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# Alignment of marketing strategies in the pharmaceutical supply chain through a system dynamics simulation modelling

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## Abstract

**Purpose** – This study aims to investigate the impact of retailer–supplier partnerships (RSP), a crucial type of supply chain-related strategic alliance, in mitigating the bullwhip effect (BWE) caused by an unintegrated, sales-focused management approach among pharmaceutical supply chain (PSC) partners. It explores how integrated management strategies in PSC, using free-of-charge (FOC) rewards as a marketing promotion tool, can optimise capillary distribution networks.

**Design/methodology/approach** – A system dynamics (SD) simulation model is developed to investigate the effectiveness of RSPs in enhancing the overall PSC performance. To do so, a PSC case study is used to conceptualise and develop the simulation model, with FOC used as the primary marketing promotion tool in capillary network sales. The model evaluates the impacts on PSC metrics, including sales loss, income, production costs and raw material purchase costs.

**Findings** – Improvement scenarios are proposed to optimise the market promotion policies, achieving sales targets while stabilising production, procurement and financial operations. The simulation results demonstrate significant improvements in decreasing sales loss, production operational costs and raw material purchase



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costs and increasing income and profitability. In addition, errors in raw material and product stocking decreased, and the market share increased notably, demonstrating the benefits of a coordinated PSC.

**Originality/value** – This study extends existing research by presenting an SD model on RSP within PSCs, emphasising the often-overlooked marketing component in integrated PSC planning. It provides insights into how strategic alliances and integrated management approaches can alleviate common PSC challenges, such as BWE.

**Keywords** Supply chain, Retailer–supplier partnerships, Pharma industry, System dynamics, Marketing promotion policies

**Paper type** Research paper

## 1. Introduction

The pharmaceutical industry is one of the fastest-growing and most complex industries in the world (Fellows *et al.*, 2022). Few studies have focused on pharmaceutical supply chain (PSC) challenges and problems (Rahman *et al.*, 2023), while pharmaceutical companies face vexing globalisation challenges, such as:

- data sharing and collaboration along the supply chain (SC) (Abdallah and Nizamuddin, 2023; Nguyen *et al.*, 2021);
- effective marketing policies for timely product launch (Hansen and Grunow, 2015);
- slow and costly regulatory processes (Marucheck *et al.*, 2011); and
- complex and sensitive manufacturing processes (Nematollahi, 2018).

A coherent framework for managing the PSC is essential to ensure a smooth flow of information, finances and materials/products by coordinating all chain components and addressing system constraints. PSC managers face various factors that create different dynamics, leading to fluctuating behaviour known as the "bullwhip effect (BWE)". The BWE occurs when order variations exceed sales rates, moving from retailers to producers (Zhou *et al.*, 2022). This challenge results in inaccurate forecasting as each section responds to its orders, compounded by a lack of direct communication along the chain, which is evident in inventory fluctuations (Wang and Disney, 2016). The BWE in the PSC arises from downstream order changes, disrupting the transfer of data and information upstream (Lee *et al.*, 1997). These large order variations cause excessive inventory, inaccurate forecasts, capacity misalignments, service shortages, production uncertainties and high correction costs, like expedited shipments and overtime (Katsaliaki *et al.*, 2022). In addition, poor production planning, inefficient transportation and rising raw material costs exacerbate the BWE in the PSC (Sudarmin and Ardi, 2020). The BWE also brings issues like over-inventory, workforce instability and poor customer service (Alabdulkarim, 2020).

Due to the unpredictable nature of customer orders in the PSC, insufficient stock at various PSC stages can result in lost customers and inventory shortages. While maintaining medicine product inventory has its benefits, poor management and analysis can lead to significant losses, potentially jeopardising the entire chain to meet customer satisfaction. A systems approach can help assess fluctuations caused by market dynamics or limitations in purchasing, production and distribution processes, which influence inventory levels in the PSC.

On the other hand, inventory fluctuations in the PSC impact its ability to fulfil retailers' orders and plan production, making it a key concern for the PSC decision-makers (Tavakol *et al.*, 2023). A lack of holistic understanding of the causal relationships within the PSC, including significant delays, results in disruptions such as sales loss, expired inventory waste and inefficient use of resources like manpower and machinery. Additional challenges include varying retailer needs, continuous changes in the chain, uncertainty, non-linear relationships and information delays, all of which contribute to the PSC's complexity (Hearnshaw and Wilson, 2013).

Efficient medicine distribution is vital for public health, as delays or imbalanced distribution can lead to serious consequences and regional disparities in access. One approach to enhance reach and availability is capillary selling, which involves the distribution of products through an extensive network of local retailers. This method utilises various marketing and sales tools, such as free samples, special discounts, loyalty programmes and digital campaigns, to incentivise purchases and stimulate demand at the community level. Capillary selling not only improves product accessibility but also strengthens market penetration, particularly in underserved or remote areas (Amin-Tahmasbi and Hami, 2019).

Fisher (1997) argues that the misalignment between product types and SC strategies is a root cause of SC underperformance. Later, Mentzer *et al.* (2001) define SC management as the systemic and strategic coordination of SC entities with the goal of enhancing the long-term performance of both individual firms and the SC as a whole. This perspective highlights the need for each SC entity to recognise the strategic and systemic implications of their activities and processes in managing the various flows across the SC. Accordingly, this research, which benefits from a PSC case study, focuses on the retailer–supplier partnership (RSP) to explore the impact of a more effective RSP on mitigating the BWE. The PSC studied in this paper includes internal and external suppliers, all of the logistics activities, manufacturing operations and activities, marketing, sales, product design, financial processes, information technology and customers. Free-of-charge reward (FOC) is used as the main marketing promotion tool in the capillary network sales in the case study. Therefore, the main research questions here are:

*RQ1.* How does the lack of effective relationships between marketing and production processes cause fluctuations and turbulence in the studied PSC?

*RQ2.* What strategies can improve the PSC performance?

In our case study, the dominance of large pharmaceutical companies and high-profit margins has hindered the adoption of integrated PSC management. In the face of intense domestic competition and the demand for new, high-quality medicines with timely delivery, maintaining market share requires a deep understanding of consumer needs and effective integration across the SC. The company's performance reports show that in some years, inventory value equalled half of sales, leading to capital sedimentation and reduced liquidity. With high raw material costs, the company aims to minimise inventory levels. Another major challenge, highlighting the need for better marketing-production integration, is the significant monthly loss of sales.

Hence, this study aims to contribute to the literature by further delving into and adding to the understanding of inventory fluctuations and also decreasing lost sales in the PSC in the studied PSC via system dynamics (SD) modelling. The studied PSC has faced BWE for a long time, with significant fluctuations in customer orders, largely due to inaccurate forecasting by the marketing department. Since there is no integrated and up-to-date communication between PSC components, as well as there are restrictions on the timely purchase of raw materials by the sourcing department, the raw materials are not purchased in the right amount and at the right time. Therefore, the accumulation of products along the PSC has caused an increase in the inventory along the chain.

The remainder of this paper is structured as follows: In Section 2, aspects of PSC performance are introduced. Section 3 introduces the research methodology. Section 4 illustrates the steps utilised for model development by establishing system boundaries and assumptions and developing causal loop diagrams (CLDs). Moreover, it presents simulation results based on different scenarios. Research and managerial implications are discussed in Section 5. Limitations and future research directions are provided in the concluding section.

## 2. Research background

This study examines capillary sales, a marketing and sales strategy used by fast-moving consumer goods (FMCG) manufacturers. Capillary sales involve distributing products directly to final dealers who sell to consumers, with a key feature being a "permanent" and "uninterrupted" flow of sales from the company to vendors. Since orders are often taken face-to-face by sales staff, having enough skilled human resources to meet customer needs promptly is crucial (Amin-Tahmasbi and Hami, 2019). Pharmaceutical manufacturers, due to their wide product range and customer base, frequently use capillary distribution for timely delivery. Effective management is essential, as neglecting key factors can increase PSC costs, such as excess inventory from slow-moving products (Hosseinpour *et al.*, 2013). Performance in capillary distribution is influenced by variables like demand volume, price ratios and discounts. Although challenging and costly in dynamic environments due to imbalances, capillary distribution offers benefits such as better information sharing, stronger bargaining power, improved customer communication and enhanced inventory control (Hosseinpour *et al.*, 2013).

### *2.1 Pharmaceutical supply chain*

The PSC starts with sourcing active and inactive ingredients for approved products, which are produced, packaged and transferred between warehouses, distributors, pharmacies, hospital pharmacies and finally to consumers (Ding, 2018). The PSC ensures essential pharmaceutical products of high quality reach the right place at the right time (Mehralian *et al.*, 2012). Medical product SCs are crucial in healthcare, as different products are distributed and priced differently, impacting healthcare system efficiency (Zheng *et al.*, 2006). Effective PSC management is vital for a well-functioning healthcare system, with managers needing to focus on forecasting, planning, procurement, financing, stock levels and marketing strategies to enhance PSC performance (Moosivand *et al.*, 2019). High competition and uncertainty at each level of the PSC drive its complexity and dynamism (Jetly *et al.*, 2012).

### *2.2 Bullwhip effect in pharmaceutical supply chain*

The BWE is a key indicator of SC performance (Goodarzi and Saen, 2020) and is a common issue in PSCs, causing supply and inventory risks that impact marketing, supply, and production (Zhou *et al.*, 2022). The BWE occurs when small fluctuations trigger major instabilities across the SC, a concept widely recognised by researchers (Udenio *et al.*, 2015). Studies have identified five main causes of the BWE: order forecasting, supply shortages, lead times, batch ordering and price fluctuations (Lee *et al.*, 1997).

Tavakol *et al.* (2023) highlighted that in PSCs, marketing strategies, particularly those linked to distribution channel structures like monopolistic or capillary models, significantly influence price fluctuations, inventory policies and information transparency, all of which are key drivers of the BWE. The high demand variability in PSCs is particularly challenging since the impact of demand variability on BWE is larger for fast-moving products (Pastore *et al.*, 2019), which are common in the pharmaceutical sector. As a result, scholars have stressed the need to integrate marketing with SC management (Jüttner *et al.*, 2007), promoting a shift towards customer-centric supply chains that better respond to market dynamics.

Accordingly, this study examines how misalignment between marketing and operations in a PSC contributes to the BWE and overall underperformance. The case study focuses on a PSC operating through a capillary sales network, where FOC promotions create significant demand variability. The selection of this case aligns with the reviewed literature, which underscores how such distribution strategies and marketing tools intensify the BWE.

Table 1 summarises the analysis of the BWE in the PSC literature. Notably, no studies have explored the BWE in capillary distribution networks within PSCs. This paper introduces a novel application of SD modelling for simulating PSC performance, focusing on inventory management in a capillary distribution system. By incorporating FOC promotions as a marketing strategy, the study seeks to mitigate the BWE and enhance operational efficiency. It highlights the need for a broader consideration of key performance variables and causal relationships when using marketing strategies in PSCs. Managers must plan these strategies with a full understanding of their impact on SC performance and associated risks.

