty, utilizing a centralized system could reduce the order variability [25]. According to the study of Xu *et al.* [26], the centralized system can bring at most 33% environmental profit compared with the decentralized system in the decision-making model.
- (3) **Price Fluctuation** can cause retailers to tend to stock up when the price is low and purchase less when the price is high. And this action will raise the variability of demand. This practice is also called forward buying, which implies that retailers make large orders during distributors' or manufacturers' discount and promotion time and order relatively small quantities at other periods [25]. By simulating the impact of price fluctuation on a supply chain, it was found that price fluctuation is the main cause of inefficiency and energy waste in a supply chain [27].
- (4) **Demand Forecasting** refers to the accuracy of the forecast of demand, which also has an impact on the intensity of the BWE. High accuracy of demand forecasting could reduce the chances of overproduction or backorder, which means a reduction of the demand variability for suppliers [25]. Several recent works focused on developing more accurate demand forecasting methods based on machine learning [28] and blockchain [29].

From the above, it can be seen that the study to evaluate the inter-relationships between contributing factors and other factors in a real-world supply chain is still currently inadequate. This situation makes it difficult to find the root cause of the BWE. Therefore, developing a bi-level SNA model is necessary to analyze real-life supply chains.

C. THE PROCESS OF THE BI-LEVEL SNA MODEL

In a social network, "node" and "edge" stand for the object in a network and the link between two objects respectively. According to the SNA approach proposed by Yip *et al.* [18], nodes can represent the factors in the manufacturing system

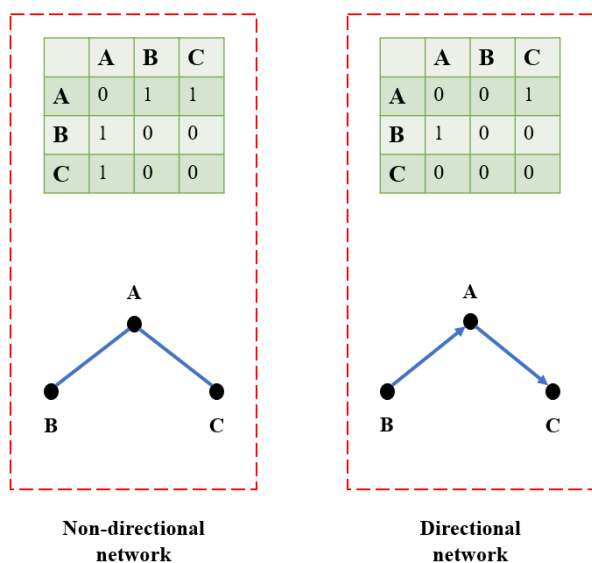


FIGURE 1. Example of a non-directional network, directional network and their adjacency matrices (the path in a non-directional network is invertible; while the path in a directional network can be non-invertible).

and the edges can represent the influencing relationships among these factors. In this study, the relevant supply chain factors (parameters) in the case study of Zara, which were represented by nodes, were linked together according to their influencing relationships. For example, if demand uncertainty increases, the inventory level needs to be increased to keep the risk of stock out at the same level. This means demand uncertainty can influence the inventory level. Therefore, an edge from the node of demand uncertainty to the node of the inventory level would be added. To construct this network, the first step was finding out these supply chain factors and their influencing relationships by conducting a literature review. Then, these relationships need to be summarized in an adjacency matrix. As this study focused on how many other factors can influence one certain factor, the binary values could be utilized to describe the relationships in this study. In this matrix, the value “1” indicates that the factor on the left-hand side has a direct impact on the factor on the right-hand side. If there is “0”, it means the left-hand side factor has no direct impact on the right-hand factor. And this adjacency matrix can be imported into Python to construction the directional network, which is the first level BWE network. Examples of non-directional network and directional network, as well as their corresponding adjacency matrices, are shown in **Figure 1**.

However, a traditional social network can only represent and evaluate the relationships among nodes at only one level. In this study, some of the supply chain factors are BWE contributing factors while others are not. And most of the influencing relationships among the BWE contributing factors are indirect. This means if a social network including all supply chain factors is structured only, the relationships among the BWE contributing factors cannot be shown directly and

clearly. To solve this problem, the two-step network model of Matous and Todo [30] could provide some inspirations. In the first step, a network representing the supply chain consisting of only energy corporations was established. Then, other corporations with trade with these energy corporations were included in the second step network. From this method, to better analyze the connections among the BWE contributing factors, the model in this study was established by two stages (shown in **Figure 2**). In the first stage, supply chain factors including BWE contributing factors were linked together to form a social network according to the inter-relationships. This large network was used in the first-level discussion about supply chain factor analysis. And then, non-contributing factors of BWE were omitted from the social network to create a smaller network which only contains BWE contributing factors. The second-level network could show the interconnection among BWE contributing factors more clearly.

The major advantage of the bi-level SNA model is that it enables the evaluation of the inter-relationships at both the supply chain factors level and BWE contributing factors level. The first-level analysis can provide an overall picture of various supply chain factors’ inter-relationships. By analyzing the first level network, it can determine the factors with a high centrality score and evaluate these factors’ role in the supply chain. And by omitting non-contributing factors of the BWE, it can transfer indirect relationships among supply chain factors in the first-level network to direct relationships among BWE contributing factors in the second-level network, which can show the relationships among BWE contributing factors directly and clearly. Therefore, a better understanding of the causes of the BWE can be grasped. Moreover, with the assistance of centrality metrics, such as betweenness and closeness, the research gaps mentioned in section 1 can be solved effectively.

D. CENTRALITY METRICS IN SOCIAL NETWORK ANALYSIS

Descriptive metrics drawn from graph theory seek to characterize the systematic patterns observed in networks [31]. As pointed out by Borgatti [32], centrality measures are indices of prestige, prominence, importance, and power. And the four most common metrics in graph theory were chosen: degree, betweenness, closeness, and eigenvector centrality. As the selected metrics measure the centrality of nodes from different aspects and distribute in different ranges, it needs an aggregated index to provide a weighted average score for each node based on the above metrics. Therefore, a metrics named “Centrality Index” was firstly developed in this study by scaling and combining the results of other metrics. The definition, description, and interpretation in BWE analysis of the above-mentioned centrality metrics are summarized in **Table 1**.

