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Third Party Logistics–SPD Model in Hospital Supply Chain

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Abstract

The complexity of the hospital supply chain results in numerous unfavorable outcomes, including out-of-stock situations, excessive inventory levels, product expiration, and medical errors. SPD, which refers to supply, processing, and distribution, has come to light as a solution for mitigating some complexities-related burdens. Nevertheless, the SPD is still immature and has limited applications. Adopting supply chain management approaches successfully implemented in other industries with the desired outcomes to strengthen the SPD's capabilities is therefore promising for the hospital. This study's objectives are to examine the third-party logistics (3PL) model functioning as SPD and to enhance its performance by incorporating it with vendor-managed inventory (VMI) and inventory policies in managing the SPD of continuous ambulatory peritoneal dialysis (CAPD) service. Therefore, this research proposes four logistics models, including an SPD with VMI (SPD-VMI) and three SPD-VMI models integrated with three different inventory policies, which include average inventory level and out-of-stock (OOS), are analyzed using discrete event simulation (DES). The results show that integrating the SPD with VMI improves inventory levels and out-of-stock incidents. When three inventory models are implemented, the results indicate a comparable out-of-stock reduction for all three policies. Additionally, the SPD-VMI with an order-up-to policy has the best performance in minimizing inventory and out-of-stock occurrences.

Keywords
SPD, VMI, 3PL, CAPD, HOSPITAL SUPPLY CHAIN

1. Introduction

Whereas the supply chain retains many positive attributes in the healthcare setting, it is paradoxically lagging behind other sectors and requires urgent consideration. The slow progress is attributed to the unique characteristics of the healthcare supply chain that makes supply chain concepts from other industries cannot be simply applied to this context (de Vries and Huijsman 2011). The dimensions of supply chain management (supplier's relationship, standardization and specification, delivery, and post-sale support) also substantially impact service quality (Jamal Al-Saa'da et al. 2013). In addition, the unique characteristics of the medical profession have aggravated the issue. Although hospitals are the official purchasers, physicians choose which items will be acquired based on non-cost-related reasons. Therefore, there may be a misalignment between hospitals' cost management targets and the preferences of the healthcare profession (Montgomery and Schneller 2007). Despite these peculiar natures, current conceptions and research support the premise that the healthcare industry can benefit from the knowledge obtained from other sectors(de Vries and Huijsman 2011). Therefore, to leverage the potential benefits of supply chain tools, healthcare practitioners' perspectives toward the use of supply chain principles must evolve (Kwon et al. 2016). Existing supply chain concepts, management philosophies, and the advancement of supply chain technologies allow for myriad opportunities to enhance the healthcare supply chain.

Supply chain complexity in the healthcare industry can be alleviated in many ways by adopting techniques that are successfully applied in other sectors. Over the past decade, research on supply chain management in the healthcare industry has become more extensive, reflecting the rising healthcare costs across the globe (Kwon et al. 2016). Healthcare supply chains also exhibit emerging features by embracing management methods from other sectors. A significant debate in the industry about autonomous distribution has arisen from the creation of the consolidated service center (CSC) in a few healthcare supply chains, which highlights a considerable ability to lower the complexity of the supply chains of a hospital in order to attain elevated rates of efficiency and innovation. The CSC depicts the unique features that effectively reduce the number of elements and interrelationships in a complex environment (Abdulsalam et al. 2015). For most businesses, outsourcing logistics to third-party logistics providers (3PL) has been a source of competitive advantage. Most organizations claim that higher flexibility, operational efficiency, enhanced quality of customer service, and higher concentration on key businesses as part of the benefits of employing 3PL providers' services. One study exhibited that outsourcing logistics is always valuable in order to alleviate the complexity of the supply chain (Azzi et al. 2010). In the healthcare context, the study of the Italian Healthcare Network indicates that outsourcing to 3PL is the most economical choice (Azzi et al. 2013). The opaqueness and intricacy of information of demand also contribute to the complexity of the health supply chain. In order to counteract these unfavorable aspects, increasing collaboration between numerous parties in the supply chain, making the supply chain more demand-driven, and implementing more and better standards are needed (Rossetti et al. 2011).