Compared with earlier studies (as summarised in Table 1), this study focuses on integrating marketing-driven factors, particularly FOC promotions as a marketing strategy, into the dynamic structure of a PSC. Previous studies have largely examined inventory management or supply-side dynamics in isolation, without considering how marketing strategies directly interact with PSC operations to influence demand variability and BWE. Our study takes a holistic approach by incorporating the causal relationships among suppliers, marketing strategies and retailers' demand within the PSC, enabling the evaluation of coordinated policies that both optimise inventory management and mitigate BWE. This integrated perspective has not been addressed in earlier SD models of PSCs. Alkhouri (2024) identified inventory management, demand forecasting errors and poor coordination as the most critical challenges in PSCs. Addressing these gaps, our study applies SD to evaluate how marketing strategies influence inventory performance and the BWE, providing managers with a robust tool for designing more effective and coordinated PSC policies.

## 3. Research methods

As the primary research method in this study, SD was used to develop a case-informed simulation model based on the qualitative and quantitative data available for a PSC case study. This approach ensures that the simulation results and the insights derived from this study remain consistent with real-world practices.

### *3.1 System dynamics modelling*

SD is a comprehensive modelling and simulation approach for analysing dynamic behaviours and long-term business decision-making (Sterman, 2000). It is particularly suited to high-level decision-making problems that require understanding the dynamic nature of complex systems (Borshchev, 2013). SD models simulate interactions between system components and the behaviour of individual elements to achieve specific outcomes. Static, linear models often fall short of capturing the dynamic nature of SCs, making SD the preferred method for such systems (Udenio *et al.*, 2015). By focusing on the dynamic environment and trade-offs between key variables, SD helps overcome complexity (Hosseini *et al.*, 2020). Managers in production systems must develop tools like SD models to align their strategic plans, manage complexity and enhance SC performance metrics (Rafiei *et al.*, 2014; Golrizgashti *et al.*, 2023). The following section provides a concise review of recent studies applying SD modelling to SC challenges, highlighting the growing interest in this field.

**Table 1.** The summary of BWE analysis in PSC literature

| Author(s) | Inventory management | Manufacturing | Capillary distribution | Marketing strategy | Research insight |
|---|---|---|---|---|---|
| Shah (2004) | ✓ | | | | • Resolved bottlenecks, optimised storage, and formulated inventory management strategies to adapt to rapid market changes |
| Jüttner *et al.* (2007) | ✓ | ✓ | | | • Investigated the integration of demand chain, marketing, and SC management, focusing on supply-demand alignment, customer segmentation, and retailer-supplier partnerships |
| Pedroso and Nakano (2009) | | ✓ | | | • Assessed technological knowledge in demand creation and its effect on inventory management, helping mitigate the BWE |
| Samuel *et al.* (2010) | ✓ | ✓ | | | • Examined the impact of supplier-buyer relationships and IT in reducing the BWE in healthcare services |
| Barlas and Gunduz (2011) | ✓ | ✓ | | | • Simulated key structural factors like ordering policies, demand, and lead times affecting the BWE<br>• Analysed the benefits of information sharing to reduce fluctuations and mitigate BWE |
| Pule and Kalinzi (2014) | | | | ✓ | • Conducted statistical analysis on collaboration and customer management in pharmaceutical companies to decrease BWE |
| Postacchini et al. (2016) | ✓ | | | | • Utilised design of experiments to evaluate transshipment, re-order policies, service levels, and van availability on SC performance |
| Mohaghar *et al.* (2017) | | ✓ | | ✓ | • Assessed customer order fulfilment rates, production systems, and uncertainties impacting BWE using an SD approach |
| Azghandi *et al.* (2018) | ✓ | | | ✓ | • Investigated SC disruptions from internal and external factors via mathematical simulation |
| Moosivand *et al.* (2019) | ✓ | | | ✓ | • Evaluated the dynamics of forecasting inaccuracies, long lead times, and high costs on BWE<br>• Explored the positive effect of strategies like supplier collaboration, new technologies, and IT establishment on BWE reduction |

(*continued*)

**Table 1.** Continued

| Author(s) | Inventory management | Manufacturing | Capillary distribution | Marketing strategy | Research insight |
|---|---|---|---|---|---|
| Goodarzi and Saen (2020) | | ✓ | ✓ | | • Proposed a novel DEA model to measure the relative BWE of non-serial SC networks |
| Bamakan *et al.* (2021) | ✓ | | | | • Ranked factors improving inventory management and SC reliability using AHP and fuzzy cognitive mapping |
| Delavar et al. (2022) | | ✓ | | | • Analysed information sharing in reducing BWE and improving economic performance |
| Tavakol *et al.* (2023) | ✓ | | | ✓ | • Investigated BWE drivers using DEMATEL and fuzzy cognitive map methods |
| Nawi, *et al.* (2023) | | | | ✓ | • Evaluated demand-supply disruptions in price-controlled markets using game theory |
| Wong *et al.* (2023) | ✓ | | | ✓ | • Assessed demand risks using fuzzy failure mode analysis and proposed blockchain to improve risk management |
| Current study | ✓ | ✓ | ✓ | ✓ | • Aims at presenting a novel application of SD modelling within the PSC performance simulation and analysis, specifically focusing on inventory management in a capillary distribution system, by incorporating free-of-charge promotion as a marketing strategy<br>• Emphasises employing marketing strategies in the PSC by focusing on the broader SC (i.e., by considering the key performance variables and their causal relationships) to mitigate BWE |

**Source(s):** Authors' own work

*3.1.1 SD modelling applied for SC challenges.* Recent studies have applied SD to various aspects of SC management. Some studies have explored resilient SC management by emphasising flexibility and portfolio design (Sáenz *et al.*, 2018) and assessing the impact of critical events [e.g. COVID (Kamran *et al.*, 2023)] as well as emerging technologies such as blockchain and 3D printing on SC resilience (Rane and Thakker, 2020; Arian *et al.*, 2021; Roozkhosh *et al.*, 2023). Roozkhosh *et al.* (2023) analysed the impact of blockchain implementation on flexible SCs using a hybrid SD and machine learning approach. Wankmüller *et al.* (2023) used SD to examine blockchain-based incentives for plastic bottle recycling, focusing on consumer behaviour.

SD modelling has also been used to address uncertainty in fast-moving consumer goods (FMCG) SCs, which include PSCs, revealing that in the presence of seasonal fluctuations, SC flexibility could be enhanced by adjusting lead times and order rates (Singh *et al.*, 2019). Esteso *et al.* (2023) used an SD model to assess uncertainty and risks throughout a FMCG SC, ultimately proposing protective strategies to mitigate these risks.

Sustainability is a key focus in supply chain research, with SD used to model various aspects. Su *et al.* (2023) applied SD simulation based on synergy theory, logistics, and trading volume, finding that recycling rates, government regulations and environmental ethics significantly impact supply chain sustainability.

In addition, SD has been applied to financial modelling in SCs to assess robustness. Zhang *et al.* (2023) evaluated production capacity and demand disruptions, finding that partial credit guarantees mitigate cash flow interruptions and enhance resilience. Mohammadi *et al.* (2022) used SD to address complexity and uncertainty, demonstrating that multiple price increases significantly raise total SC costs.

As knowledge management gains importance in healthcare SCs, researchers have modelled information sharing using both traditional and modern methods. Kochan *et al.* (2018) compared performance indices like inventory levels, lead times and unfilled orders using SD Their findings showed that cloud-based information sharing enhances visibility, improving hospital responsiveness, reducing supply lead times and lowering costs.

Existing research highlights the BWE as a major SC disruption, yet gaps remain in its modelling due to evolving competition and environmental changes. Poornikoo and Qureshi (2019) addressed this using a hybrid SD and fuzzy logic model, demonstrating that despite its complexity, their approach significantly reduced the BWE. SD has been used to assess SC performance during complex disruptions, focusing on service levels, costs, profits and inventory (Olivares-Aguila and ElMaraghy, 2021). Their findings highlight that disruptions at downstream levels have a more pronounced impact on overall performance.

### *3.2 Research procedure and methods*

To develop the case-informed SD model to answer the main research questions, different qualitative and quantitative tools were used. This research benefited from reliable historical data and the participation of experts from the case study PSC. After conducting a brief literature review and analysing historical data, the problem boundary was established through semi-structured interviews with experts from the studied PSC. A panel of nine expert managers, each with over five years of experience, contributed to identifying key variables and their relationships, contributing to the development of the SD model for the case study PSC. The panel included the CEO, supply planning, sales, marketing, R&D, finance, production and two programme managers.

The underlying dynamics contributing to the problem were then represented using CLDs, which were validated by experts from the PSC case study. CLDs are a powerful visual tool to represent the dynamic causal relationship among influential variables shaping system behaviour over time (Sterman, 2000). Links with positive polarity indicate that a change (an increase or decrease) in the "cause" variable leads to a change in a similar direction in the "effect" variable, while negative polarity indicates a change in the opposite direction. Correspondingly, there are positive (or reinforcing) loops and negative (or balancing loops). CLDs are helpful tools for analysing the feedback structure and its implications for the system behaviour.

In the next stage, the CLDs were converted into a stock-flow diagram (SFD), serving as the foundation for the mathematical simulation model. This model enables the projection of system behaviour over time under different scenarios. Focusing on the system's structure, SFD shows how stocks (accumulated quantities representing the system's state) change over time through flows (rates of change that regulate stock levels) (Sterman, 2000). SFDs translate conceptual CLD models into mathematical equations, enabling simulation and quantitative analysis of the system behaviour.

Following model validation using system data and expert feedback, different scenarios were defined, and the corresponding simulation results and implications were subsequently developed. The research procedure is presented in Figure 1.

*3.2.1 Modelling approach and assumptions.* This study developed a case-informed SD simulation model to address the main research question:

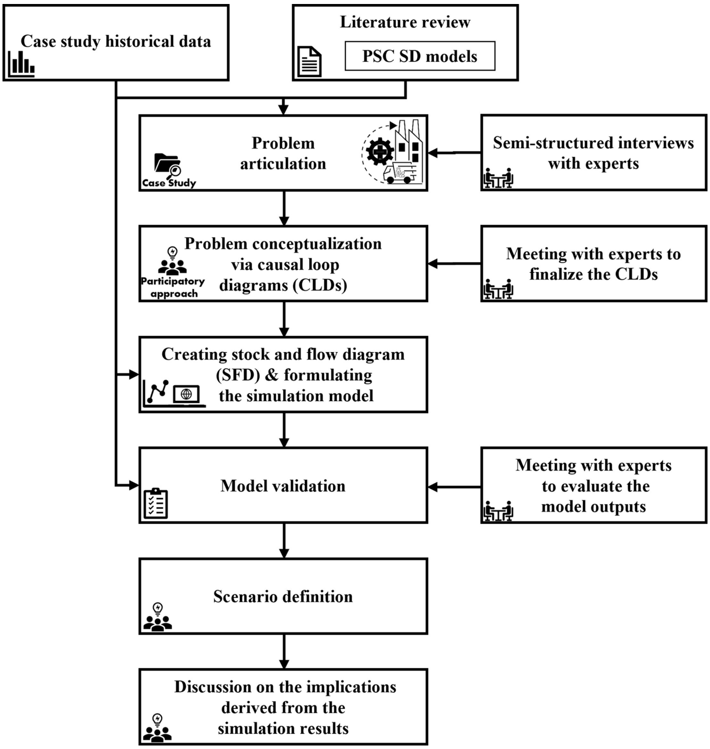



**Figure 1.** The research methodology
**Source:** Authors' own work

*RQ3*. How does misalignment between marketing and operations contribute to fluctuations and underperformance in a PSC?