1) DEGREE DISTRIBUTION

Degree centrality is a measure of immediate relationships only [33]. The in-degree centrality $C_I(n_i)$ and out-degree

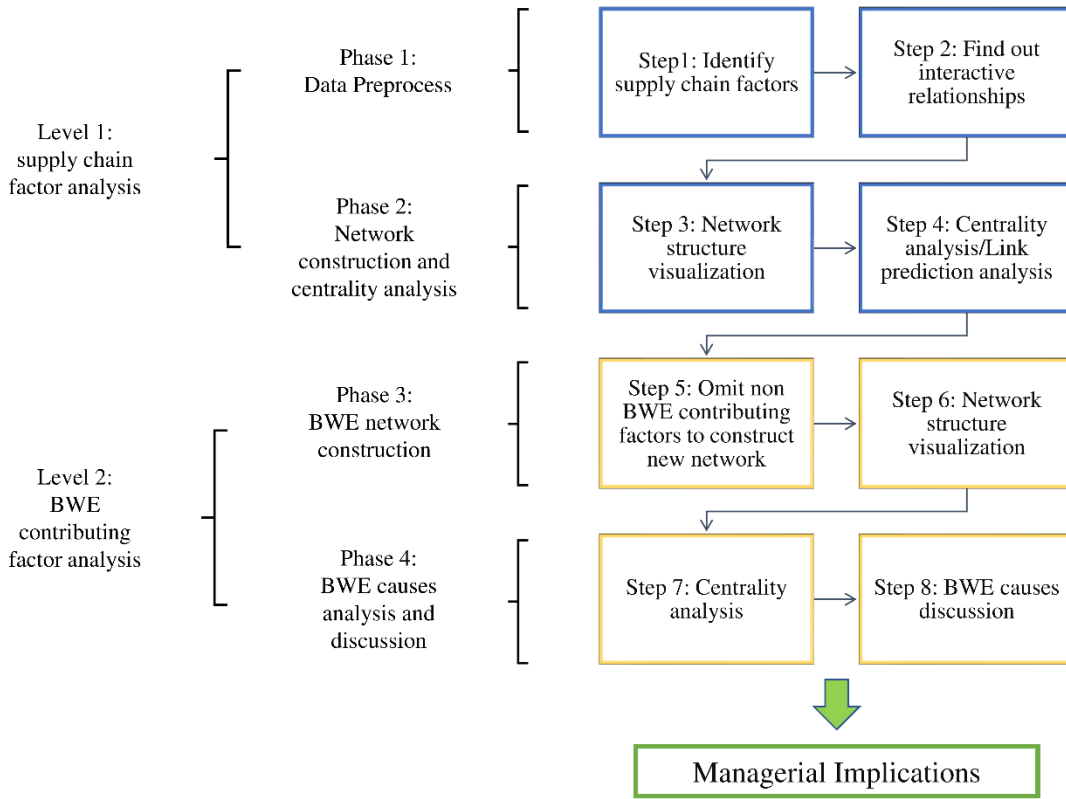


FIGURE 2. The process of the bi-level SNA approach for BWE contributing factors analysis.

centrality $C_O(n_i)$ of node i (denoted as “ n_i ”) are calculated as below [34]: C_C

$$C_C C_I(n_i) = \frac{\sum_j x_{ji}}{g - 1} \tag{1}$$

$$C_O(n_i) = \frac{\sum_j x_{ij}}{g - 1} \tag{2}$$

where x_{ji} is the number of edge from node j to node i while x_{ij} is the number of edge from node i to j , which can only be 0 or 1. And g is the number of nodes in the network. Therefore, the possible maximum number of edges of n_i is $g - 1$.

In this model, in-degree centrality indicates the number of possible causes when a factor is changing. A factor with a high in-degree centrality score performs as a “collector” of different kinds of impacts from upstream factors. Out-degree centrality refers to the variance of the downstream factors influenced by this node. Thus, a factor with a high out-degree centrality score performs as an “influencer” in the network, which has a larger impact on the complexity of eliminating BWE.

2) BETWEENNESS CENTRALITY

Betweenness is a measure of the probability that a node lies on the shortest path (geodesic) between other nodes in the network [35]. The betweenness centrality of n_i is defined as

below [36]:

$$C_B(n_i) = \sum_{j < k} \frac{g_{jk}(n_i)}{g_{jk}} \tag{3}$$

where g_{jk} is the total number of geodesics between n_j and n_k . And $g_{jk}(n_i)$ is the number of these geodesics which passing through n_i . In this study, it is normalized into the range from 0 to 1 by:

$$C'_B(n_i) = \frac{C_B(n_i)}{(g - 1)(g - 2)} \tag{4}$$

Betweenness is a measure of the influence a node has over the spread of information through the network assuming that the information only spreads along the shortest paths [37]. In the BWE analysis model, it plays the role of a “bridge” to control the influences flow and measures the ability to transform the influences from upstream to downstream.

3) CLOSENESS CENTRALITY

A higher value of closeness stands for greater centrality [38]. In a directional network, the closeness is defined as [12]:

$$C'_C(n_i) = \frac{(g' - 1)^2}{(g - 1)[\sum_{j=1}^{g'} d(n_j, n_i)]} \tag{5}$$

where i is not equal to j , and g is the number of nodes in the network. Moreover, g' is the number of nodes in

TABLE 1. Centrality metrics and their interpretations in BWE analysis.

Centrality metrics	Definition	Description	Interpretation in BWE analysis
In-degree centrality	The number of incoming edges pointing to one node divided by the possible maximum number of edges.	Measure the degree of nodes influencing a given node [61].	The degree of response in reacting incoming influences from other supply chain factors.
Out-degree centrality	The number of outgoing edges starting from one node divided by the possible maximum number of edges	Measure the degree of nodes influenced by a given node [61].	The degree of response in influencing other supply chain factors.
Betweenness centrality	The number of shortest paths between a pair of non-adjacent nodes where a node lies [61].	Measure the ability to “control” the shortest path in a network.	The degree that a supply chain factor controls the impacts of supply chain efficiency and sustainability.
Closeness centrality	Reciprocal of the distance between a given node to all other nodes [61].	An index of “center” in a network according to the distance.	The extent to which a supply chain factor has the closest impact to control the whole supply chain performance.
Eigenvector centrality	Centrality based on the level of connectedness of a node’s connections, taking the whole network structure into account.	Measure the connectivity of a node according to its neighbors’ connectivity.	The measurement of supply chain factors’ influences according to their neighbors’ influences in a supply chain.
Centrality Index	A weighted average of the above metrics by scaling all other metrics’ results.	A scaler of other centrality metrics.	The centrality of a supply chain factor when considering all metrics comprehensively.

the connected component where n_i located in. And if n_i is unreachable for all other nodes, the closeness will be 0. Therefore, $\sum_{j=1}^{g'} d(n_i, n_j)$ is the total distance from node i to all other nodes in the same connected component.

In the BWE analysis, high closeness means that the supply chain factor can receive influence from upstream factors and transform it into downstream factors faster. This indicates that factors with high closeness have a more direct impact on the sustainability and efficiency of the supply chain and perform the role of “controllers”.