Vendor-Managed Inventory (VMI) has been regarded by pharmaceutical companies, medical and pharmaceutical firms, and healthcare providers, including hospitals, to be highly effective in performance improvement, cost reduction, and enhanced customer satisfaction in other sectors, particularly in retail (Mustaffa and Potter 2009; Turhan and Vayvay 2009). The later research proposed five VMI patterns for implementation in the supply chain of public healthcare, indicating that VMI could deliver advantages to the public sector, whereas there are major public sector constraints linked to health programs, infrastructure, products, prospective VMI contributors, and stakeholders (Watson et al. 2012). VMI enables versatile vehicle planning and creates the opportunity to decrease transport expenses by organizing shipments with the hospitals. Considering the challenges of inventory management in the healthcare setting and the modernization at the point-of-use of medicines, inventory policies have been implemented to achieve service improvement and cost reduction objectives. The use of advanced identification technologies such as barcodes and radio-frequency identification (RFID) enables the development and expansion of inventory policies (Volland et al. 2017). Another supply chain management model called SPD (supply, processing, and distribution) are getting more attention from Chinese and Japanese researchers in the field of the hospital supply chain. Recently, it has been used to solve management difficulties and complexities and reduce the logistics costs of managing medicine with favorable results (Liu et al. 2016). Although the implementation of the SPD showed decent results, the model needs to be enhanced to be more intelligent in handling more complex challenges. Furthermore, the SPD implemented in Japan and China is operated by internal departments of hospitals.

Recently, Thailand has established services for patients undergoing Continuous Ambulatory Peritoneal Dialysis (CAPD) as the first service for dialysis for patients with renal failure, commonly known as the Peritoneal Dialysis (PD) First policy. With the CAPD program, the peritoneal dialysis fluids (PD fluids) are delivered to patients' houses, and patients can undergo treatment at home without being hospitalized. Therefore, CAPD services are predicted to be more cost-effective than HD because the majority of the expenditures are for the peritoneal dialysis fluid (PD fluid), which is likely to decrease if handled efficiently. However, due to the numerous linkages between a large number of various stakeholders, the supply chain for CAPD services is distinct in many ways, resulting in certain undesirable outcomes such as PD fluid inadequacy, expiry, overstock, and high delivery cost. These issues might have a significant influence on the patient's safety or even cost a life that cannot be fully compensated financially. To address issues related to complexity, it is vital to evaluate current supply chain flows, identify unnecessary operations that contribute to system inefficiencies and build efficient supply chain models capable of decreasing complexity while enhancing overall performance. An effective supply chain will not only minimize CAPD out-of-stock incidences and inventory levels, but it will also give various other important advantages, such as reducing the stress on PD nurses, boosting supply resilience, improving care delivery, and preventing drug expiry.

Regarding the previously indicated negative issues of performance in managing CAPD service and the benefits of applying VMI, 3PL, SPD, and inventory policies from past research, this study integrates these four to construct a new logistics model (SPD-VMI) to improve out-of-stock and overstock problems. Furthermore, Discrete Event Simulation (DES) is regarded as the instrument for modeling and assessing the performance of the 3PL in the SPD

model when combined with VMI. The study also includes inventory policies to see if they improve the performance of the SPD-VMI model.

1.1 Objectives

The purpose of this study is to examine logistics models of SPD that are operated by 3PL through the combination of SPD and VMI concepts. Additionally, the study integrates inventory policies to enhance the performance of SPD operations in terms of inventory management of CAPD service. Discrete event simulation (DES) is employed to evaluate and compare the performance of SPD models.

2. Literature Review

Vendor-managed inventory (VMI) is a technique in inventory management in which a product's supplier, frequently the manufacturer, takes responsibility for managing inventory held by a distributor. A communication platform, typically electronic data interchange (EDI) or the Internet, is required to provide the supplier with the distributor sales and inventory information needed for planning inventory and placing the order. In the healthcare sector, the early study indicates that the VMI can reduce inventory while confronting the absence of standards of information sharing and participation of crucial stakeholders (Kim 2005). Another study proposes five VMI models for the public sector. One is the 3rd Party Replenished Inventory (3RI), where The third party manages replenishment decisions for the health commodities custodian. The study indicates that VMI could deliver benefits to the public sector with some limitations (Watson et al. 2012). This study uses this model in combination with SPD, 3PL, and inventory policies to build novel logistics models for simulations. In the operation of VMI, a number of providers rely on third-party logistics (3PL) as their logistics capabilities are restricted. To date, 3PL, in combination with VMI, has been extensively used in many sectors. On the one side, this hybrid operating model mixing VMI and 3PL guarantees that data on the supply chain is fully exchanged on a single central system. On the other side, it can fully exploit the benefit of 3PL and decrease the overall operating costs of the supply chain (Li et al. 2013). Although VMI and 3PL are widely utilized in various sectors, academics have paid little attention to the composite of these two in the healthcare field.

