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Information Distortion in a Fast Fashion Supply Network: the impact of digitalization

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Abstract. During the last decades, Information Sharing has gained a global attention among academic researchers. It has been widely demonstrated that such strategy improves the supply chain management and mitigates the bullwhip effect. In this research, the information distortion and its impact on a Fast Fashion Supply Chain has been modeled. The aim of this paper is to analyze how false data can affect the system performance. A simulation model has been developed in order to reproduce the behavior of the players. Then, different scenarios with different levels of digitalization and distortion have been tested. Results show that both upstream and downstream distortions have a disruptive impact on the system and a strong ripple effect. Moreover, negative effects result to be not linear, and small distortions already show great disruptive effects.

Keywords: Information Sharing, Ripple Effect, Fast Fashion, Information distortion

1 Introduction

Information sharing (IS) is a well-known collaboration strategy widely analyzed in literature. Information flow and communication in the network allows people to exchange information and data, improving the robustness and the resilience of the system [1].

The aim is to connect players, in order to receive and use information to enhance flexibility and make decisions [2]. Information sharing is considered one of the best ways to solve the bullwhip effect (BWE) [3]. BWE is defined as the amplification of the order variability moving upstream the supply chain (SC) [4]. Its propagation depends on the structure of the network and the behavior of the supply chain players [5]. Such phenomenon well describes the effect of the distortion of information or the lack of communication in the supply chain. Lee et al. [6] stated how the information related to the order quantity falsifies the real needs increasing upstream the inventory level. In general, the benefits provided by the information sharing on BWE and SC performance have been widely debated and they continue to be discussed [7, 8]. Costantino et al. [9] tested different inventory policies to quantify the impact of the information sharing on both inventory level and variance. Tang et al. [10] have investigated the need of sharing information and its effect on the SC robustness. However, the accuracy of the infor-

mation was not enough discussed in literature, and many studies start from the assumption that transmitted data are true [11]. Nevertheless, in practice, distorted information is often shared among the supply chain partners, either willfully or unintentionally [12]. For such reasons, our research aims at evaluating the disruptive effect of distorted information on the SC. The focus of the study is on information distortion and the research question is: how does information distortion affect the supply chain success?

The purpose of this study is to quantify the impact of the false-data sharing on the SC performance. A simulation model has been developed in order to reproduce the behavior of the SC players and test different levels of distorted communication. Moreover, scenarios with distortions are compared with a system where digitalization assures the information truthfulness. The Fast Fashion sector has been chosen because of its variable environment and its need of flexibility. In fact, the fashion industry is characterized by rapid changes in trend and demand. For such reason a reactive SC is required. In such context, a good and real information sharing can strongly influence the Supply chain success. In the same way, a distorted data sharing can have a disruptive effect on the network.

Starting from the previous considerations, the blockchain has been chosen as suitable technology to exchange information in the network. The inalterable nature of the blockchain promotes collaborative relationships among players and it makes the supply chains more transparent and efficient [13]. Moreover, the quality and security of the information enhances the inventory control accuracy, reduces the errors, and improves the decision-making processes [14]. Finally, recent studies indicate that the blockchain has a good applicability in all industries, including the fashion sector [15, 16].

The rest of the paper is organized as follows: Section 2 defines the logics and the structure of the simulation model; Section 3 introduces the numerical example. Simulation results are presented in Section 4 and the last section deals with the main findings of the study.

2 Simulation Model

A three-level supply network has been modelled to test the impact of the information distortion on the performance of a Fast Fashion SC. The flow of both material and information have been designed starting from a framework developed by Martino et al. [17]. In particular, the authors have identified three SC levels and three different phases of production and distribution considering the characteristics of the sector. Moreover, other researchers have modeled the same network and phases including production, distribution, and sale for a generic Fast Fashion product life cycle [18]. Wang et al. [19] have also summarized the potential benefits provided by the adoption of the blockchain for each production phase in the Fast Fashion industry. Thus, starting from the analysis of the current literature, three phases that characterized the fashion supply chain have been considered: Pre-Season, In-season and Post-Season (Figure 1). The flow of material starts with the Suppliers, which deal with the production and provide goods to a single Central Warehouse and ends with the Retail Stores that directly face the final

customers. The main logic of the system and the information exchange has been developed considering the specific content.