The primary aim of the modelling effort is not to predict exact numerical values for the key indicators (e.g. inventory levels, production rates, sales, costs, etc.), but rather to investigate how misalignment between marketing and operations influences the trends and dynamic behaviour of these variables.

By adopting a participatory approach, the study benefited from the active involvement of an expert panel from the case PSC, who provided essential contextual knowledge and data throughout the model development, validation and analysis. It is important to emphasise that this work constitutes a case-informed SD simulation modelling exercise, rather than qualitative case study research.

### *3.3 Case study*

This section considers a PSC as a business case, focusing on one of Iran's largest and oldest pharmaceutical manufacturers. The company manages PSC activities, including sourcing, R&D, manufacturing, marketing and sales, in collaboration with partner organisations, all within an extensive SC. The firm offers a wide range of medicines, with corporate priorities on innovation, new product development, skilled human resources and continuous improvement. It controls raw material sourcing, logistics and distribution. An overview of pharmaceutical manufacturing in Iran reveals a traditional focus primarily on medicine production and R&D. The industry is largely limited to the secondary production of pharmaceuticals, mainly converting imported active ingredients into consumable medicines. Most products are generic, resulting in a competitive market with numerous firms offering similar or alternative medicines in diverse packaging. This study develops a SD model, using historical data and expert interviews, to reflect the performance of the company's PSC. A significant issue faced by the case study is the undesirable fluctuations in inventory throughout the PSC processes, leading to substantial costs from overstocking and product shortages. In recent years, one marketing strategy employed by the company has been offering an FOC reward within its capillary network sales.

The FOC tool, often referred to as a premium, bonus offer, or discount, allows the company to provide an additional similar product as a bonus with the purchase of a specific item, encouraging increased sales. While FOC is an effective marketing strategy, it can lead to changes and fluctuations in the PSC due to its potential to impact short-term product demand. Given the high inventory values in the pharmaceutical industry, there is a pressing need for inventory optimisation to avoid detrimental fluctuations. Figure 2 illustrates significant fluctuations in the inventory level of a specific product within the case company, ranging from 10,000 to 80,000 boxes over 24 months, indicating an overall upward trend in inventory levels.

*3.3.1 Model boundary selection.* The model boundaries in this paper include both internal and external PSC entities. Based on several meetings and interviews with managers, the focal firm's PSC system includes four major subsystems respectively, sourcing, operations (planning, production, storage), marketing and sales, and financial.

The primary dynamic hypothesis is that the absence of effective relationships between key decision variables across the marketing subsystem and sourcing, operations, and finance subsystems causes fluctuations, leading to adverse outcomes such as sales losses or expired materials. Each subsystem acts independently to meet its own objectives, but misalignment or delays in understanding these actions by other subsystems create imbalances within the SC. For example, marketing promotions can trigger sudden surges in order rates, causing

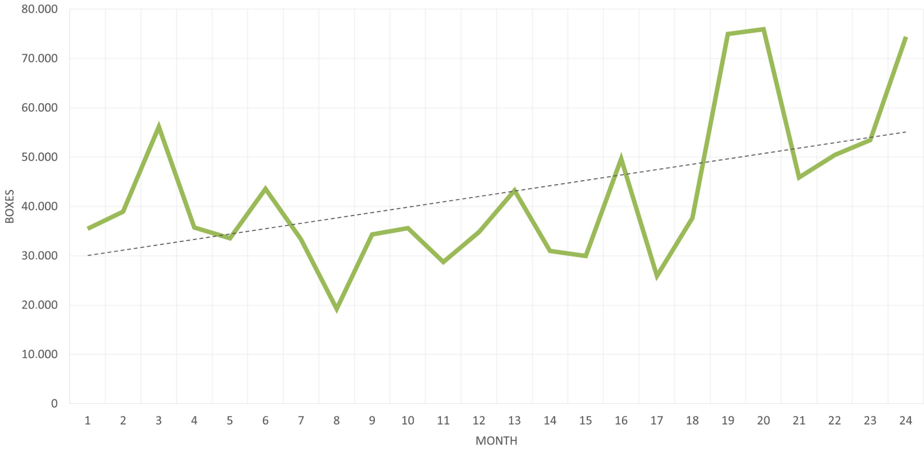



**Figure 2.** Fluctuation of the inventory of a certain product in the case company
**Source:** Created by the authors using data from the case PSC (used with permission)

inventory disruptions. However, due to long lead times in raw material supply and production, the operations team lacks the agility to respond swiftly to these market changes, resulting in shocks to production levels, raw material inventories and work-in-progress orders. To clarify the structure of the case study, Figure 3 presents an overview of the PSC, highlighting the key subsystems defined within the case study.

We hypothesise that establishing dynamic relationships between actual inventory, target inventories and marketing promotion strategies to account for forecasted sales and market demand changes can enable simultaneous and integrated management of PSC processes. This SD practice aims to highlight how improvements in these relationships can prevent or reduce undesirable behaviours such as sales losses or excessive inventory accumulation. The case study historical data for four years (48 months) was used in the model development process, ensuring sufficient historical coverage to validate the model's accuracy in capturing system behaviour.

The CLD and SFD are introduced respectively in the next section and the Appendix as built-in Vensim® PLE.

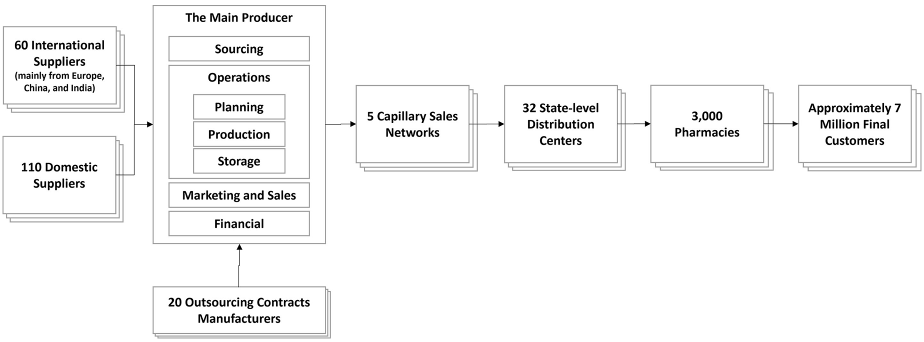



**Figure 3.** The entities within the case study PSC
**Source:** Created by the authors using data from the case PSC (used with permission)

## 4. An SD model for analysing marketing strategies in PSC

### *4.1 The qualitative model (CLDs)*

A complex system like a PSC involves numerous feedback loops, as depicted in the CLD in Figure 9. In the case company, operations planning follows a make-to-stock strategy, where inventory acts as a control lever to balance the system. This stock is crucial in mitigating fluctuations in market demand (actual orders) and supply, ensuring system stability. Planned inventory is intended to fulfil market demand while providing a buffer against unforeseen changes. Maintaining balance in the flow of raw materials and products is essential. Inventory management is influenced by sales forecasts and storage policies, which are constrained by factors such as cash flow delays, limited financial resources, storage space, optimised costs and product life cycles. Thus, an optimal storage policy should minimise costs while maximising protection against market fluctuations and supply disruptions.

The supply and production processes are initiated based on demand forecasts from the marketing and sales department. The planning department then estimates allowable inventory limits based on predetermined storage policies. If the projected inventory at the end of each period falls within the acceptable range, it is deemed satisfactory. However, if it falls below the permissible limit, this triggers production or raw material purchasing. Inventory at the end of each period is influenced by starting inventory, production volume and expected sales. Inventory fluctuations are a key challenge in the case company's SC, leading to significant costs from excess inventory or shortages. Given the high value of inventories in the pharmaceutical industry, optimising inventory management is crucial to prevent disruptive fluctuations.

*4.1.1 Sales forecasting, production and final sales causal loop.* Loop R1 in Figure 4 illustrates the dynamic interaction between sales forecasts, storage targets, production levels, product inventory and actual sales. Changes in market demand drive adjustments in sales forecasts, prompting the operations subsystem to revise inventory limits. This, in turn, influences the production rate, leading to fluctuations in product inventory. The level of inventory directly impacts the company's ability to meet market demand, ultimately affecting final sales outcomes.

*4.1.2 Marketing, demand, sales forecasting, production and final sales causal loop.* Loop B1 in Figure 5 highlights the dynamic impact of marketing activities on demand, sales forecasting, storage targets, production, inventory and final sales. The marketing department aims to secure a specific market share, with FOC used as a promotional tool to influence market demand. As demand shifts, sales forecasts, storage targets, production levels and inventory adjust accordingly, affecting final sales. In this balancing loop, if the market share falls below the target, increasing FOC stimulates demand to compensate, and vice versa.

*4.1.3 Purchasing orders and supplying raw materials causal loop.* As shown in loop B2 in Figure 6, the estimation of ordering raw materials is done based on the storage policies and by comparing the stock of raw materials. This comparison yields the ideal order rate, which is then adjusted according to supply constraints (e.g. minimum order quantity). The raw material orders are fulfilled after a delay, determined by the supply lead time, and subsequently added to the material inventory.

*4.1.4 Fulfilment of purchase orders causal loop.* This dynamic illustrates how finalised purchase orders trigger financial credit requests within the financial system. Depending on the financial resources allocated for purchases, these requests are fulfilled, with orders being delivered after the specified lead time. In-transit inventories are then converted to available stock. Additional internal loops depicted in Figure 7, such as loops B3 and R2, show how pending orders are balanced, while loops R3 and B4 highlight how pending financial requests are managed.

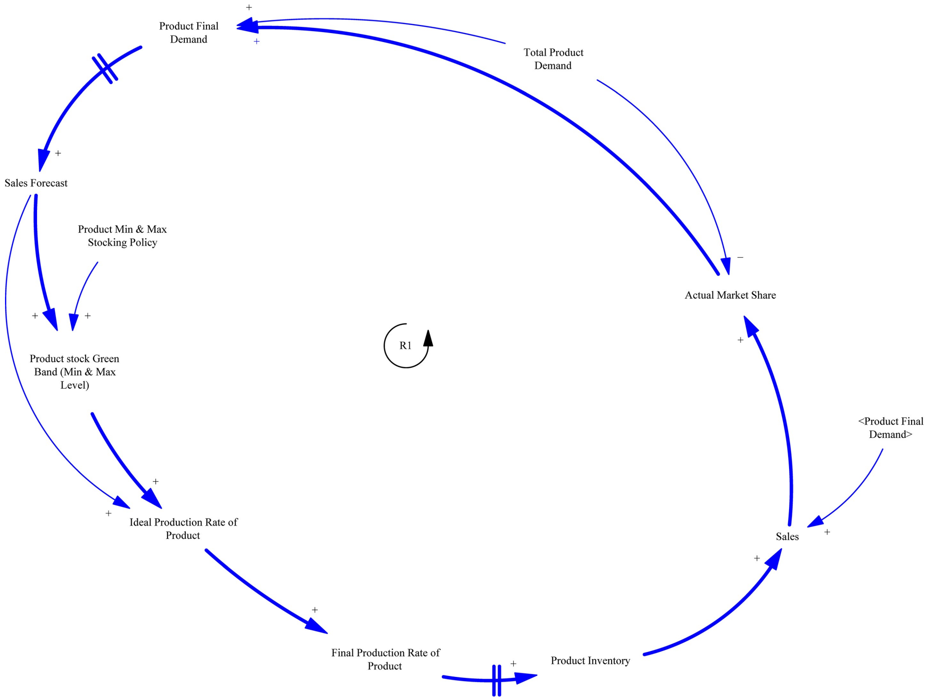



**Figure 4.** Sales forecasting, production and final sales causal loop
**Source:** Authors' own work

*4.1.5 Realisation of income causal loop.* Loop R4 in Figure 8 illustrates that sales occur based on available product inventory and demand. These sales generate financial resources after the repayment period, according to the product price. The funds are then used to fulfil orders, turning into raw material inventory. The raw materials are used in production to replenish product inventory, completing the loop.