4) EIGENVECTOR CENTRALITY

The eigenvector centrality of n_i is defined as below [39]:

$$C_E(n_i) = \frac{1}{\lambda} \sum_{n_j \in M(n_i)} n_j \tag{6}$$

where $M(n_i)$ is the set of the neighbors of n_i and λ is the largest eigenvalue of the network’s adjacency matrix. The key concept of eigenvector centrality is that the importance of a node can increase if this node connects to more nodes with high importance [40]. This means that the node with high eigenvector centrality performs as the “connector” of important nodes in the network.

5) CENTRALITY INDEX

To achieve the overall measurement (Centrality index) of the above metrics and determine the ranking of each factor, the

first step is scaling the results of different centrality metrics into the same range. Therefore, the result c_{ij} of metric j for factor i is scaled as below:

$$c'_{ij} = \frac{c_{ij} - c_{j,min}}{c_{j,max} - c_{j,min}} \tag{7}$$

where $c_{j,min}$ and $c_{j,max}$ are the minimum and maximum value of the metric j . If c_{ij} is the maximum value of metric j , which is $c_{j,max}$, c'_{ij} will be equal to 1. If c_{ij} is the minimum value of metric j , which is $c_{j,min}$, c'_{ij} will be equal to 0. Therefore, the values of c'_{ij} are distributed in $[0, 1]$. However, in some cases, it is necessary to set different weights to different centrality metrics and make their results distributed in different ranges. Thus, Eq. (7) is updated as below:

$$c''_{ij} = a_j + c'_{ij}(b_j - a_j) = a_j + \frac{(c_{ij} - c_{j,min})(b_j - a_j)}{c_{j,max} - c_{j,min}} \tag{8}$$

where a_j and b_j are the lower and upper bounds of the target distribution range, which can be set to assign the weight to metric j . As c'_{ij} distributes in $[0, 1]$, the distribution range of c''_{ij} would be $[a_j, b_j]$. The final step is summing all scaled centrality metrics values of factor i , which is c''_{ij} , to get the Centrality Index score of factor i (CI_i). And it is calculated as below:

$$CI_i = \sum_j [a_j + \frac{(c_{ij} - c_{j,min})(b_j - a_j)}{c_{j,max} - c_{j,min}}] \tag{9}$$

TABLE 2. The definition and description of link prediction metrics.

Link prediction metrics	Definition	Description
Common Neighbors	A measurement of the likelihood of two nodes being linked in the future according to their common adjacent nodes [62].	The basic principle of it is that two strangers with a friend in common are more likely to be introduced.
Jaccard coefficient	It is a normalized version of common neighbors [62].	It measures the likelihood by comparing the number of common neighbors with the total neighbors.
Resource Allocation	A measurement based on the fraction of a “resource” that a node can send to another through their common neighbors [63].	It was developed from the physical process of resource allocation.
Adamic-Adar index	It is similar to resource allocation, but with a log in the denominator [64].	This index can give a better match between the actual network and predicted link.
Preferential attachment	It is calculated by multiplying the degrees of two nodes [45].	The principle of it is that the two strangers with more friends have a higher chance to be introduced.
Community common neighbors	It considers the community structure of the link prediction [46].	Based on common neighbors, it gives a bonus to the common neighbor in the same community.
Community resource allocation	It only counts common neighbors in the same community divided by the number of common neighbors [46].	Similar to resource allocation, but only considers the nodes in the same community.

By this equation, different weights can be given to different centrality metrics because it can assign different lower and upper bounds to these centrality metrics. Therefore, the centrality index can perform as the “aggregator” to provide a weighted average of all other centrality metrics scores.

E. LINK PREDICTION METRICS IN SOCIAL NETWORK ANALYSIS

To discover the possible linkages between two different factors, several link prediction metrics in SNA were utilized (as shown in Table 2), such as common neighbors, and Jaccard coefficient. It assumes the network is a non-directional one when applying these metrics.

Common neighbor is a metric to predict the linkage between two nodes based on the number of their common adjacent nodes [41], the common neighbor between n_i and n_j is calculated by:

$$cn(n_i, n_j) = |N(n_i) \cap N(n_j)| \tag{10}$$

where $N(n_i)$ and $N(n_j)$ are the collections of the neighbors of n_i and n_j .

Jaccard coefficient is also developed from common neighbors [42]. It can be expressed as:

$$jc(n_i, n_j) = \frac{|N(n_i) \cap N(n_j)|}{|N(n_i) \cup N(n_j)|} \tag{11}$$

where $|N(n_i) \cup N(n_j)|$ is the total number of neighbors of n_i and n_j . It measures the chance of potential linkage by comparing the percentage of common neighbors in the total number of their neighbors.

Resource allocation is a metric based on the share of one unit of “resource” that a node can send to another node through the common neighbors. The resource allocation is formulated as [43]:

$$jc(n_i, n_j) = \sum_{n_k \in N(n_i) \cap N(n_j)} \frac{1}{|N(n_k)|} \tag{12}$$

where $N(n_k)$ is the collection of the neighbors of n_k .

The Adamic-Adar index is similar to resource allocation, but it has a log function in its denominator [44]. The formula of Adamic-Adar index is expressed:

$$aai(n_i, n_j) = \sum_{n_k \in N(n_i) \cap N(n_j)} \frac{1}{\log(|N(n_k)|)} \tag{13}$$

According to some studies [45], the nodes with a high degree get more neighbors. Therefore, the preferential attachment can be calculated as:

$$pa(n_i, n_j) = |N(n_i)| |N(n_j)| \tag{14}$$

where $|N(n_i)|$ and $|N(n_j)|$ are the number of neighbors of n_i and n_j .

Some metrics consider the community structure of the link prediction. The community common neighbor defined as [46]:

$$ccn(n_i, n_j) = |N(n_i) \cap N(n_j)| + \sum_{n_k \in N(n_i) \cap N(n_j)} f(n_k) \tag{15}$$

TABLE 3. Supply chain factors in the product dimension [49], [50].

No.	Factor	Description
1	Product Design Process (PDP)	The process of product designing such as drawing sketches, and sample production.
2	Design Lead Time (DLT)	The time interval from coming up with design inspiration to start the production of the item based on this design. It is a kind of lead time, which is a BWE contributing factor.
3	Inventory Turnover Rate (ITR)	The times of inventory being sold out and replaced by new inventory over a certain period
4	Centralized System (CS)	The distribution system of a supply chain. It is a BWE contributing factor (i.e. Decen./Centralized System)
5	Inventory Level (IL)	The average inventory amount stored in the distribution system.
6	Order Cycle (OC)	The average time interval between placing one order and the next order. It is also named as Order Lead Time, which is a kind of BWE factor.
7	Product Variability (PV)	Measured by how many kinds of products are sold in a certain period.
8	Product Sales (PS)	The sales amount of products.
9	Built to Order Rate (BTOR)	The rate of the product manufacture after receiving the orders of a retailer.
10	Production Quantity (PQ)	The amount of finished product which has been manufactured.
11	Product Sold Rate (PSR)	The percentage of inventory that can be sold.
12	Transportation Distance (TD)	Consists of inbound and outbound transportation distance.
13	Transportation lead time (TLT)	Similar to Transportation Distance, which consists of inbound and outbound transportation lead times. It is a kind of lead time, which is a BWE contributing factor.
14	Transportation Method (TM)	Air transportation is the fastest and most expensive transportation method while road transportation is cheaper but slower.

where

$$f(n_k) = \begin{cases} 1, & n_k \text{ in the same community as } n_i \text{ and } n_j \\ 0, & \text{otherwise,} \end{cases}$$

which could give a bonus for a common neighbor in the same community.