Managing inventory is related to the maximization of service level and the minimizing of costs (Tiwari and Acharya 2013). Establishing an inventory policy is one of the inventory management strategies for achieving those goals. Inventory policy is a technique for determining the optimal product flow within a supply chain. It is a set of rules that govern the quantity and timing of the purchase or production of a product. Inventory policies come in a variety of format. According to prior research, inventory policies are classified into two types: continuous review policies and periodic review policies. Previous research has found that the most widely used policies in healthcare supply chain management are the continuous review policy (s, S), the continuous review policy (s, Q), and the periodic review policy (R, S) (Volland et al. 2017). Under the continuous review policy (s, Q), the predetermined amount of Q is ordered whenever the inventory level falls to or below the reorder point s.

In this context, the inventory position is evaluated (not the inventory level (net inventory)) since it includes the on-order inventory and takes into account the pipeline inventory that the supplier is delivering. In the continuous review policy (s, S), the system generates an order if the inventory position falls to or below the order point s. In contrast to the (s, Q) policy, this system's order quantity is variable (the order quantity is the difference between order-up-to level S and the inventory position). Lastly, in the (R, S) policy, the inventory level is monitored periodically with a specific time interval, and an order is issued to boost the inventory to a predetermined level. This policy fixes the interval between orders. However, the quantity of each order varies based on demand and inventory positions. The control mechanism dictates that every R time unit is ordered in sufficient quantity to bring the inventory position to S level (Silver et al. 2016).

The emersion of SPD has been promising for alleviating the management issues and complexity associated with managing medicines in the hospital supply chain. The first era of implementation of this supply chain model was introduced in Japan to alleviate the burden related to inventory management. The model evolved from the notion of process optimization used to cope with problems in managing medical consumables (MCs). Thereafter, researchers improved the model by incorporating just-in-time (JIT) into the existing paradigm and introduced the SPD concept for hospital logistics (Liu et al. 2016). The study at the University of Tokyo Hospital shows desirable results in terms of inventory reduction as well as the decrease in preparation time and stress of the staff (Ito et al. 2006). The research in this field remained dormant for quite some time until several studies in China reignited it. The second realm of the SPD is related to the incorporation of other supply chain management tools, optimization techniques, information

technologies, and management philosophy (Lean). Perhaps the most comprehensive structured model is the study in 2016 in China that clearly identified each element's functions of the SPD. In that study, the supply chain functions under the SPD model are performed by internal departments in the hospital. The model for MC logistics management was successfully realized through the creation of a supply-procurement platform and a Lean logistics management system. Consequently, SPD plays a vital role in improving the logistics operations of MCs, maximizing the efficiency of logistics management, and decreasing the logistics cost of hospitals (Liu et al. 2016). Even though the findings are positive, implementing the SPD requires collaboration from many hospital departments and a prompt response from suppliers. Accordingly, the later study introduced the collaborative business intelligence (BI) system to SPD by employing data mining techniques to extract insights from complex data and coordinated tactics to improve hospital logistics operations (Liu et al. 2017).