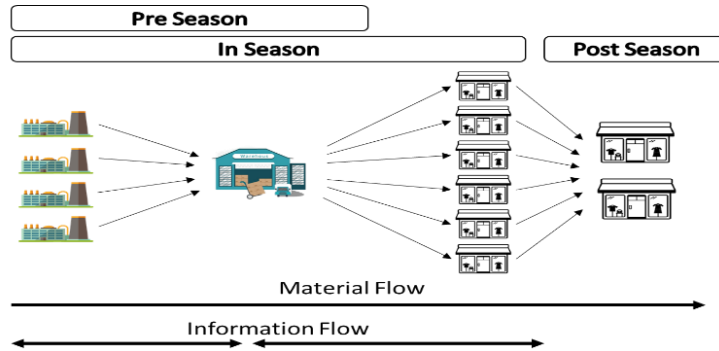


Fig. 1. Supply Chain Network

The Pre-Season phase defines the beginning of the whole process with the development of the New Collection and a first forecast of the demand. Then, orders are scheduled and assigned to suppliers. In fact, the first batch is produced before the sales season and delivered to the warehouse. During the In-Season phase the Central Warehouse manages orders to Suppliers and deliveries to the Retail Stores. A constant monitoring of the deviations between the expected orders and the real sales is carried out. The aim is to quickly respond to changes and adapt the production to the request. In such stage, the level of communication between partners and the accuracy of the information shared between them play a crucial role for the success of the whole system. For such reason, the model mainly focuses on such central phase. However, the pre-season phase has been considered since it defines the starting point of the system, while the outcomes of the simulation model represent the input data of the next phase. In fact, the unsold goods are moved from Stores to the Factory Outlet Stores, with the beginning of the Post-Season phase. Since each level of the SC deals with different activities, specific logics have been modelled to reproduce the behavior of the players, according to their role in the network. Moreover, a single product has been modelled.

2.1 First level: Suppliers

As already asserted, each player plays a specific role, according to the level of the network. Suppliers handle the production process: they receive orders from the Central Warehouse, and they weekly update the production quantity. In fact, the model allows choosing between three different production batches, defined considering the production capacity and the level of flexibility of the player. Moreover, a double check is performed to define the right quantity to produce, matching the demand forecasting and the current stock position. This control is fundamental to continuously align the expected events with the real situation.

Concerning the delivery flows, if possible, the supplier prepares the order and sends it on time. In fact, if the real daily demand is lower than the inventory position, orders

are sent the same day; otherwise, the orders will be joined to the orders of the following week and delivered late.

2.2 Second level: Central Warehouse

The Central Warehouse is the central player of the network; he manages and supervises the whole process, choosing the right quantity to order to each supplier and the right quantity to deliver to each retailer. In fact, the warehouse handles two different flows of materials, both upstream and downstream. Moreover, he has to communicate with the partners in order to collect and update the real-time data, with the aim of making the supply chain flexible to the variable environment.

The player adopts a classical economic order interval (EOI) policy, based on periodic orders and variable order quantities. In fact, at fixed periodic interval (T), the inventory level is checked, and an order is placed. The quantity ordered allows the current stock to reach the order-up-to level (OUTL) which is the level of stock that should allow to satisfy the demand since the next order. The theoretical order (TO_t) placed at time T is computed as:

$$TO_t = OUTL - TI_t \quad (1)$$

Where, the theoretical inventory position (TI_t) is calculated considering the stock quantity (I) at t-1, the order placed (O) at t-LT and received at t and the expected demand (E) at t:

$$TI_t = I_{t-1} + O_{t-LT} - E_t \quad (2)$$

In fact, the reorder process depends on the demand forecasting, which is based on the study of the trend of sales of the previous seven days. Once the order quantity is defined, the warehouse assigns a production amount to the suppliers, according to their performance. In fact, he defines at the beginning of the pre-season phase the percentage of orders to assign to each supplier. Then, during the sales season, he starts from such defined percentage, but he also checks the stock level; if the supplier is not able to satisfy on time the order, he assigns to another player the quantity that would be send late. For this reason, suppliers could tend to alter the data relating to their stock, in order to receive the higher number of orders.

Looking to the second flow of material, the warehouse has to manage and decide the quantity to deliver to each retail store. If possible, the orders are sent and delivered on time. Otherwise, if the stock level is not high enough to satisfy all the retailers, a new distribution based on the order percentage is planned. In fact, the warehouse organizes the daily shipping to the i-th store (S_i) considering its order quantity at t (Q_i), all the orders received at time t and the available amount in stock:

$$S_{i,t} = \frac{Q_{i,t}}{\sum_i Q_{i,t}} \times I_t \quad (3)$$

For such reason, the shops could tend to falsify and increase the data relating to their order to obtain as many goods as possible.