Figure 9 shows the integrated and detailed structure of the model.

### *4.2 The quantitative model (SFD)*

The relationships presented in CLDs are used to draw an SFD. The simulation model structure (SFD) and the main important equations are explained in the Appendix.

In this study, the simulation model uses data for a specific product within the PSC, with total demand treated as a random exogenous variable averaging 100,000 boxes per month. This demand fluctuates according to external environmental conditions. The target market share for the product is set at 60%. By considering the product's sales price and the average competitor prices, the ideal net price for customers is determined mathematically, along with the necessary FOC allocation to achieve the desired market share. The marketing team compares this desired FOC with that of the previous period, applying it gradually with an exponential delay to mitigate unintended fluctuations. Consequently, the determined FOC informs the net product price perceived by the market (Co. Net Price), which in turn helps ascertain market demand through a mathematical function.

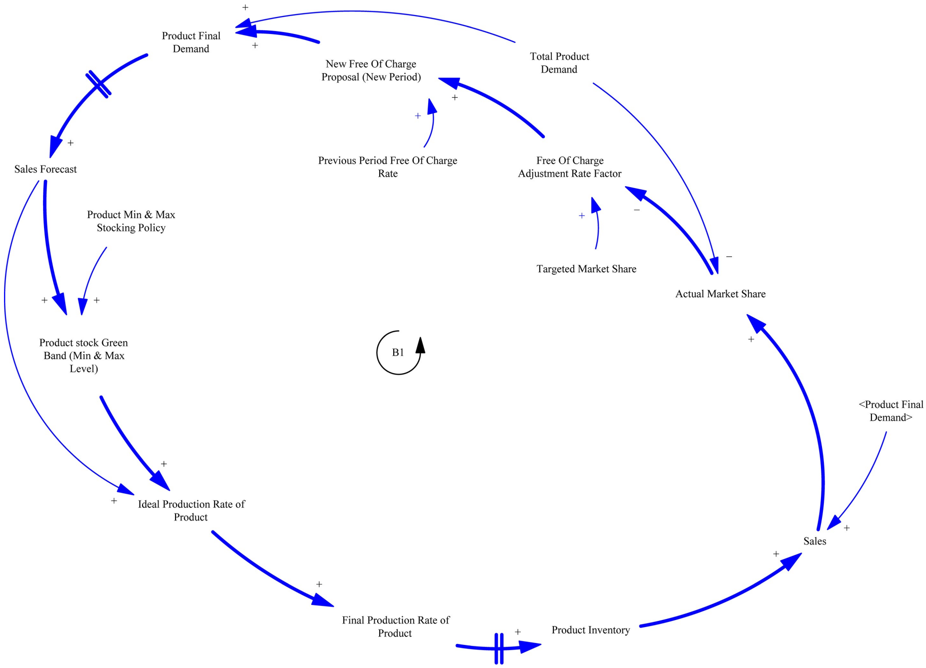



**Figure 5.** Marketing, demand, sales forecasting, production and final sales causal loop
**Source:** Authors' own work

The marketing and sales sub-system forecasts future market demand based on historical records (Sales Forecast $T_n$) and allocates it to operational units for production and material supply planning. As discussed earlier regarding auxiliary variables, each period involves estimating sales forecasts for the upcoming months to account for the minimum and maximum storage policies for products and materials, along with a long-term material supply period of six months, ensuring sustainable management of PSC processes.

Production planning is based on maximum and minimum product storage levels (Product Max/Min inventory) and the allowed inventory limitations to meet market demand and improve responsiveness to demand fluctuations or raw material shortages (Ideal Production Rate). In addition, if sufficient raw materials are available, production occurs at the determined Production Rate.

After production, the product enters the active inventory (Product Stock) for sale. If product inventory is sufficient, sales will align with market demand; insufficient inventory leads to sales losses. Product warehousing costs are incurred based on production volume, production costs and remaining stock. In addition, operational costs, including maintenance of production systems (Overhaul Costs) and materials, impact financial resources.

The logic behind raw material supply planning mirrors that of production planning, focusing on maintaining raw material inventory within permitted limits. This subsystem's complexity arises from two factors: firstly, raw materials are secondary to production, necessitating independent planning while being directly influenced by production strategies. Market demand fluctuations and marketing team decisions impact product inventory and production planning,

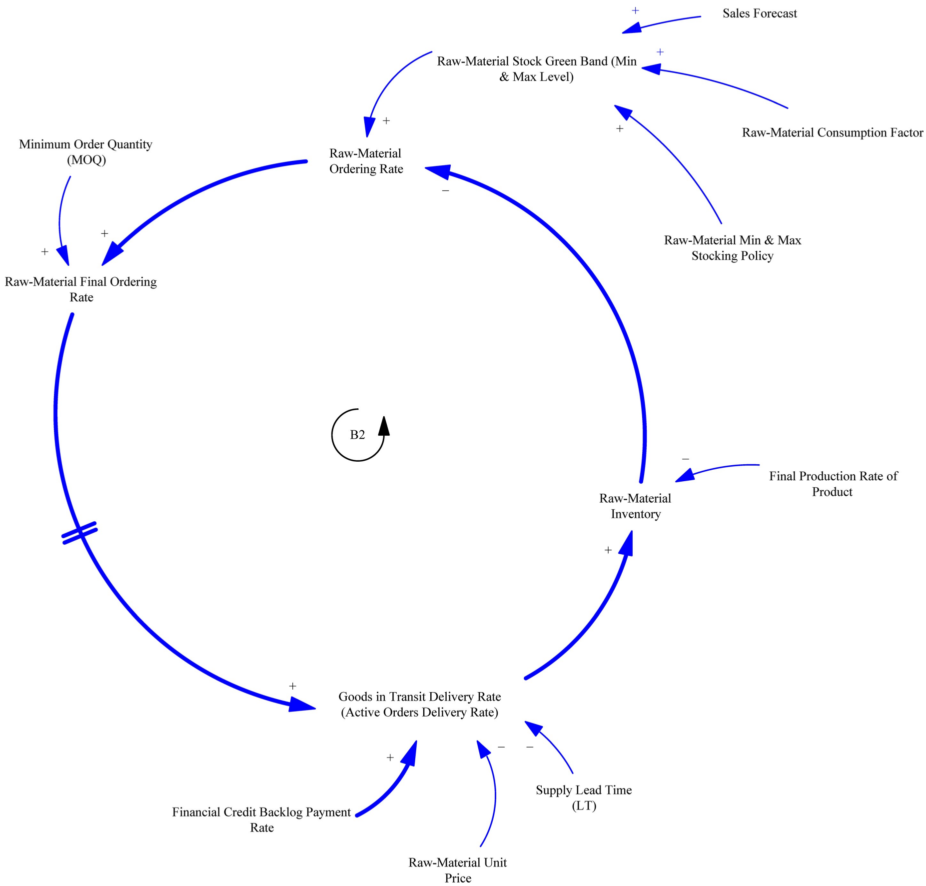



**Figure 6.** Purchasing orders and supplying raw materials causal loop
**Source:** Authors' own work

which in turn affect material planning. In addition, fluctuations in production and inventory also influence raw material supply. The challenge lies in that Material Max/Min Stock is derived from sales forecasts, but with a six-month supply lead time, the system must anticipate raw material needs for the subsequent six months, leading to significant forecasting errors.

The material consumption during this period must align with the production forecast for the next six months, which also involves significant errors. Consequently, the forecasted material inventory will dictate the required raw material ordering rate, which is supplied after six months, ensuring system sustainability. This forecasting considers allowed inventory limits, resulting in long-term projections that may contain inaccuracies. Activated orders are queued in the financial resources allocation system (Purchase Backlog), and if sufficient financial resources (Available Funds) are present after the six-month supply period (Orders Fulfilment Rate), they enter active material stock (Material Stock). In addition, the purchase order costs for each period (Purchase Cost Rate − Purchase Fulfilment Rate) and material warehousing costs contribute to operational costs and impact financial resources.

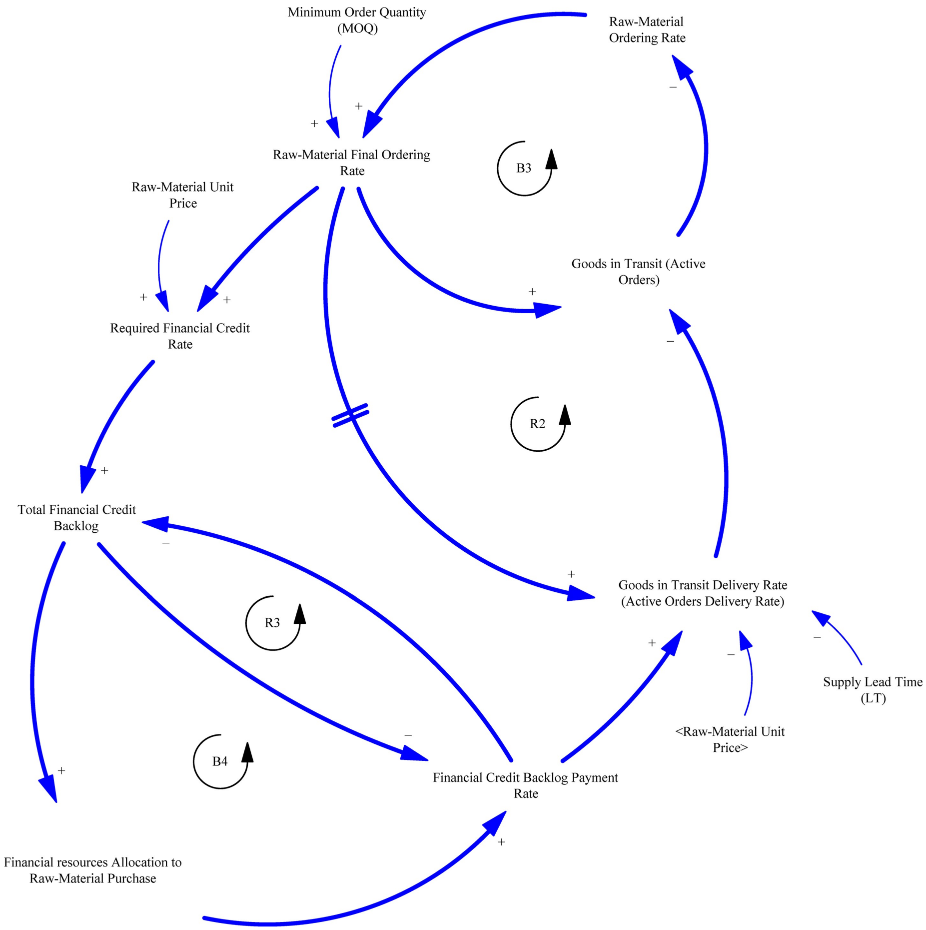



**Figure 7.** Fulfilment of purchase orders causal loop
**Source:** Authors' own work

### *4.3 Model robustness check*

Before analysing the model results, validation tests are conducted on SD models to ensure their validity and robustness under varying conditions. This research includes a structure evaluation test to assess the model's capability to replicate the system's problematic behaviour amidst fluctuating FOC rates. These fluctuations occur when the marketing and sales team opts for a higher FOC at different times, aiming to enhance price competitiveness and secure a greater market share. Figure 10(a) illustrates the variations in FOC communicated to the market. A critical stock variable is product inventory, which must achieve two primary objectives: maintaining sufficient inventory within the permitted range and fulfilling market demand to prevent sales losses.Figure 10(b) depicts the product inventory within the allowed policy range, with Curve 1 representing the inventory status, while the other curves indicate the minimum and maximum permitted inventory thresholds.