The community resource allocation is developed from resource allocation, but it only considers the nodes in the same community [47]. And it is calculated as:

$$ccn(n_i, n_j) = \sum_{n_k \in N(n_i) \cap N(n_j)} \frac{f(n_k)}{|N(n_k)|} \quad (16)$$

Similar to the centrality metrics, link prediction metrics also need an aggregated index to show the overall result of the possibility of two unlinked factors will be studied in the future. Therefore, a Link prediction index is calculated as

below:

$$LPI_i = \sum_j [a_j + \frac{(l_{ij} - l_{j,min})(b_j - a_j)}{l_{j,max} - l_{j,min}}] \quad (17)$$

where l_{ij} stand for the result of link prediction metric j for factor i . $l_{j,min}$ and $l_{j,max}$ are the minimum and maximum value of the metric j . And a_j and b_j are the lower and upper bounds of the Link prediction index value.

III. CASE STUDY

To evaluate the causes of BWE by using the bi-level SNA model, a typical examination of the supply network in Zara was conducted. Zara is one of the most successful apparel companies, which produces fashionable clothing and targets the international market between the ages of 18 and 35 [48]. The construction of the first-level and second-level BWE analysis network is presented in sections 3.1 and 3.2.

TABLE 4. Supply chain factors in the financial dimension [49], [50].

No.	Factor	Description
1	Inventory Holding Cost (IHC)	The cost incurred by the space and energy used to store inventory.
2	Ads Cost (AC)	The Cost incurred by advertising activities.
3	Full Price Sold Rate (FPSR)	The percentage of inventory that can be sold at full price.
4	Price Fluctuation (PF)	The degree of price fluctuation, which is a BWE factor.
5	Transportation Cost (TC)	Consists of inbound and outbound transportation costs.

TABLE 5. Supply chain factors in the information dimension [49], [50].

No.	Factor	Description
1	Forecast Horizon (FH)	It refers to the length of time for which the forecast is generated, which can measure the degree of information delay. It is a dimension of the BWE contributing factor (i.e. Demand Forecasting).
2	Forecast Accuracy (FA)	The accuracy of demand forecasting can measure the reliability of information (forecast result). It is a dimension of the BWE contributing factor (i.e. Demand Forecasting).
3	Advertising (AD)	The activities to deliver information that can promote products or services.

TABLE 6. Supply chain factors in the customer dimension [49], [50].

No.	Factor	Description
1	Demand Uncertainty (DU)	The fluctuation of customer demand can be measured by the standard deviation of customer demand quantity.
2	Customers Visiting Times (CVT)	The average visiting times of one customer in a certain period, which can measure the frequency of customer behavior.
3	Sense of Urgency (SU)	The customer's feeling of "if you do not purchase immediately, you will lose the chance".
4	Service Level (SL)	It refers to the probability that the inventory can fulfill customer demand.

A. CONSTRUCTION OF THE FIRST-LEVEL BWE ANALYSIS NETWORK

A total of 26 supply chain factors in Zara were identified and grouped into four dimensions [49], [50] according to the properties of these factors (as presented in **Tables 3 to 6**). As a supply chain consists of material flow, information flow, and financial flow, most supply chain factors can be divided into the product dimension, financial dimension, and information dimension. Besides that, the remaining factors are relevant to customer behaviors or feelings and could be included in the customer dimension. By this clustering, more information can be provided to perform the result analysis. These factors were represented by nodes in the network. And their influencing relationships were summarized in an adjacency matrix (as shown in **Supplemental material 1**) based on previous studies [49], [50]. In this way, the first level BWE network can be established. Moreover, both centrality analysis for the factors and link prediction metrics for the pairs of non-adjacency factors were utilized in this part.

B. CONSTRUCTION OF THE SECOND-LEVEL BWE ANALYSIS NETWORK

For the rule of node conversion, the representative relationships between BWE contributing factors, and the supply chain factors are summarized in **Table 7**. As design lead time, transportation lead time, and order cycle (i.e. order lead time) are three kinds of lead time; all these three factors can be aggregated and replaced by lead time in the second-level BWE analysis. And because the forecast horizon and forecast accuracy are two dimensions of demand forecasting, these two factors were aggregated and represented by demand forecasting. Therefore, the paths between the forecast horizon and forecast accuracy were also omitted after this conversion. The centralized system in the case study of Zara was represented by the Decen./Centralized system in the second level BWE analysis. And price fluctuation was unchanged as it is already a BWE contributing factor mentioned in section 2.2. Finally, all other supply chain factors, which are not included in **Table 7**, were omitted from the second-level

TABLE 7. The representative relationships between supply chain factors and BWE contributing factors.

No.	supply chain Factors	BWE contributing Factors
1	Design Lead Time (DLT)	Lead Time
	Transportation lead time (TLT)	
	Order Cycle (OC)	
2	Centralized System (CS)	Decen./Centralized System
3	Price Fluctuation (PF)	Price Fluctuation
4	Forecast Horizon (FH)	Demand Forecasting
	Forecast Accuracy (FA)	

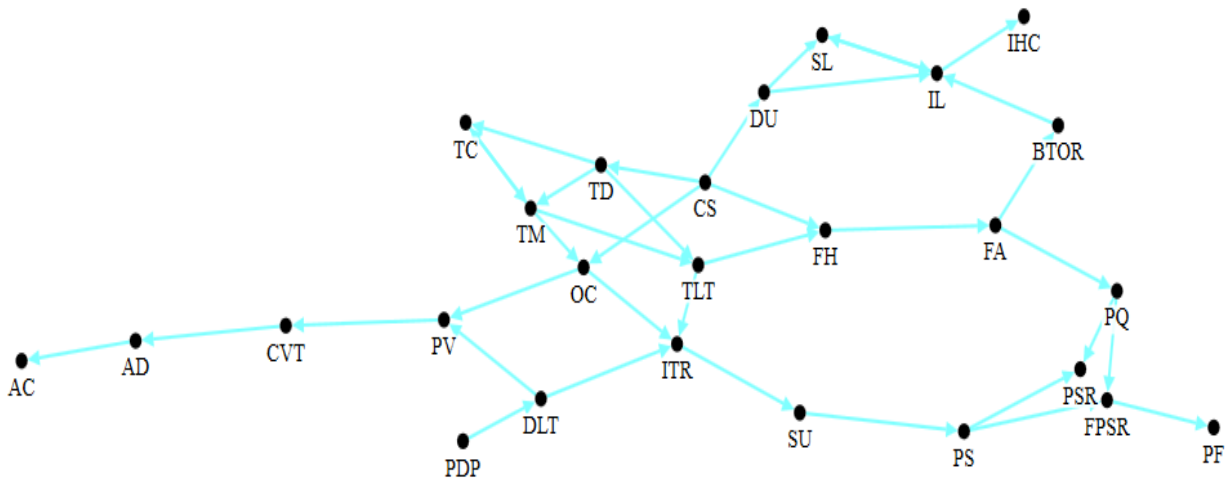


FIGURE 3. First-level BWE analysis network (black dot indicates a “node” and the blue arrow indicates an “edge”; full names and descriptions of factors are shown in Table 3-6).