2.3 Third level: retail Stores

The stores are the final players of the supply chain, and they directly face the customers. The inventory management is based on a particular inventory policy, which joins the EOI and the economic order quantity (EOQ) policy. In fact, when the inventory position is lower than the order point (OP), an order is placed. The order quantity is variable, and it allows to replenish the shelf considering its maximum capacity. In fact, in such case, it is important to respect the capacity restriction due to the available space in the shop. Moreover, a particular logic has been implemented in the model, which lead to satisfy the higher number of customers. In fact, if a retailer is not able to satisfy a customer, the model chooses randomly another store with enough capacity to provide the product to the customer the same day. Thus, a stock-out situation leads to a loss of sale.

2.4 Key Performance Indicators

A set of key performance indicators (KPIs) have been defined to analyze the performance of the Fashion Supply Chain, and to test the negative effect due to a distorted information. Four KPIs strictly related to the bullwhip effect have been chosen. In particular, the KPIs evaluate and quantify the main factors related to the distortion of demand and its propagation through the supply chain. Moreover, some indicators aim at highlighting the difference between the scenarios with and without digitalization. A brief description of the KPIs and their formulation are presented below:

— *Deviation between the orders placed by the Warehouse and the customer demand ($O_w D_C$):* it is calculated as the deviation between the orders placed by the central warehouse (O_w) and the real requests of the end customers (d). It is computed at the end of the sales season. The KPI provides information on the ripple effect due to the distortion:

$$O_w D_C = \frac{\sum_t O_{w,t} - \sum_t d_t}{\sum_t O_{w,t}} \times 100 \quad [\%] \quad (4)$$

— *On time deliveries (OTD_w):* it is computed as the number of days (NOTD) in which the all the order placed by the retailers have been sent on time over the total days of the year (N):

$$OTD_w = \frac{N_{OTD}}{N} \times 100 \quad [\%] \quad (5)$$

— *Orders recovered from the best Supplier (OR_w):* it indicates the number of items that cannot be fulfilled on time by a supplier and are assigned to another one. The KPI sums all the items recovered and delivered on time because of such practice.

- *Supply chain Inventory level (I_{SC})*: it reflects the average amount of items in stock considering all the players of the supply network. It is computed as the sum of the average inventory position of retail stores (I_R), suppliers (I_S) and the warehouse (I_W):

$$I_{SC} = \sum_R \bar{I}_R + \bar{I}_W + \sum_S \bar{I}_S \text{ [item]} \quad (6)$$

3 Numerical application

A discrete event simulation model was developed using Microsoft Excel. A supply chain composed of 3 suppliers, one central warehouse and 10 retail stores have been modelled. For each level, the logics described have been implemented. The main objective of the study is to evaluate how the negative effect varies increasing the data falsification. For this purpose, four-scenarios have been tested in order to study the impact of the false-information sharing on the system performance. The scenarios differ from each other in terms of percentage of distortion between the central warehouse and the other SC players. In particular, retail stores falsify the order quantity increasing their request, in order to reach a higher order percentage and prevent late deliveries. Suppliers alter the inventory position data in order to receive higher order quantities, trying to satisfy the request on time exploiting their flexibility. Following, the four scenarios are described:

- *Scenario 1*: retail stores alter data; the retail stores increase the order quantity by 1%, 5%, 10% respect to the reorder lot defined by the order policy, while the suppliers communicate the real inventory data.
- *Scenario 2*: suppliers alter data; suppliers communicate a higher stock amount, increasing the real data of 5%, 25%, 50%, while the retailers place an order in according to the reorder policy.
- *Scenario 3*: both retailers and suppliers alter data; suppliers share the data on the level of stock increasing the real inventory position by 25% and stores grow the order quantity of 5%.
- *Scenario 4*: information distortion is avoided. In such case, a digital technology (blockchain) is implemented and used to share information. Digitalization allows transferring real-time data. Moreover, the truthfulness of information is assured.

3.1 Input Data

Input data have been set considering the high variability of the sector. The data have been set considering a real context; however, the flexibility of the model allows changing and testing different data. The average expected customer demand has been fixed at 150 items/day, which consists of 50'400 items/year considering a simulation period of 12 months with time step of 1 day. The daily customer demand has been modelled as a normal distribution with $N(d, \sigma_d)$. Retail stores have been grouped in two groups (group one includes retailers from 1 to 5 and group 2 the other ones); groups differ in input parameters (Table 1).