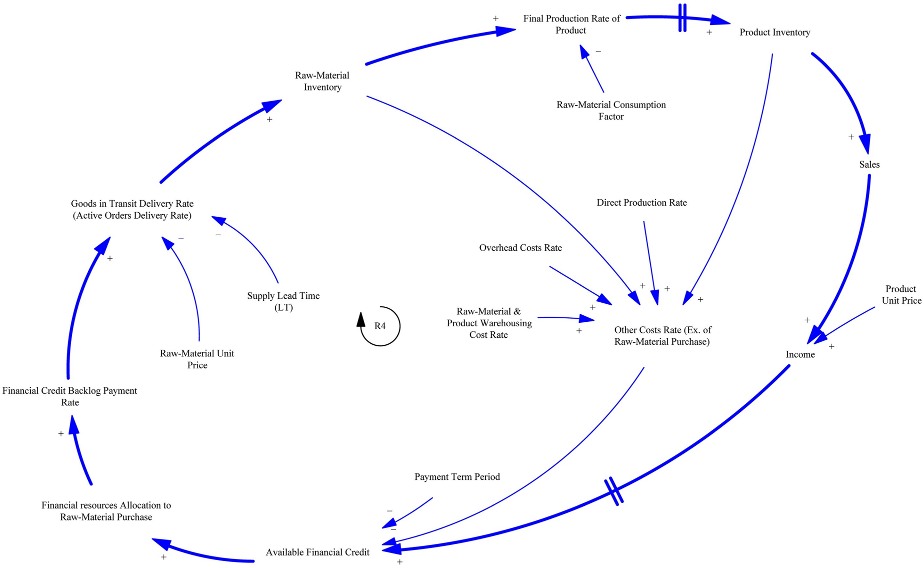



**Figure 8.** Realisation of income causal loop
**Source:** Authors' own work

Unlike the final product, the model reveals significant fluctuations in material inventory levels. The material inventory often exceeds permitted limits and, at times, falls below the minimum required for production. The material supply planning loop is heavily influenced by the long supply period (six months), forecasting errors and fluctuations in the preceding demand and production planning loops.

The simulation results align with the problem statement and the dynamics outlined in Ssection 3.3, indicating that the model's structure, developed through the participation of the PSC case experts, accurately reproduces the system's behaviour.

### *4.4 Simulation scenarios*

The purpose of this research is to create an effective relationship between demand planning (marketing and sales) and operations (production planning, materials planning and financial planning) to have a more stabilised PSC in a case company by considering the occurrence of destructive fluctuations and the costs of excess inventory or sales loss. So, in this section, three improvement scenarios are presented and analysed to prove their functionality to improve the model outputs. To implement these scenarios, some changes were made to the initial version of the model, which is shown in green in Figure A1 in the Appendix.

*4.4.1 Scenario 1: controlling demand forecast changes.* If the range of demand forecast changes for the upcoming period is kept within a permissible range, the market can adapt more smoothly, reducing shocks to the SC. The marketing team determines the desired demand forecast (Demand*) based on total demand and target market share. This scenario aims to mitigate fluctuations by limiting new demand changes relative to the previous forecast, thus adding a section to the model for comparison. This scenario will directly influence various parts of the model, including production, final product inventory, and sales

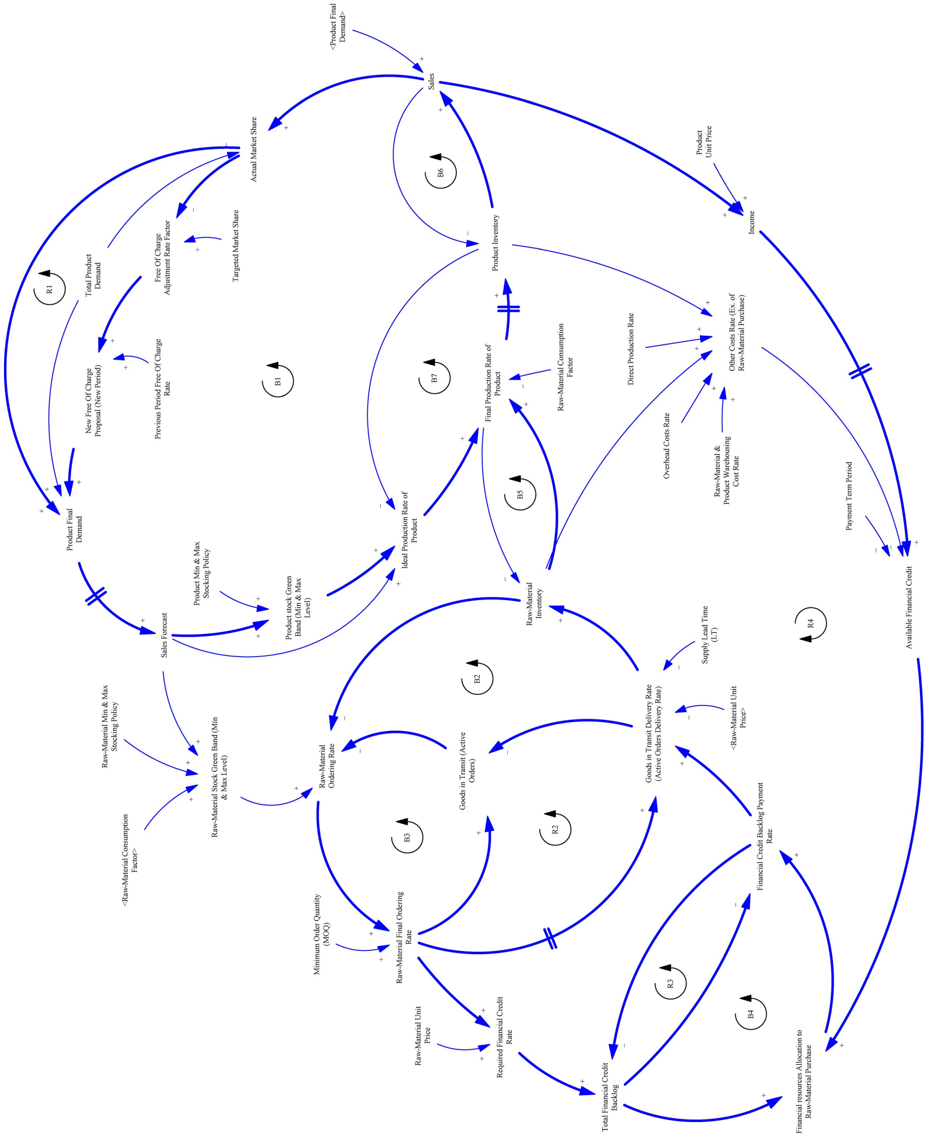


**Figure 9.** The studied PSC causal loop diagram
**Source:** Authors' own work

within the R1 and B1 loops, as well as purchasing orders and raw material supply within the B2–B4 and R2 loops.

An auxiliary variable, Acceptable Tolerance, is defined to manage these changes, accepting input as a percentage. Another variable, Accurate Demand, checks whether new demand stays within this tolerance; if not, it adjusts the forecast accordingly. This Accurate Demand then informs the desired FOC, leading to a gradual correction rate of FOC. In this

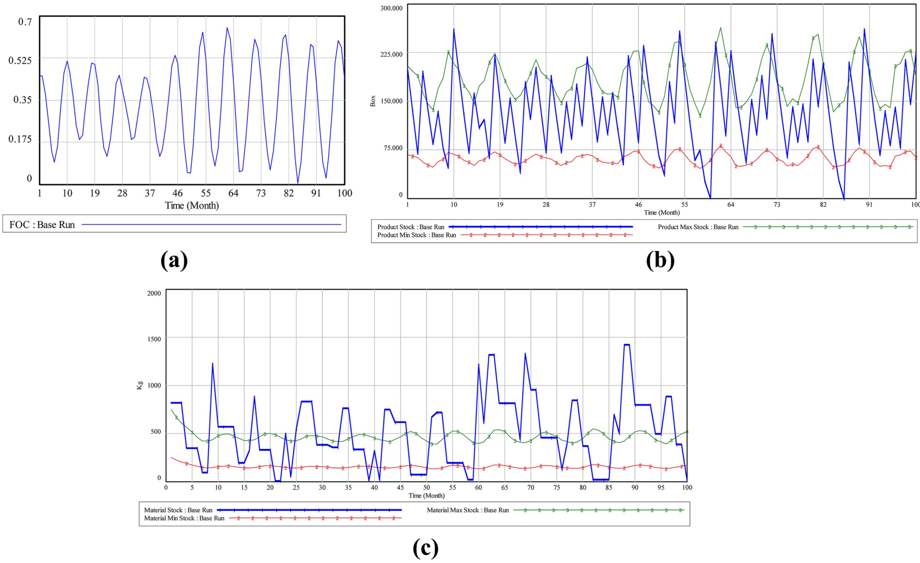



**Figure 10.** The model's performance in producing the problematic behaviour of the system in the presence of FOC fluctuations
Source(s): Authors' own work

scenario, several variables are replaced by their trends to promote compliance with past patterns, including FOC Rate, FOC, Co. Net Price and Demand.

*4.4.2 Scenario 2: using FOC based on the product inventory level.* This scenario aims to prevent sales loss, a critical indicator of PSC performance with significant long-term consequences for the company. The marketing and sales team must monitor product inventory to adjust market demand and avoid exceeding response capabilities. Therefore, the announced FOC is reviewed based on available inventory levels. If inventory exceeds the demand created by the targeted FOC (FOC Trend), adjustments will be made to prevent sales losses. This introduces a new feedback structure within the R1 and B1 loops by transmitting inventory information to the marketing and sales subsystem, enhancing alignment and coordination between these two components of the overall PSC.

Two important points must be noted:

(1) First, if inventory is reduced to zero, regulating the market through FOC becomes impossible, leading to guaranteed sales losses.

(2) Second, this adjustment affects only the FOC for the specific period when inventory is insufficient; it does not influence the system's demand forecast (Demand Trend).

Thus, the demand for the initial period is announced separately from the demand trend.