A later study examines the impact of the SPD after introducing amount-based packages (ABP) and procedure-based packages (PBN) that leverage the information for a quick response code (QR code). The findings indicate that the time required to arrange the collection has dropped, inventory has declined dramatically, the warehouse is well-maintained and organized, and both the frequency and duration of claim processing have fallen sharply (Chai et al. 2019). Gearing toward the more sophisticated SPD, researchers adopted an optimization approach to identify the routes between distributing and consuming nodes. Compared to the pre-optimization distribution scheme, the optimized distribution route lowers hospital distribution costs while improving medical service levels and management efficiency (Gao et al. 2021). Despite the noticeable expansion of the SPD deployments and desired results, all prior studies only involved medicine used or distributed inside hospitals. The medicine in this study, in contrast, is delivered to the patient's house, where tracking a real-time inventory is challenging. In light of this, a 3PL with the necessary technology could be a suitable option for fulfilling this voice. On top of that, using a 3PL partner to manage logistics frees up resources to concentrate on the key areas that grow and develop business and relieve the burden of day-to-day operational logistic problems. Furthermore, the supply chain activities under the SPD are carried out by the internal departments of the hospital. Therefore, introducing SPD for the CAPD service, where the medicine is delivered to patients' houses, and a 3PL handles its supply chain functions with the VMI and inventory policy concepts, would be a novelty and an innovative solution for existing problems.

3. Methods

The research focuses on building the SPD models and evaluating them by using DES. Therefore, the methodology of this study consists of nine steps as follows.

Step 1: Identifying existing processes and associated issues. This was performed by examining data gathered from secondary sources, such as online materials from government websites, seminar materials, and publications from prior research on CAPD. After identifying the issues associated with CAPD management, the problems this research aimed to address are specified. According to preliminary data, it can be concluded that the existing system's problems include out-of-stock (OOS), expiration, inefficient demand management, inaccurate stock information, and an inappropriate buffer stock and safety stock at the patient's residence leading to either out-of-stock or overstock. This research aims at improving OOS and overstock. Therefore, the experiment sets the OOS and inventory levels as measurement metrics.

Step 2: Building logistical models and conceptual models for simulation. In this stage, the logistical processes are established, explaining how the CAPD is ordered and delivered to the patient. Primarily, there are two models developed. The first model is the traditional model, which represents existing CAPD management logistical operations. Under this model, the order of PD fluid is pressed by the hospital, and Thailand Post Distribution (THPD) delivers it to the patient's house. The second model, defined as the SPD-VMI model, is constructed based on the principles of the SPD that apply VMI concepts handled by 3PL(Liu et al. 2016; Watson et al. 2012). With this model, THPD, which acts as SPD, monitors and replenishes PD fluid based on actual use and the current inventory level. Subsequently, the logistical processes are turned into conceptual models that will then be utilized to develop simulation models. The conceptual models assist in identifying the data necessary for the simulation runs.

Step 3: Data gathering for the simulation experiment. The data utilized to conduct the simulation include the demand rate per patient, the delivery lead time of PD fluid, the number of patients, the order frequency, and the number of bags the PD's nurse orders for patients on average. The data are gathered through interviewing PD's nurse from Srinagarind Hospital. Before building a simulation, the following constraints are defined. 1. Demand rate per day per

patient is stochastic with considerable volatility. The demand per patient is 4 bags a day (an average of 112 bags for 28 patients). 2. Lead time of ordering from the hospital to the the Government Pharmaceutical Organization (GPO) is constant at 14 days. 3. Order frequency in the Traditional Model is constant with the frequency of once a month. 4. Production capacity of suppliers is infinite. 5.The products delivered to patients are in perfect condition. This assumption is slightly unrealistic as patients rarely find the product with quality concerns. With the limitation of information, however, this incident is disregarded in this study. 6. The number of patients is assumed to be deterministic at 28 patients for home delivery. In the real case, this number can fluctuate over time. 7. The capacity of the logistics provider is infinite. Therefore, the logistics provider can deliver whenever the products are shipped, regardless of how many they are. 8. All order is fully fulfilled; thus, there is no backorder happening under any circumstances.

Step 4: Constructing and executing simulation models. The conceptual models are translated to simulation models created using Arena software. Defined running parameters include replication length, warm-up period, and replication count. In this study, the simulation is defined to run under the termination condition that the simulation will terminate after the replication length has been justified. In this study, the inventory position is plotted and observed while running the simulation to identify the warm-up time. In this experiment, the warm-up time of 60 days is defined based on the starting point of the persistent inventory level, and pipeline inventory visualized. Therefore, the application length is 425 days (365 days of the period that is evaluated + 60 days of the warm-up period). In addition, this experiment calculates the sample size using the normal approximation and the half-width ratio approaches. The results from the two approaches are compared, and the maximum number is selected as a sample size. Furthermore, this study evaluates two performance metrics; therefore, the maximum values from both KPIs are compared (Rossetti 2021). As a result, the number of replications used in the experiment is 120 replications

Step 5: Performance comparisons. Average inventory level and out-of-stock incidences (OOS) are the performance metrics utilized to evaluate the models. The OOS metric quantifies the length of time a specific product is out of stock. It can be measured by counting how many days the inventory of a particular product went exhausted (Gallien et al. 2021). The simulation yields these two KPIs, which are compared using a paired sample t-test. The model that is superior to each other is then picked to be the base model for constructing scenarios.