Table 1. Input data – Retail Stores

	Demand Mean (items)	Demand Dev. Std. (items)	Procurement Lead Time (days)	Shelf maximum capacity (items)
Group 1	10	10	2	147
Group 2	20	20	2	207

As already explained, two production periods are identified and the 65% of the total production is assigned to the In-season phase. Moreover, the warehouse shares the orders among the suppliers starting from a fixed percentage due to their reliability. Suppliers input data are shown in Table 2.

Table 2. Input data – Suppliers

	Supplier 1	Supplier 2	Supplier 3
Production flexibility (%)	5%	10%	25%
Delivery Lead time (days)	7	6	5
Order percentage (%)	20%	30%	50%
Nominal production quantity (item/day)	30	45	75

4 Results and discussion

In this section, the outcomes of the four scenarios are discussed. In particular, scenarios 1, 2, and 3 are compared with the last one, which reflects a situation without distortion. Since the customer demand has been generated randomly, 20 replications have been run for each scenario. Results show the mean value derived from all the replications.

Looking to the first scenario, data falsification is relating to the orders placed by the retailers, which lead to a higher SC average stock (Table 3). Moreover, even though suppliers are flexible, they are unable to adequately respond to such request, which results in a decrease of on time deliveries and recovered orders. A strong ripple effect is shown by the increasing distance between the warehouse's orders and the customer demand. Moreover, the trend seems to be not linear, since the first small increases show a greater effect compared to the worst scenario.

Table 3. Results of first scenario

	1%	5%	10%	Digitalization
$O_w D_c$	8,28%	57,56%	63,80%	3,40%
OTD_w	90,96%	52,60%	47,12%	96,44%
OR_w	970	779	612	1267
I_{SC}	4537	4864	5342	4354

In the second scenario, suppliers falsify data (Table 4). Therefore, orders recovered by the central warehouse strongly decrease, with a consecutive effect on the on time deliveries. Overall, the SC average stock decreases, since suppliers are unable to satisfy requests and stock out situations occur. For such reason, the warehouse tends to increase the order quantity, increasing the ripple effect.

Table 4. Results of second scenario

	5%	25%	50%	Digitalization
$O_w D_C$	14,17%	23,94%	29,54%	3,40%
OTD_w	82,47%	74,25%	68,77%	96,44%
OR_w	599	379	172	1267
I_{SC}	4180	4076	4014	4354

In the last scenario, all the players falsify information (Table 5). Such double distortion causes a negative propagation and joins effects of the previous scenarios: the SC average stock reaches the worst result, but at the same time recovered orders and on time deliveries fall. The negative impact is confirmed by the amplification of the distance between orders and real customer demand.

Table 5. Results of third scenario

	5%-25%	Digitalization
$O_w D_C$	62,40%	3,40%
OTD_w	49,04%	96,44%
OR_w	357	1267
I_{SC}	4600	4354

5 Conclusions

Information sharing is a well-known topic of research. This study focuses on information distortion and proposes a simulation model to test the effect of altered data on a three-echelon Fast Fashion Supply Network. The sector is characterized by rapid changes in trend and demand, and short product life cycles. In such context, the supply chain needs rapid adaptations to the customer requests and the information sharing can play a crucial role providing strong benefits. Different levels of digitalization and distortion have been tested with the aim of understanding the impact of the information sharing on the supply chain performance. Thus, different scenarios have been modelled to quantify the impact of the false data sharing. Moreover, this study proposes the blockchain as suitable technology to exchange information in the network because it guarantees the truthfulness and security of the shared data.

Results show an evident impact of false information sharing on the network. Small distortions cause great ripple effects increasing the deviation between the orders placed by players moving upstream the supply chain. Such phenomenon strongly affects the performance of the system, causing two opposite effects on the inventory level of the whole SC. In fact, when retail stores alter data, the inventory level of the SC increases, since more quantities are requested. When suppliers alter data, the stock out situations increase, since suppliers are not able to satisfy the request. In both cases, the on time deliveries decrease.

The study shows that such negative effects could be eliminated using a digital technology, able to avoid false communications. In fact, the introduction of the blockchain leads great improvements if compared to the previous scenarios. Thus, this research offers an interesting starting point to the Fast Fashion practitioners and suggests the use of the blockchain to share information and increase the performance of the system.

Future researchers will focus on the impact of the technology on the economic and environmental performance of the supply chain to test its applicability.

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