BWE analysis network. By these steps, only the four BWE contributing factors were included in the second-level BWE analysis, which clearly shows the inter-relationships. As the second level network is really small, link prediction metrics are not applied to it.

For the rule of linkages (edges) creation, if there is a path between two supply chain factors in the first level BWE analysis network and both of the factors can be represented by two different BWE contributing factors included in **Table 7**, the representative BWE contributing factors of these two supply chain factors should be linked together in the second level BWE analysis network. In this way, the inter-relationships among supply chain factors can be transformed into the relationships among BWE contributing factors.

IV. RESULTS AND DISCUSSION

Supply chain factors and their inter-relationships mentioned in section 3 were performed as nodes and edges to construct a directional network. The visualization of the first-level BWE analysis network is shown in **Figure 3**. To construct the second-level BWE analysis network, the supply chain factors mentioned in **Table 7** were replaced by the relevant BWE contributing factors. Then, other supply chain factors were omitted from the new network. Finally, the paths among

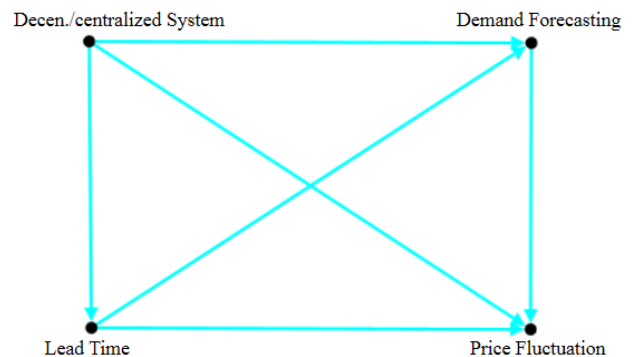


FIGURE 4. Second-level BWE analysis network.

supply chain factors included in **Table 7** were aggregated into one single edge between the represented BWE contributing factors. The visualization of the second-level BWE analysis network is shown in **Figure 4**.

A. FIRST-LEVEL BWE ANALYSIS

The first-level BWE analysis consists of both centrality metrics and link prediction metrics. Their calculated results are presented in **Table 8** and **Supplemental material 2**.

TABLE 8. First-level BWE analysis result.

Factors	In-degree centrality	Out-degree centrality	Betweenness centrality	Closeness centrality	Eigenvector centrality	Centrality Index	Ranking
IL	0.120	0.080	0.028	0.133	0.578	0.735	1
ITR	0.120	0.040	0.053	0.183	0.003	0.619	2
TLT	0.080	0.080	0.057	0.107	0.001	0.529	3
TM	0.080	0.120	0.040	0.090	0.001	0.509	4
SL	0.080	0.040	0.000	0.108	0.577	0.501	5
FH	0.080	0.040	0.058	0.111	0.001	0.490	6
OC	0.080	0.080	0.040	0.107	0.001	0.477	7
FA	0.040	0.080	0.063	0.096	0.001	0.472	8
PV	0.080	0.040	0.035	0.140	0.001	0.447	9
FPSR	0.080	0.040	0.023	0.160	0.004	0.434	10
SU	0.040	0.040	0.047	0.141	0.003	0.419	11
PS	0.040	0.080	0.037	0.121	0.003	0.416	12
IHC	0.040	0.000	0.000	0.118	0.577	0.396	13
PQ	0.040	0.080	0.023	0.089	0.001	0.338	14
CVT	0.040	0.040	0.027	0.116	0.001	0.329	15
PSR	0.080	0.000	0.000	0.160	0.004	0.310	16
BTOR	0.040	0.040	0.030	0.089	0.001	0.309	17
TC	0.080	0.040	0.000	0.090	0.001	0.282	18
AD	0.040	0.040	0.015	0.105	0.001	0.279	19
TD	0.040	0.120	0.005	0.040	0.000	0.276	20
DLT	0.040	0.080	0.017	0.040	0.000	0.263	21
DU	0.040	0.080	0.005	0.040	0.000	0.226	22
PF	0.040	0.000	0.000	0.141	0.004	0.222	23
CS	0.000	0.160	0.000	0.000	0.000	0.200	24
AC	0.040	0.000	0.000	0.098	0.001	0.174	25
PDP	0.000	0.040	0.000	0.000	0.000	0.050	26

1) IN-DEGREE CENTRALITY

According to **Table 8**, the inventory level and inventory turnover rate had the highest in-degree centrality in the first-level BWE analysis network, and both the factors belong to the inventory concept. This result shows that inventory is a key factor in BWE reduction and performs as a collector in the supply chain network. As inventory reduction to improve profitability is one important purpose of BWE analysis [51], the high in-degree centrality value shows that trade-offs need to be made among inventory, lead time, service level as well as demand uncertainty to reduce the BWE.

2) OUT-DEGREE CENTRALITY

According to **Table 8**, the centralized system has the highest out-degree centrality value of 0.16. This result shows that the centralized system is the “influencer” in the first-level BWE analysis network. The distribution system has a direct impact on transportation distance, demand uncertainty, order

cycle, and forecasting horizon. And this impact could bring a complex chain reaction to the whole supply chain.

From the network graph, it can be seen that a centralized system has a direct or indirect link to all supply chain factors in the financial dimension, information dimension, and customer dimension (shown in **Figure 5 to 7**). It indicates that the centrality of the distribution system could significantly influence the financial flow, information flow, and customer behaviors.