*4.4.3 Scenario 3: combination of scenarios 1 and 2.* The final scenario analyses the model outputs based on a combination of Scenarios 1 and 2. Initially, the ideal demand model is compared to previous forecasts to meet the targeted market share, ensuring it falls within acceptable tolerance limits and is adjusted if necessary. This process generates a "trended" FOC, which prevents wild fluctuations, leading to a more stable demand forecast (Demand Trend). Consequently, fewer fluctuations in product and material inventory control are expected within the allowed range.

While this demand trend will guide production and material supply planning, it is crucial to make timely reactive decisions to prevent sales losses in the first period. The initial period's demand trend is compared with product stock (Product Stock); if the stock falls short, a contingent FOC is introduced to control demand and avoid sales loss. This scenario aims to prevent zero product inventory, making sales loss inevitable.

Table 2 outlines the setup of various simulations implemented with the model.

### *4.5 Simulation results under scenarios*

*4.5.1 Sales loss.* Sales loss arises when demand exceeds available inventory. Over 100 months, the simulation results for the base run and three improvement scenarios in Figure 11 reveal that only Scenario 3 completely prevented sales loss, while the other scenarios did not. The graph below illustrates that the base run incurred the highest cumulative sales loss, with Scenario 1 being the least effective in controlling sales loss (by a 41.9% decrease in cumulative sales loss compared to the base run), followed by Scenario 2 (by a 45.2% decrease in cumulative sales loss compared to the base run). Scenario 2 aims to control sales loss but fails to prevent fluctuations, leading to instances of zero product inventory and resulting in sales loss in some months. In contrast, the combined approach of Scenario 3 yields the best results by effectively addressing these issues.

*4.5.2 Gross profit.* Scenarios 1 and 3 demonstrate lower operating costs, including production, maintenance and material storage, alongside reduced raw material purchases, which usually represent 60%–70% of total costs. This results in lower overall costs compared to the base run and Scenario 2, showcasing the effectiveness of the Accuracy Ctrl

**Table 2.** Setup of different simulated scenarios

| Scenario | | Explanation |
|---|---|---|
| S0 | Base run | Based on the basic parameters which model has been constructed |
| S1 (Accuracy Ctrl) | Control of demand forecast changes | This scenario introduces a section to the basic model that compares the new period's demand with its predicted equivalent from the previous period, controlling the limits of changes. Two auxiliary variables, "acceptable tolerance" and "accurate demand", are included to determine whether the new demand falls within the acceptable tolerance range compared to the previous forecast |
| S2 (Stock Ctrl) | Demand control based on product inventory | This scenario emphasises the effective use of FOC tools to manage product inventory and temporarily reduce market demand, preventing lost sales. If the product inventory exceeds the demand generated by the targeted FOC (FOC trend), the marketing and sales team will adjust the FOC accordingly to avoid sales losses |
| S3 (Accuracy Ctrl+Stock Ctrl) | Combination of scenarios 1 and 2 | This scenario analyses the model outputs based on the combination of Scenarios 1 and 2 |

**Source(s):** Authors' own work

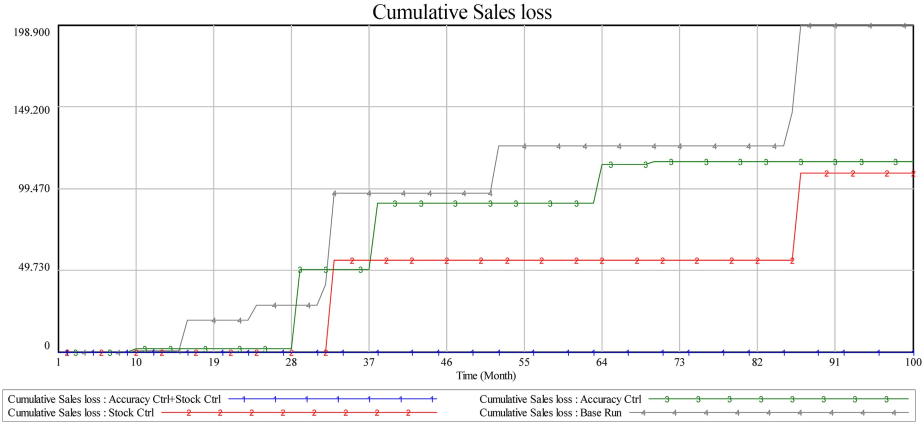



**Figure 11.** Comparative cumulative sales loss under improvement scenarios
**Source:** Authors' own work

scenario in cost management. Ultimately, controlling demand fluctuations caused by erratic FOC market promotions contributes positively to cost reduction.

Net income here refers to the income after FOC deductions. Notably, simulation results reveal that net income in combined Scenario 3 surpasses all others, followed by Scenarios 1 and 2, and then the base run. Although gross sales (goods shipped) were higher in the base run and Scenario 2, net income was lower due to excessive FOC expenditure, which ultimately reduced long-term net income. This effect can be represented by an index indicating net income loss from decreased net prices due to FOC spending.

Subsequently, as is shown in Figure 12, gross profit in Scenario 3 exhibits a higher growth rate than the base run (4.6 times compared to the base run) and Scenarios 1 (3.2 times compared to the base run) and 2 (1.2 times compared to the base run). This improvement is crucial, as the profitability of the PSC is essential for its survival and development.

*4.5.3 Market share.* This model focuses on maximising market share while minimising losses. Figure 13(a) displays market share realisation across the discussed scenarios. In Figure 13(b), negative deviations from the targeted market share are significantly lower in Scenarios 1 and 3 (by 26.4% reduction in the cumulative deviation, compared to the base run), where Accuracy Ctrl is implemented. The marketing and sales team might mistakenly believe that swift responses to competitors and drastic FOC fluctuations reduce long-term market share risk; however, the model results suggest otherwise.

*4.5.4 Product stock error.* A key indicator of PSC stability is inventory compliance within permitted stock ranges; the related simulation results are illustrated in Figure 14(a)–(c). The effectiveness of the four scenarios in managing stock can be assessed by measuring errors against these limits. Results indicate that the cumulative error in Scenarios 1 and 3 is 43.2% lower than in the base model and Scenario 2, confirming that Accuracy Ctrl operates more effectively, as shown in Figure 14(e).

*4.5.5 Material stock error.* Figure 15(a)–(c) illustrates the compliance of raw material inventory with stock limits. The effectiveness of the four scenarios in managing this stock can be evaluated by measuring errors against these limits. Results reveal that the cumulative error in Scenarios 1 and 3 is 62.5% lower than in the base run and Scenario 2. Since material planning is more detached from marketing and sales decisions and influenced by long lead times, it is increasingly affected by demand fluctuations. The analysis of these scenarios

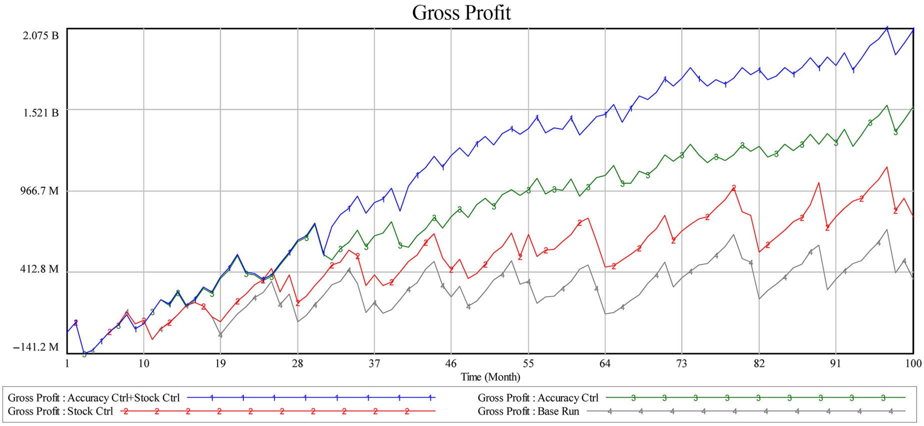
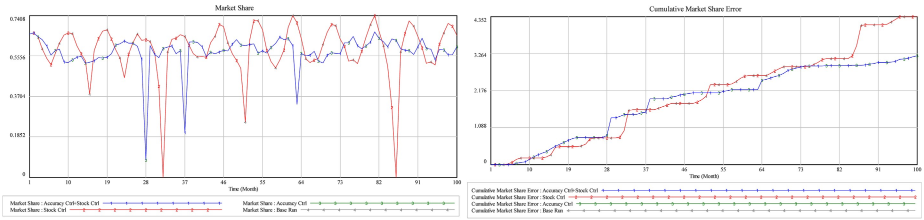



**Figure 12.** Comparative cumulative gross profit after applying improvement scenarios
**Source:** Authors' own work




**(a)** **(b)**

**Figure 13.** The realisation of market share under the improvement scenarios
**Source:** Authors' own work

demonstrates that Accuracy Control significantly aids in managing errors in raw material stock, as shown in Figure 15(e).

## 5. Discussion

The ability of proposed scenarios to improve PSC performance criteria based on obtained results has been presented in Table 3.

The marketing team tailors various FOCs based on market price conditions, requiring one month to balance inventory throughout the chain. Simulation results suggest predicting market conditions, competitor behaviour, and seasonal medicine orders to propose suitable FOC rates for more accurate planning. In the studied case, announcing the FOC rate a month in advance significantly reduces BWE. Results from the demand forecast changes scenario highlight this approach, as it effectively manages operational costs, including production and material maintenance expenses.

Given the raw material supply lead time of six months, errors and fluctuations in demand and production planning loops increase inventory fluctuations (see Figure 9). To enhance production planning flexibility and improve the accuracy and speed of material supply, it is

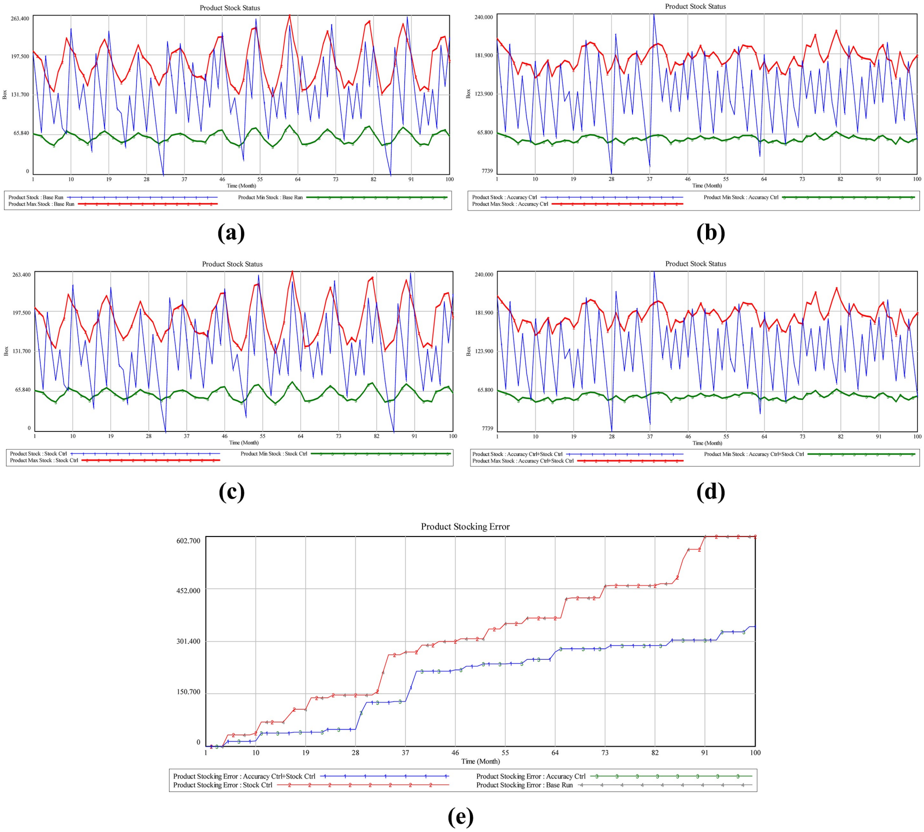



**Figure 14.** Product stock status and stocking error under scenarios
**Source:** Authors' own work

essential to strengthen continuous relationships between retailers and the marketing department and implement more accurate demand forecasting models. Updating market demand data through an integrated management information system within the chain will also contribute to these improvements.