Step 6: Developing scenarios to enhance performance. Three distinct inventory policies from the literature are added to the base model specified in the previous experiment stage (Cachon and Terwiesch 2012; Silver et al. 2016). Thus, three alternative SPD models are suggested. The first model is the combination of the SPD-VMI model and the continuous review policy (s, Q), named the SPD-VMI (s, Q). A predetermined amount of Q (Q=10,119) is ordered whenever the inventory position (IP) falls to or below the reorder point s (s = 3,438). The second model employs the continuous order-up-to-inventory system (s, S), entitled SPD-VMI (s, S). With this policy, when the IP drops to s (s=3,438) level, the inventory system is continually monitored, and order for S (S= 4,224) - s units is placed promptly. The last model is the integration between the SPD-VMI and the periodic review policy (R, S) called SPD-VMI (R, S). In this model, the inventory level is audited periodically based on the frequency defined for the model. The system will suggest an order to raise inventories to S levels (S=4,643) regardless of the IP at the time of calculation. This experiment assumes that the order can be pressed once every week. Therefore, the value of the R parameter is 7 days.

Typically, the decision-makers take different approaches to balancing these risks by establishing the safety stock based on either cost or service objectives (Silver et al. 2016). This study employs the service approach to calculate the parameters of inventory models since stockouts may severely impact the patient's health.

Table 1. Scenarios and parameters

Model	Review interval (days)	Par level	Re-order point	Order Quantity
Traditional	30	3,360	Every 30 days	3360
SPD-VMI	1	3,360	IP < 3,360	3,360-IP
SPD-VMI (s, Q)	1	-	IP < s	Q
SPD-VMI (s, S)	1	S	IP < s	S-s
SPD-VMI (R, S)	7	S	IP < S	S-IP

Step 7: Running simulations of scenario models. The procedures outlined in step 4 are repeated. Each of the three models is executed using the identical running setting (warm-up time, replication length, and the number of replications). In this step of the experiment, the simulation models are embedded with logical processes based on inventory policies in order to evaluate the inventory and compute the order quantity. After conducting the initial run of all models, the running parameters are the same: warm-up time, replication length, and the number of replications equal to 60 days, 425 days, and 120 replications, respectively.

Step 8: Comparing the performance of all models. In this phase, the ANOVA test is used to determine if the means of KPIs across all models are the same. The post-hoc test is also undertaken to determine which models have different or the same performance as each other.

Step 9: Conducting sensitivity analysis. The demand is altered by plus and minus 10% in order to determine whether performance measurement (average inventory level and OOS) changes in the relative direction. The simulations performed in this phase continue to use the parameters specified in step 7.

4. Data Collection

The data utilized in this study are separated into two categories: preliminary data and quantitative data for the simulation procedure. The preliminary information on CAPD, including the logistical process, current difficulties, and other particular information, is gathered from secondary sources, such as the National Health Security Office (NHSO) and the Government Pharmaceutical Organization (GPO) websites and seminar materials. This study requires the rate of PD fluid usage rate, the lead time of delivery, the number of patients, and the rate of order frequency. This information is gathered from Srinagarind Hospital by interviewing the PD's nurse responsible for ordering the PD fluid. According to collected data, the demand can be described as stochastic with considerable volatility. This study assumes that the aggregate demand for various types of PD fluids constitutes the demand, and it follows normal distributions with a dispersion of around 10%. The vast majority of patients typically consume four bags of PD fluid each day. However, certain patients may require variable quantities of PD fluid, dependent on their condition. Another source of variation is the change in the number of patients (28 patients in this study) due to death, new registration, and shift-mode patients. In this study, the aggregate demand per day is defined as normally distributed (NORM(112,11.2)). This number is used to compute the parameters of inventory models throughout the simulation. Lastly, the lead time for delivery of PD fluid to the patient's house is approximately 14 days.