3) BETWEENNESS CENTRALITY

Forecasting accuracy and forecasting horizon have the highest betweenness centrality values, which are 0.063 and 0.058. This shows that demand forecasting performs as the bridge for influences from upside factors to downside factors and indicates that demand forecasting is quite complex and important for the whole system. According to **Figure 3**, the centralized system and lead time can distribute their impact

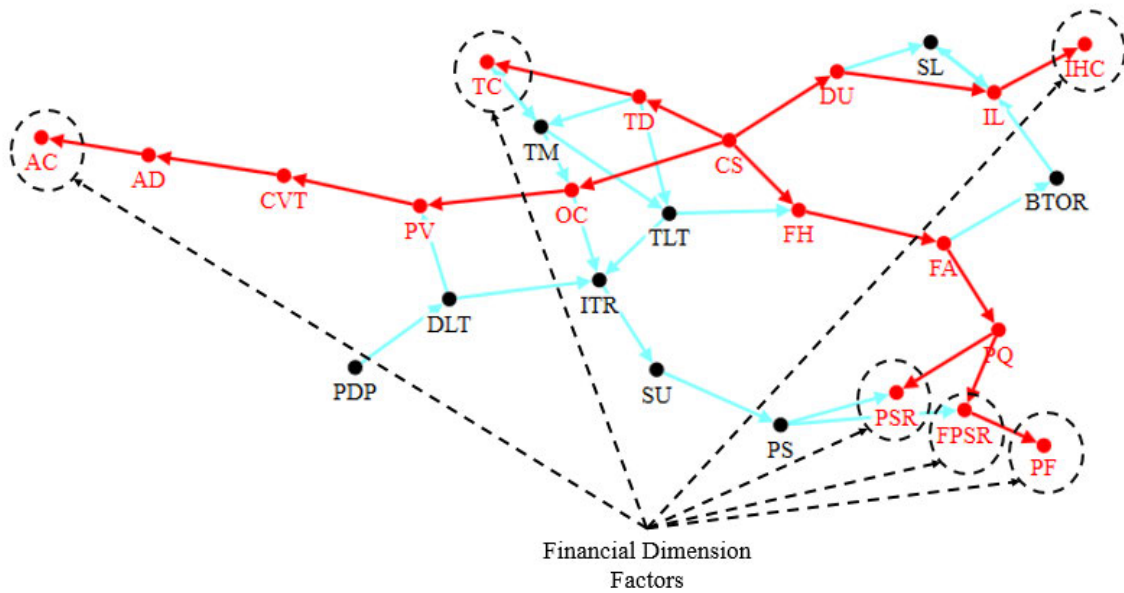


FIGURE 5. Impact of the centralized system on financial dimension factors (all financial dimension factors are highlighted by cycles; the path from the centralized system to customer dimension factors is highlighted in red).

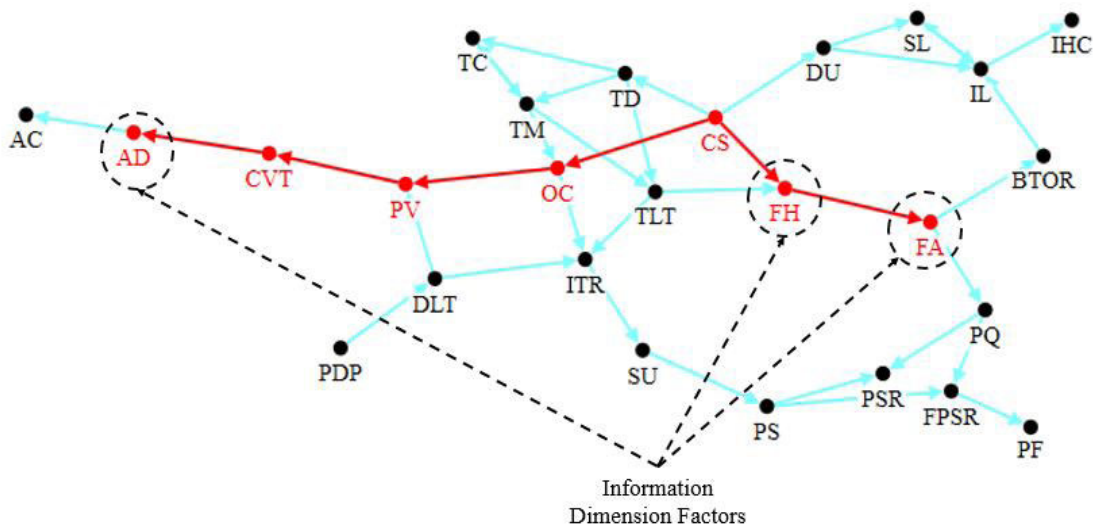


FIGURE 6. Impact of the centralized system on information dimension factors (all information dimension factors are highlighted by cycles; the path from the centralized system to information dimension factors has been highlighted in red).

on product-level factors such as product quantity and BTO rate through forecasting horizon and forecasting accuracy. Therefore, demand forecasting is the gateway for the system-level factors to transform their impact on supply chain factors about product arrangement. And product arrangement is directly related to the intensity of the BWE and efficiency of the whole supply chain.

4) CLOSENESS CENTRALITY

According to the result of closeness centrality, inventory turnover rate has the highest value, which is 0.183, which implies that it performs as the “controller” among the

supply chain factors and has the most direct impact on the whole system’s performance. This indicates that the inventory turnover rate can control the integrated efficiency of the whole supply chain system by delivering its impact to all downstream factors through the shortest path. Meanwhile, all the factors having a direct impact on inventory turnover rate belong to lead time including design lead time, transportation lead time, and order cycle. Thus, when designing or modifying distribution systems, it requires a strategic analysis of the influence on lead time and inventory turnover rate firstly. At some levels, Inventory Turnover Rate is an index of the system effectiveness.

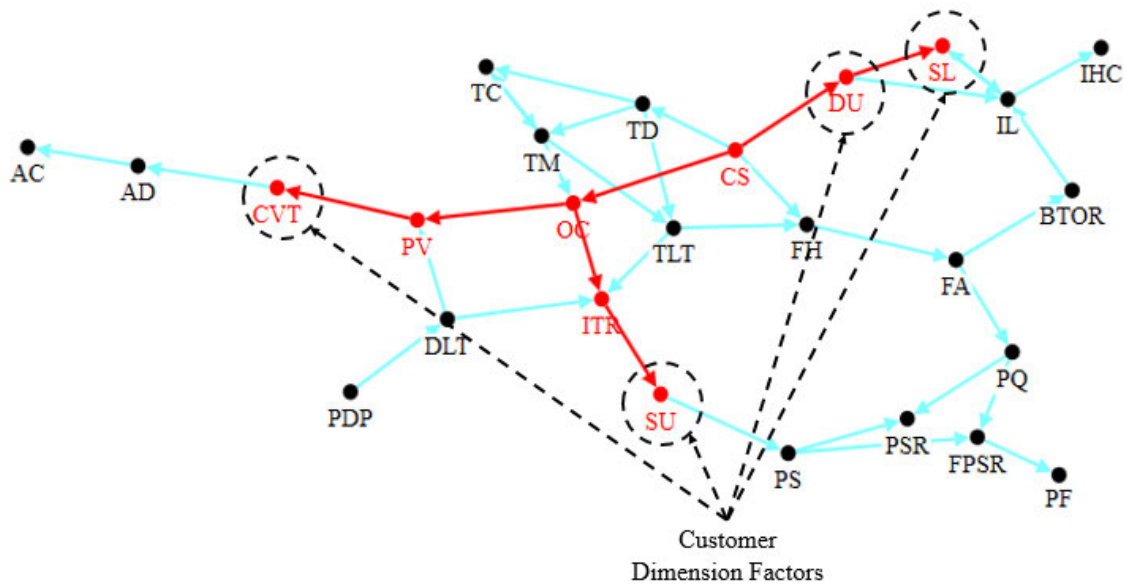


FIGURE 7. Impact of the centralized system on customer dimension factors (all customer dimension factors are highlighted by cycles; the path from the centralized system to customer dimension factors is highlighted in red).