Scenario 2, by design, restricts the offer of FOC to pharmacies based on the existing inventory levels. This limitation results in greater cumulative sales losses and a consequent decline in market share. Compared to Scenario 3, the limitations of Scenario 2 become more pronounced when demand forecasts are less accurate than those in Scenarios 1 and 3. Under such conditions, marketing and sales efforts are less effective in gaining market share through FOC incentives, as product availability (stock levels) is tied to inexact forecasts. In contrast, the third scenario, which involved controlling demand forecast changes and adjusting FOC based on product inventory levels, eliminated lost sales while preventing excess stock and reducing BWE. In most periods, implementing scenarios 1 and 3 led to a balanced material inventory, decreased BWE, and a reduction in total raw material purchasing costs, thus lowering the overall cost of the PSC. Although sales in the third

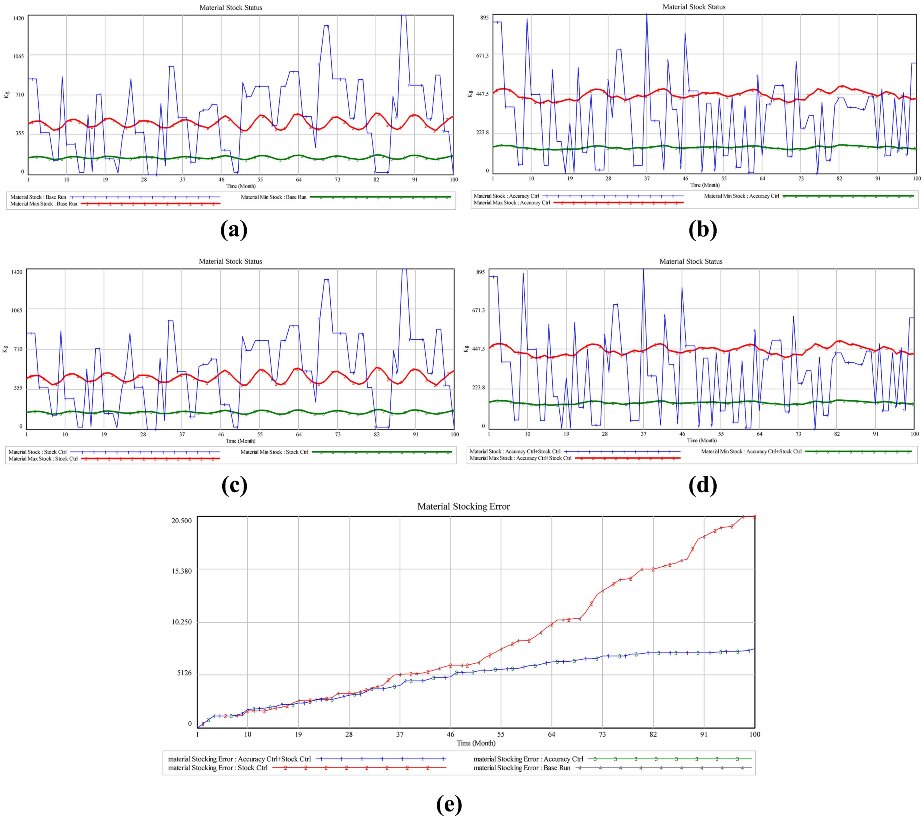



**Figure 15.** Material stock status and stocking error under scenarios
**Source:** Authors' own work

scenario were lower than in the others, it resulted in increased net income. Therefore, managers can reduce costs and enhance net income by implementing this scenario and minimising BWE. Accurate calculation of FOC concerning competitors' prices and market elasticity can further mitigate inventory fluctuations and BWE, leading to lower pharmaceutical product prices and higher profit margins.

Scenarios 1 and 3 effectively reduced negative deviations from the targeted market share. While a quick response to competitors' sales growth through increased FOC may boost market share in the short term, the simulation indicated a heightened long-term risk of losing market share. In addition, the simulation results demonstrated that both Scenarios 1 and 3 exhibited lower deviations from permissible limits in raw materials and medicine inventory, significantly reducing BWE compared to Scenario 2.

Finally, the obtained results of the simulation showed that the first scenario is very effective in reducing the BWE, but if the third scenario, which is the combination of the first and second scenarios, is applied, it will have a significant effect on the PSC performance indicators, including net profit and market share.

**Table 3.** The comparison of the obtained results of three scenarios

| Scenario | The ability of the scenario to improve PSC performance: High: 1, 2: Good, 3: Weak, 4: Very weak | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | Sales loss | Total operational (production) costs | The total cost of purchasing raw materials | Total cost | Net income | Gross profit | Market share | Product stock error | Material stock error |
| S0 | 4 | 3 | 3 | 3 | 4 | 4 | 3 | 3 | 3 |
| S1 (Accuracy Ctrl) | 3 | 1 | 1 | 1 | 2 | 2 | 1 | 1 | 1 |
| S2 (Stock Ctrl) | 2 | 3 | 3 | 3 | 3 | 3 | 3 | 3 | 3 |
| S3 (Accuracy Ctrl+Stock Ctrl) | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |

**Source(s):** Authors' own work

*5.1 Implications*

Market promotion solutions significantly affect both strategic and operational aspects of PSC operations. Managers must recognise the intended and unintended consequences of marketing decisions on PSC performance. Effective policies and promotions can enhance sales, inventory management, income, costs, market share and gross profit. Decision-making should consider procurement, marketing, production, operations and accounting (Zhu and Shah, 2018). Solutions must ensure timely delivery to customers while minimising inventory. It is also essential to mitigate the negative effects of demand fluctuations on order rates. Accurately predicting market demand through available data and evolving statistical methods is crucial.

The findings of this study offer significant implications for both PSC managers and scholars, particularly those focused on strategic decision-making in the context of managing simultaneous sales fluctuations and inventory management challenges. From a practical standpoint, the results emphasise the importance of integrating advanced sales forecasting analytics and dynamic pricing strategies to enhance PSC resilience. This aligns with previous works highlighting how effective information sharing and collaborative planning between supply chain entities, particularly between marketing, procurement and production, can mitigate the BWE, leading to more synchronised and efficient operations (Barlas and Gunduz, 2011; Merkuryeva *et al.*, 2019). Also, this study highlights the potential of the facilitative role of blockchain and AI-driven tools to further support PSCs in this regard (Abdallah and Nizamuddin, 2023; Nguyen *et al.*, 2021; Yani and Aamer, 2023). Strengthening these connections can help firms navigate disruptions and enhance overall supply chain stability. Accordingly, greater deployment of digital technologies such as AI and blockchain is recommended for policymakers to enhance coordination across national healthcare logistics, reduce the BWE and ensure resilient medicine delivery and timely access to essential medicines, especially in underserved or remote areas. Consequently, this can enhance healthcare equity, particularly in emerging economies, by reducing regional stockouts and improving the timely supply of essential medicines at more affordable prices for those in need.

From a research perspective, this study contributes to the growing body of literature on SD modelling in pharmaceutical logistics, providing a framework to simulate policy interventions aiming at testing different alignment and coordination strategies throughout the PSC. Moreover, considering the critical role of advanced sales forecasting analytics and dynamic pricing strategies in enhancing PSC resilience, integrating hybrid machine learning techniques with SD modelling for demand prediction and disruption management is proposed as a promising avenue for future research (see Roozkhosh *et al.* (2023) and Bussieweke *et al.* (2025) as examples of the approach).

While the model developed in this study is based on a single PSC case study, the core dynamics, such as the interaction between marketing strategies, inventory management and the BWE, are common across other PSCs. Although parameter values and specific decision-making processes may differ, the insights and framework can be adapted to both emerging and developed pharmaceutical markets.

## 6. Conclusion

This research examined challenges stemming from inconsistencies between marketing and sales entities in the PSC. Using a case study, an SD model was developed to simulate PSC operations. Achieving optimal performance indicators remains a key challenge for PSC managers. The findings highlight the role of endogenous system drivers in exacerbating internal inconsistencies, emphasising the need to redesign internal strategies and relationships within the SC. A key driver identified is the improper use of FOC promotions, a conventional marketing method.

This research proposed three improvement scenarios to better control market promotion policies, balancing sales targets with the objectives of other PSC functions like production, procurement and finance, while maintaining sustainability. Implementing “sales forecast accuracy check”, “stock check,” and their combination led to reduced sales loss, increased income and lower production and raw material costs, boosting PSC’s profitability. In addition, raw material and product stocking errors significantly decreased, and the company’s market share showed substantial improvement.

This study made certain assumptions to simplify the problem, such as excluding the impacts of competitor behaviour, regulatory constraints and sustainability variables. The model also does not account for product consumption periods or expiration dates of perishable materials. Moreover, performing a sensitivity analysis addressing uncertainties in the model parameters could enhance the robustness of the results. Future research could expand the model to explore other market promotion policies beyond FOC and assess their combined effects. In addition, further data collection could validate the findings of this simulation. These limitations present opportunities for future research to incorporate additional factors and parameters for a more comprehensive analysis.

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## Appendix

### Stock and flow diagram (SFD)

The green parts in the diagram represent the updated version of the model, which is explained in Section 4.4.