5. Results and Discussion

5.1 Results and analysis

After running 120 replications, the experiment provided results, as displayed in Table 2. Firstly, the ANOVA test (p-value less than 0.05) demonstrates a statistically significant difference between the mean of average inventory levels. The post hoc test (Table 3.) indicates that the means of average inventory levels can be divided into four distinct groups. The test results reveal that the SPD-VMI with (s, S) represents the lowest inventory level. The SPD-VMI and SPD-VMI (R, S) models are second, while the standard model is fourth. Lastly, the greatest level of stocks is represented by the SPD-VMI (s, Q). In the SPD-VMI (s, Q) model, the inventory level is determined by the parameter Q, which is influenced by the relatively high ordering cost that is related to inspection activities. Considering the OOS performance measurement, the ANOVA test reveals (p-value less than 0.05) a substantial difference between the OOS mean values in terms of out-of-stock performance. With this measurement, the traditional model's out-of-stock performance is the poorest, with 28.8 incidents per year. On the other hand, the post hoc test in Table 4 indicates that the SPD-VMI models with three separate inventory policies produce the fewest OOS with no statistically significant difference. With this performance assessment, the SPD-VMI depicts the neutralized result. Due to the fact that the traditional method creates orders based on outdated information, it cannot adjust to altering demand. With the lack of real-time monitoring, the model cannot capture the change in demand and inventory between the interval of orders. This results in several out-of-stock occurrences. In contrast, the visibility of inventory and demand improves the performances of other models since orders are created based on the most updated data.

Table 2. Simulation results

Model	Number of Replications	Average Inventory Level	Out of Stock (OOS)/year
Traditional	120	2,523.54	28.80
SPD-VMI	120	2,426.04	3.03
SPD-VMI (s, Q)	120	4,583.01	0
SPD-VMI (s, S)	120	2,252.22	0.21
SPD-VMI (R, S)	120	2,431.90	0.26

Table 3. The post hoc test of average inventory level

	Model	N	Subset for alpha = 0.05			
			1	2	3	4
Duncan[a]	3	120	2252.2233			
	2	120		2426.0365		
	4	120		2431.9012		
	1	120			2523.5421	
	5	120				4583.0093
	Sig.		1.000	.849	1.000	1.000

1 = Traditional, 2 = SPD-VMI, 3 = SPD-VMI (s, S), 4 = SPD-VMI (R,S), 5 = SPD-VMI (s,Q)

a. Uses Harmonic Mean Sample Size = 120.000.

Table 4. The post hoc test of OOS

	Model	N	Subset for alpha = 0.05		
			1	2	3
Duncan[a]	5	120	.0000		
	3	120	.2083		
	4	120	.2583		
	2	120		3.0333	
	1	120			28.8000
	Sig.		.851	1.000	1.000

1 = Traditional, 2 = SPD-VMI, 3 = SPD-VMI (s, S), 4 = SPD-VMI (R,S), 5 = SPD-VMI (s,Q)

a. Uses Harmonic Mean Sample Size = 120.000.

5.2 Sensitivity analysis

Sensitivity analysis (SA) is a method for evaluating the influence of uncertainty on one or more input variables on output variables. This analysis is advantageous because it improves the accuracy of the model's predictions by assessing qualitatively or quantitatively the model's response to changes in input variables or by elucidating the phenomena explored by the variable interaction analysis. In this instance, sensitivity analysis is performed to determine the impact of varying independent variable levels and demand on the final conclusions (average inventory level and out-of-stock incidents). The first step in conducting SA is determining the parameter uncertainty. The variable range of the unknown parameter, demand, is then calculated. The final step involves calculating the outcomes based on the most likely prediction and the direction of the findings. By adjusting the need for PD fluid, a local SA with One-at-a-Time is undertaken in this work.