5) EIGENVECTOR CENTRALITY

Inventory level, inventory holding cost, and service level had the highest eigenvector centrality scores, which are 0.578, 0.577, and 0.577 respectively. And the top two factors are relevant to inventory. This indicates that inventory and service level have the highest importance when considering its neighbors' importance and serves as the "connector" of the influences among important factors in this BWE analysis network.

6) CENTRALITY INDEX

Among all supply chain factors, the top four factors with the highest CI value were inventory level, inventory turnover rate, transportation lead time, and transportation method. The top two factors are related to inventory management and the other two belong to the transportation aspect. This indicates that the key aspect of supply chain management is inventory management. And all these four factors belong to the production dimension, which performs as the decisive position for a supply chain's efficiency. This result shows that inventory and transportation are the two most important parameters in the supply chain of Zara.

7) LINK PREDICTION ANALYSIS

The results of link prediction metrics are summarized in **Supplemental material 2**. It shows that the non-edge between production quality and product sales has the highest link prediction index value, which indicates the influencing relationships between production quality and sales amount has the highest potential value to be investigated in the case study of Zara. And the company needs to pay more attention to balance the quality and other factors to achieve higher sales. Moreover, the relationships between product availability and inventory turnover rate may also need to study as it has the second-highest link prediction index result.

B. SECOND-LEVEL BWE ANALYSIS

This section consists of two parts: the second-level BWE centrality analysis was discussed in part 1), while the relationships among contributing factors of the BWE were illustrated in part 2). The calculated results of the second-level BWE analysis are presented in **Table 9** where the factors are ranked by centrality index.

1) SECOND-LEVEL BWE CENTRALITY ANALYSIS

From **Figure 4** and **Table 9**, the structure of the second-level BWE analysis network consists of only four nodes and six edges. As there is no shortest path including two edges, all the betweenness centrality values are 0. However, all other metrics have non-zero value except betweenness. This means that the second-level BWE centrality results are still able to provide a reliable reference. Among these four BWE contributing factors, price fluctuation has the highest in-degree centrality, closeness centrality, eigenvector centrality, and centrality index. This indicates that price fluctuation performs as the collector, controller, and connector of influences because the other three BWE contributing factors have an impact on price fluctuation. Moreover, demand forecasting has the second-highest in-degree centrality, closeness centrality, eigenvector centrality, and centrality index. Besides that, the decen./centralized system and lead time have the first- and second-largest out-degree centrality. This indicates that the decen./centralized system and lead time perform as the influencers. These two contributing factors exert their influences on the downstream BWE contributing factors including demand forecasting and price fluctuation to control the strength of the BWE and the sustainability of the supply chain system.

Moreover, a demand forecasting error is regarded as distorting information about demand quantity [52]. Price

TABLE 9. Second-level BWE analysis result.

Factors	In-degree centrality	Out-degree centrality	Betweenness centrality	Closeness centrality	Eigenvector centrality	Centrality Index	Ranking
Price Fluctuation	1.000	0.000	0.000	1.000	1.000	0.600	1
Demand Forecasting	0.667	0.333	0.000	0.667	0.003	0.334	2
Lead Time	0.333	0.667	0.000	0.333	0.000	0.267	3
Decen./Centralized System	0.000	1.000	0.000	0.000	0.000	0.200	4

fluctuation is another kind of temporary distortion of product value information. This means that other BWE contributing factors transform their impact to the information distortion. And then the information distortion controls the intensity of the BWE because both of the top two factors with the highest CI values belong to information distortion.

2) THE MODEL OF MULTI-LEVEL CAUSES OF THE BWE

According to the calculated results and network structure in **Figure 4**, both the decen./centralized system and lead time can influence demand forecasting and price fluctuation. However, neither demand forecasting nor price fluctuation has an impact on the decen./centralized system and lead time. In other words, both the decen./centralized system and lead time are upstream factors of demand forecasting and price fluctuation. Moreover, price fluctuation and demand forecasting are the top two BWE contributing factors with the highest centrality index values, and both price fluctuation and demand forecasting belong to information distortion. Based on these facts, the contributing factors of BWE can be divided into two groups and form the multi-layer structure of the BWE causes as shown in **Figure 8**. The direct cause of the BWE is information distortion no matter whether it is about product value or demand quantity. Other BWE contributing factors can only influence the intensity of the BWE indirectly by influencing the intensity of information distortion. For example, longer lead time could cause longer forecasting horizons, which may contribute to the information distortion of demand. It is shown that the designs of supply chains need to eliminate the degree of information distortion from different dimensions. Although revenue sharing was considered as an important strategy to deal with market uncertainty [53], information sharing is the key principle to reduce the BWE and improve the efficiency and sustainability of the whole supply chain system. In a previous study [24], the impact of lead time and demand forecasting on the BWE were highlighted. However, it lacks discussion about the relationship between lead time and demand forecasting. This study is, therefore, the first of its kind to highlight the multi-layer causes of the BWE.

V. POLICY AND MANAGERIAL IMPLICATIONS

According to the results in section 4, the below policy and managerial implications are suggested:

- (1) The information distortion is pointed out as the root cause of BWE. And the importance of information collaboration was also highlighted by Jiang [54]. Therefore, the level of information sharing in a supply chain needs to be improved by collaboration among supply chain members, like POS data sharing between the retailer and supplier.
- (2) The effectiveness of demand forecasting by machine learning algorithms has been proved [55, 56]. It shows that utilizing new technology can improve forecasting accuracy. Therefore, the information distortion and intensity of the BWE can be reduced.
- (3) Companies need to consider the impact on forecasting performance when modifying the distribution system, as the centralized system had the highest out-degree centrality in the first-level BWE analysis. And it has been reported that lack of chain integration is one main cause of BWE [57]. Normally, it is suggested to improve the centrality of the distribution system in a supply chain.
- (4) Inventory level has the highest in-degree centrality and eigenvector centrality. This means that inventory management is a critical issue to improve the overall efficiency and sustainability of a supply chain. Therefore, production and purchasing planners could track the inventory status in real-time by utilizing an IoT system.
- (5) As price fluctuation and demand forecasting had the highest centrality index values in the second-level BWE analysis, a key method for reducing the BWE is controlling the intensity of information distortion in a supply chain, especially price fluctuation. Therefore, “everyday low pricing (EDLP)” is an effective strategy to reduce the BWE.