In terms of maintaining the inventory level, the SPD-VMI (s, S) model provides the best results based on simulation results obtained by varying the PD fluid demand. On the other hand, the SPD-VMI (s, Q) policy model continues to exhibit the greatest value, as shown in a tornado chart (Figure 1). It depicts that inventory fluctuates in the same direction as demand. Table 5 illustrates that when demand grows from 90% to 110%, inventory also increases proportionately and vice versa. In the OOS perspective, the direction of out-of-stock follows that of the average inventory level, with the exception of the (s, Q) model in which OOS remains steady while demand fluctuates. In all demand intensities, the SPD-VMI with (R, S), SPD-VMI with (s, Q), and SPD-VMI with (s, S) perform comparably. SPD-VMI with (s, Q) continues to display zero OOS regardless of demand intensity, similar to the previous experiment. The sensitivity analysis reaches the same conclusion as the preceding experiment.

Table 5. Average inventory level from altering demand

Demand variability	Traditional	SPD-VMI	SPD-VMI (s,S)	SPD-VMI (R,S)	SPD-VMI (s,Q)
90% demand	2,277.06	2,184.60	2,176.38	2,256.87	4,126.71
100% demand	2,523.54	2,426.04	2,252.22	2,431.9	4,583.01
110% demand	2,761.45	2,668.02	2,354.17	2,492.16	4,671.11

Table 6. OOS incidents from altering demand

Demand variability	Traditional	SPD-VMI	SPD-VMI (s,S)	SPD-VMI (R,S)	SPD-VMI (s,Q)
90% demand	28.11	2.95	0	0.28	0
100% demand	28.8	3.03	0.21	0.26	0
110% demand	29.40	3.04	0.18	0.27	0