By utilizing a comprehensive supply chain upgrading plan to include the above implications, a company could achieve a sustainable supply chain because of higher efficiency and low material waste.

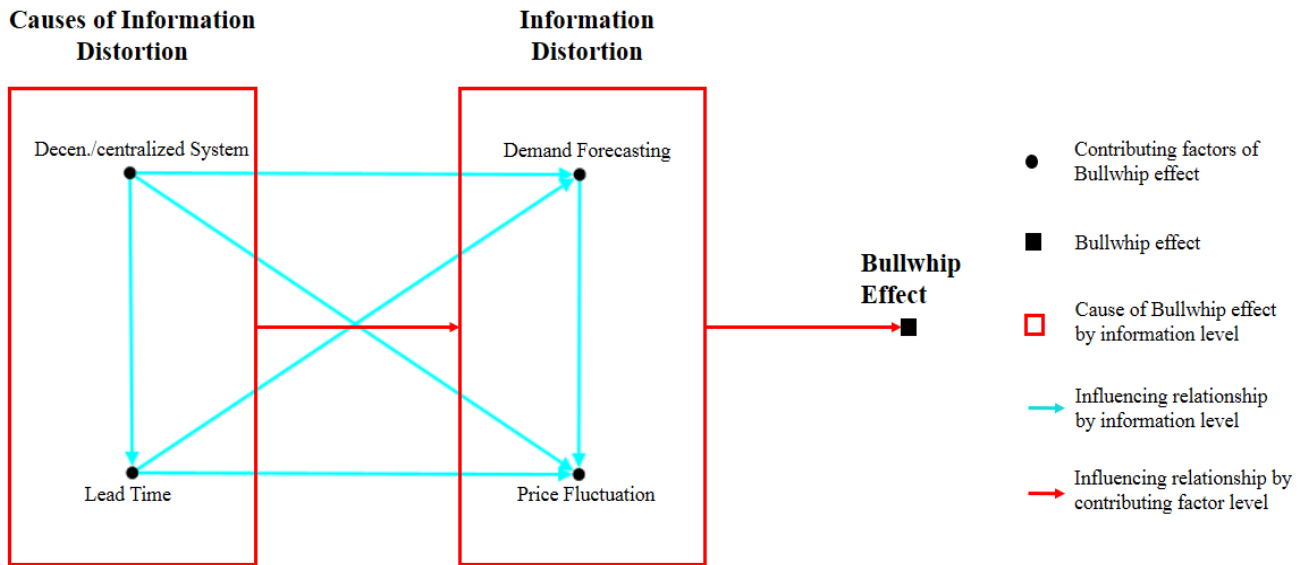


FIGURE 8. Model of the multi-level causes of the BWE.

VI. VALIDATION FROM INDUSTRY

A. COMBINED EFFECTS ON INVENTORY

According to a study about the archival sales data of a major snack distribution company, Wan et al. [58] pointed out the complex combined effects on inventory from different factors like product variety and demand variability. From Table 8, inventory level and inventory turnover rate had the highest in-degree results, which indicates that inventory performs as the roles of influence collector. This case also shows the complex combined influences on inventory exists in multiple industries.

B. ADDITIONAL INFORMATION AND DEMAND FORECASTING

Based on the investigation of six oil and gas companies in North America, Zhu et al. [59] found that the demand forecasting could be more accurate if it can consider multiple types of additional information such as seasonality and refinery activity. And it was also pointed out that the use of the additional information can reduce oil order variability, which is the BWE intensity. From Table 8, it shows that forecasting accuracy and forecasting horizon have the highest betweenness centrality values, which means demand forecasting plays a key role in transforming different influences to downstream factors. Therefore, considering additional information in demand forecasting could transforming the impacts from different aspects to reduce the information distortion and BWE intensity.

VII. CONCLUSION

The BWE is still a significant issue that needs to be addressed to achieve economic and environmental benefits. One cause is that the relationships among BWE contributing factors and

other supply chain factors are quite complex, which makes the problem hard to control. This study provides a new approach to quantify these interactive relationships and analyze the roles of supply chain factors at two levels.

Concerning the conceptual bi-level SNA model, the interpretations in the BWE analysis concept were applied to the centrality metrics, and the bi-level BWE analysis model was established. The concept of social networks and centrality metrics were also reviewed. Then the centrality index was defined to measure the integrated centrality level of each factor. In the case study section, a total of 26 supply chain factors, their inter-relationships as well as four main BWE contributing factors were identified. By setting these factors and relationships as nodes and edges, the first-level BWE analysis was established. After calculating in-degree centrality, closeness centrality, and eigenvector centrality, it was found that inventory performs as the collector, controller, and connector of the influencing flow. As a centralized system has the highest value of out-degree centrality, it plays the role of the influencer in the supply chain. Moreover, demand forecasting operates as the bridge of influences flow with the highest betweenness centrality. Besides, link prediction metrics have also been applied to find out the undiscussed influencing relationships between two factors with high potential value to investigate.

By omitting non-BWE contributing factors, the second-level BWE analysis network was constructed. According to the metrics result and network structure, it shows that information distortion, which includes demand forecasting issues and price fluctuation, is the root cause of the BWE. Other contributing factors, such as lead time, can only increase the intensity of the BWE by influencing the information distortion level. To reduce the impact of the BWE and improve the

sustainability level in supply chain management, implications including optimization of supply chain design, increasing the level of information sharing, as well as utilizing new technologies are suggested. This will help to reduce the waste of material, improve effectiveness, and promote sustainability in supply chains.

All in all, this study has four main contributions. For social network analysis, the bi-level structure was firstly established in this study compared with other research utilizing traditional social networks [60]. For the SNA method, the formula of the centrality index was firstly defined to measure the integrated centrality degree of each node and provide an overall metric by scaling and combining other metrics' results. Moreover, information distortion was pointed out to be the root cause of the BWE according to the multi-layer causes of the BWE, which can show the relationships among different BWE contributing factors more clearly than other studies [24]. For the case study of Zara, this study found that inventory and transportation are the two most important factors based on previous studies [49], [50].

However, there were several limitations in this study. Firstly, the relationships among supply chain factors were described by binary value, which may not be able to quantify these relationships sufficiently. What's more, there was no comparison between Zara and other supply chains in the case study section. Therefore, future research could develop a new method to quantify the relationships among factors and include an analysis of two or more supply chains to obtain more findings by comparison.

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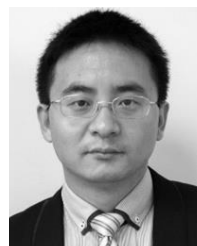


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