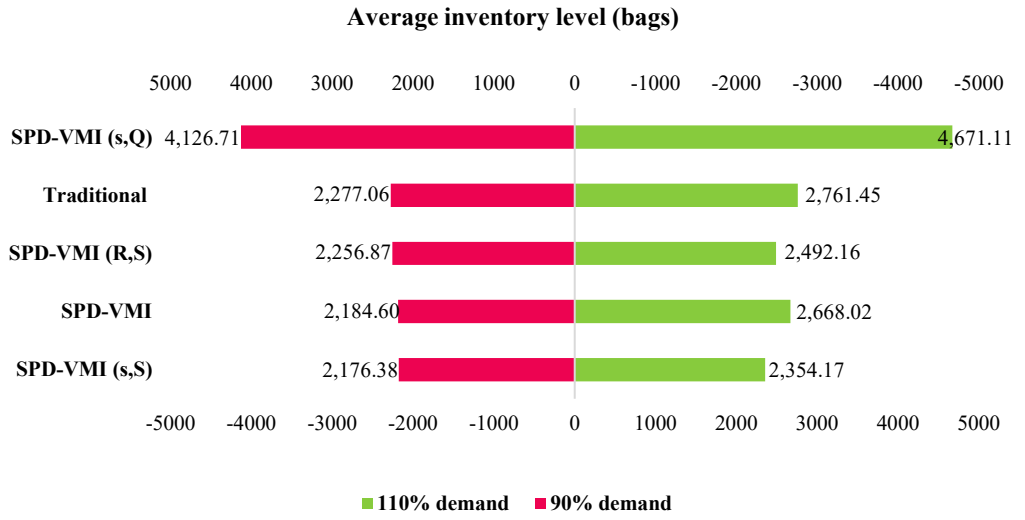

Figure 1. Average inventory level from varying demand

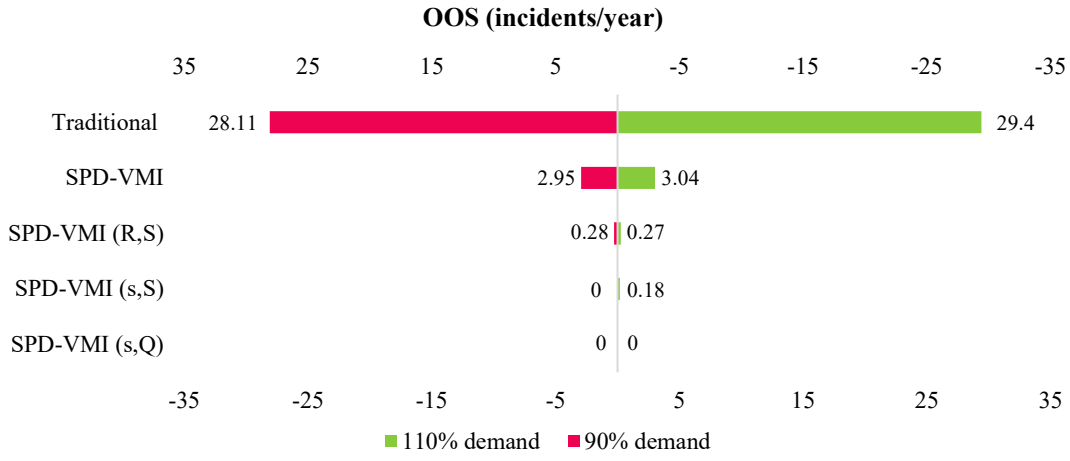

Figure 2. OOS incidents from varying demand

6. Conclusion

In this study, the effect of inventory policies that are applied to the SPD-VMI models is investigated to establish whether or not these policies will assist in improving the performance of the SPD. The average inventory level and the number of occurrences of "out-of-stock" (OOS) are both measured throughout the simulation for the purposes of this study. In light of the findings of the simulation, the following research question and conclusion are drawn. The combination of 3PL and VMI operations as an SPD (SPD-VMI model) results in improved performance in terms of lowering average inventory levels and reducing the number of instances of out-of-stock conditions. The SPD is able to effectively manage the PD fluid inventory thanks to real-time monitoring and stock replenishment that is based on the most current data. Incorporating inventory regulations into the SPD-VMI model produces interesting results for

future investigation of appropriate models. Utilizing inventory policies further reduces the burden of out-of-stock situations (OOS). In this context, the OOS reduction capabilities of the SPD-VMI models with three alternate inventory policies are equivalent. Nonetheless, concentrating on the SPD-VMI (s, Q) model, eliminating OOS comes at a cost as the average inventory level increases significantly. This is mostly owing to the inspection process's high ordering cost, which causes the economic order quantity, Q, to be extraordinarily large. Positively, the analysis demonstrates that the SPD-VMI (s, S) has the best performance in both metrics since the SPD's monitoring of real-time information allows it to refill its supply at any moment.

There are some aspects of CAPD management that are worth further studying. Firstly, this study investigates a way to reduce the amount of inventory that must be carried and the number of out-of-stock incidents throughout the year. The task transfer from the hospital to the SPD, which is part of the ordering process, is a step that needs deeper investigation. Because of this development, a new policy is required, which in turn will call for extra study.

Secondly, information technology (IT) initiatives can aid supply chain practitioners in enhancing the hospital supply chain (Beaulieu and Bentahar 2021). IT systems would be a vital aspect of the proposed solution, as such a system would facilitate the exchange of GPO, SPD, patient, and hospital information. IT systems can be quite expensive, and the cost of the project often increases substantially once it has begun. It would be prudent to determine how much automation and complexity a solution would entail, as well as the type of IT system that could manage it. If no system is available, it is necessary to estimate the expenses associated with implementing one. In terms of quality control, monitoring the state of PD fluid will be the focus of future studies, given that a faulty product might affect inventory levels. Real-time updates of the PD fluid's defect enable the system to determine the incident's missing inventory. This will increase the inventory calculation's precision. Third, in this experiment, the total demand for all PD fluid types is determined and used to run the simulation. Therefore, studying the studying type of PD fluid may give more ideas and a more effective inventory control policy for each item. Given that there are two suppliers of PD fluid, the same principle would apply.

Lastly, to be fully integrated, the hospital's supply chain must be entirely transparent and founded on the basis of trust. With a more holistic view of the hospital's supply chain, the 3PL provider can accurately assess demand and proactively refill inventory. Establishing an integrated system necessary for data collecting is the first step of the process. The next crucial step is professional analysis to determine the demand volume for various patient conditions and inventory level-influencing trends. With this information, the SPD can accurately predict demand and successfully manage inventory. Regulations and key controls can obscure visibility, making it difficult to anticipate inventory levels and lowering the provider's capacity to respond to swings in order volume. Vendor-managed inventory systems offer real-time demand forecasting and supply level changes if comprehensive transparency data is provided and the inventory management tools are integrated. This presents an opportunity for suppliers to manage inventory more efficiently since PD fluids are either quality-sensitive or have a short shelf life.

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