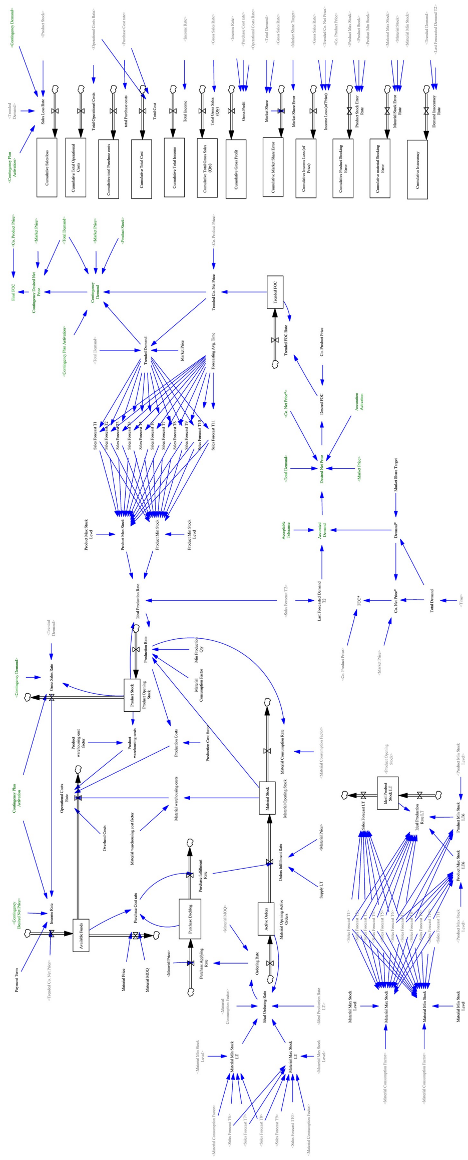

**Figure A1.** The overall simulation model structure

**Equations**

*Stock variables*

This model consists of 7 stock variables, 13 flow variables and 52 auxiliary variables (which include coefficients and exogenous variables). In this section, some key stock variables are explained as follows. Please refer to Sterman (2000) for definitions and technical terms used in this section.

The product stock ($PS_t$) shows the inventory of the products in the supply chain, which is the difference between production ($P_t$) and sales ($S_t$). The product stock is analytically represented as follows:

$$PS_t = \int_{t_0}^{t} (P_t - S_t)dt + PS_{t_0} \tag{1}$$

The material inventory ($MS_t$) shows the amount of materials provided and usable for production, which is the difference between the order fulfilment rate ($OF_t$) and material consumption rate ($MC_t$):

$$MS_t = \int_{t_0}^{t} (OF_t - MC_t)dt + MS_{t_0} \tag{2}$$

Active orders ($AO_t$) show the amount of in-the-way orders (goods in transit) that are realised in the case of financial resource allocation; with a supply lead time (LT), they are entered into the system as an active inventory:

$$AO_t = \int_{t_0}^{t} (O_t - OF_t)dt + AO_{t_0} \tag{3}$$

where $O_t$is the ordering rate and $OF_t$ is the order fulfilment rate.

Available funds ($AF_t$) indicate the financial resources available based on the current income ($I_t$) and expenses (operational costs [$OC_t$] and purchase cost [$PC_t$]) of the company:

$$AF_t = \int_{t_0}^{t} (I_t - OC_t - PC_t)dt + AF_{t_0} \tag{4}$$

Purchase backlog ($PB_t$) is another stock variable. Every new purchase order that is created in the material ordering system is backlogged until the allocation of financial resources:

$$PB_t = \int_{t_0}^{t} (PA_t - PF_t)dt + PB_{t_0} \tag{5}$$

where $PA_t$ is the purchase applying and $PF_t$ is the purchase fulfilment rate.

The variable $FOC_t$ represents the free-of-charge proportion that the sales and marketing division allocates to trigger its market. This variable is determined by the effect of the correction rate on the FOC of the past periods:

$$FOC_t = \int_{t_0}^{t} FOCR_t \; dt + FOC_{t_0} \tag{6}$$

*Flow variables*

The production quantity in each month is determined according to the status of the product inventory compared to the allowed inventory limits, and on the other hand, the presence of sufficient raw materials and the minimum amount that can be produced ($P_{min}$):

$$P_t = min\left(\left(\left[\frac{P^*{}_t}{P_{min}}\right] + 1\right) \times P_{min}\ ,\ \ \left[\frac{\frac{MS_t}{MCF}}{P_{min}}\right] \times P_{min}\right) \tag{7}$$

where $MCF$ is the material consumption factor:

$$\begin{aligned} P^*{}_t = If\ \left(PS_t - SF_t^{T2}\right) < PS_{min} \\ then\ \ PS_{max} - PS_t + SF_t^{T2} \\ else \quad 0 \end{aligned} \tag{8}$$

where $SF_t^{T2}$ is the forecast of sales at period T2.

Similar to the production flow, the material ordered each month is also obtained based on the comparison of the material inventory and the permitted limits of the material inventory. Of course, considering the six-month lead time of material supply, this review must be done based on material inventory forecasting and forecasting the allowable limitations of the inventory in the future and after the lead time period, which is calculated in the form of the Ideal Ordering Rate. Finally, the ordering rate is based on the minimum order quantity (MOQ):

$$O_t = \left(\left[\frac{O^*{}_t}{MOQ_{material}}\right] + 1\right) \times MOQ_{material} \tag{9}$$

$$\begin{aligned} O^*{}_t = If \quad \left(MS_t + AO_t - LT^{P^*} \times MCF\right) \geq LT^{MS_{min}} \\ then \quad LT^{P^*} \times MCF - \left(MS_t + AO_t\right) + LT^{MS_{max}} \\ else\ \ 0 \end{aligned} \tag{10}$$

The raw materials purchase costs ($PC_t$) is calculated according to the queue of pending purchase orders and available financial resources. Basically, this value is a certain coefficient of the MOQ. As a result, the deferred purchase fulfilment rate ($PF_t$) is estimated to be equal to the material purchase cost rate. Regarding the fulfilment rate of material orders ($OF_t$), based on the purchase fulfilment rate, the orders whose financial resources are secured are physically fulfilled and placed in the active material inventory after the LT period of material supply has passed:

$$PC_t = min\left(\left[\frac{PB_t}{MOQ_{material} \times Pr_{material}}\right],\ \ \left[\frac{AF_t}{MOQ_{material} \times Pr_{material}}\right]\right) \times MOQ_{material} \times Pr_{material} \tag{11}$$

$$PF_t = PC_t \tag{12}$$

$$OF_t = Delay_{Fixed}\left(\frac{PC_t}{Pr_{material}},\ \ LT, 0\right) \tag{13}$$

A variable is defined in the model to reflect the corrections in the FOC announced to the market to adjust the market total demand ($TD_t$). In this regard, to obtain the desired demand ($D_t^*$) of the supply chain from the total demand, the net price perceived by the market is obtained compared to the normal market price ($Pr_{Mt}$) and based on this price, the ideal FOC is estimated. As a result, the reward rate of a commodity is calculated from the gradual change of the previous FOC towards the ideal FOC:

$$FOC_t = Delay_{1I}(FOC^*{}_t - FOC_{t-1},\ \ 2, 0) \tag{14}$$

$$FOC^*{}_t = max\left(0, 1 - \frac{NPr_C^* t}{Pr_{Ct}}\right) \tag{15}$$

$$NPr_C^* t = Pr_{Mt} \times \frac{TD_t - D_t^*}{D_t^*} \tag{16}$$

$$NPr_{Ct} = Pr_{Ct} * (1 - FOC_t) \tag{17}$$

*Auxiliary variables*

The market reaction is determined by the product demand according to the product price offered in each period (through the lookup function $f$ which is derived from the company's experts' opinion). Therefore, the demand is formulated based on the customers' understanding of the net price of the product offered by the company and in comparison to the average price of other competitors:

$$D_t = f\left(\frac{NPr_{Ct}}{NPr_{Ct} + Pr_{Mt}}\right) \times TD_t \tag{18}$$

Forecasting the company's sales ($SF_{T_j}$) is estimated according to the sales trend of the previous periods. In this regard, the forecast function is used, and the focus is on the last three periods:

$$SF_{T_j} = FORECAST(D_t, AT, j)\ \ (j : 1, 2, 3, 4) \tag{19}$$

In each period, the sales forecast for the next few months is estimated. The first reason is the definition of the minimum and maximum storage limits of products in the form of "number of months". This means that if, for example, the upper limit of product storage is announced as four months, then the product should be stored for as much as the sales of the $T_1 + T_2 + T_3 + T_4$ period. The second reason is that the ordering system and supplying materials also operate based on the same logic of storage, and since the lead time of supplying materials is six months, it is necessary that the amount of delivery of orders on the way, the amount of production, and consequently the amount of material consumption in this six-month should be simulated so that the material requirements can be obtained to meet the minimum and maximum stock levels of the materials at the end of the $T_6$ period, and based on that, the materials must be ordered in the current period.

Product Max/Min Stock Level and Product Max/Min Stock variables represent product storage policies and are expressed as the number of months. Basically, the higher these numbers are, the higher the reliability of the system in responding to the market's needs against the changes and fluctuations of the system and supply/supplier delays, and as a result, the costs of the system will also be higher. Consequently, the limitations and sales forecasting for future periods are obtained by summing up the amount of sales forecast for *n* specific months, and the maximum and minimum amount of storage.

*Performance indicators of the model*

The performance of this supply chain under different policies is examined through the measurement of several indicators. These indicators are defined in the form of five variables in the model, each of which has a specific meaning. In this section, these indicators are explained.

*Cumulative sales loss:* Sale loss ($SL_t$) occurs due to insufficient inventory compared to the announced demand from the market in every period. Therefore, one of the most important indicators of system adequacy is the absence of occurrence or minimal sales loss. To measure this indicator, a stock variable of the cumulative sales loss is embedded:

$$SL_t = \int_{t_0}^{t} SLR_t \; dt \tag{20}$$

*Product stocking error/ material stocking error:* The main design of the supply chain in this model is based on the make-to-stock logic. Therefore, it should maintain the amount of product and material inventory within the permitted range of product and material inventory. To measure the successful implementation of the make-to-stock production system, the cumulative amount of deviations (both positive and negative) from the targeted inventory levels is defined as a stock variable; basically, the lower amount shows more stability in the system:

$$MSE_t = \int_{t_0}^{t} MSER_t \; dt \tag{21}$$

$$PSE_t = \int_{t_0}^{t} PSER_t \; dt \tag{22}$$

*Total income/total cost/ income loss (of price)/gross profit:* Principally, the performance of a system that manages the process of income, costs and profitability will be more suitable. Therefore, the system should provide more appropriate outputs within the general framework of restrictions, including compliance with the targeted inventory limitations, maximum acquisition of the targeted share of market demand and higher profitability (spending less FOC). In this regard, the following indicators are defined:

$$TI_t = \int_{t_0}^{t} TIR_t \; dt \tag{23}$$

where the income rate is multiplied by the monthly product sales and the net product price announced to the market (after deducting the FOC of that period):

$$TC_t = \int_{t_0}^{t} (OC_t + PC_t)\ dt \tag{24}$$

$$TIL_{Prt} = \int_{t_0}^{t} (Pr_{Ct} - NPr_{Ct}) \times S_t\ dt \tag{25}$$

This indicator presents the amount of lost income as a result of paying more FOC. It means that the more FOC is paid, the more the lost income will be, and it would be less desirable.

Gross profit ($GP_t$) in each period is also obtained from the result of income and the deduction of operating expenses and the purchase of raw materials:

$$GP_t = \int_{t_0}^{t} (TI_t - OC_t - PC_t)\ dt \tag{26}$$

*Cumulative market share error:* In this model, the goal of the strategy of the marketing and sales team is defined as achieving the target market share. As a result, the level of success of the system in supporting the goals of the marketing and sales team is important as one of the subsystems of the model. In this regard, an index that shows the negative deviations of the targeted market share has been defined:

$$CMSHE_t = \int_{t_0}^{t}\ MSHE_t dt \tag{27}$$

$$MSHE_t = If\ \ MSH_t \geq MSH^*{}_t$$

$$then\ \ MSH^*{}_t - MSH_t$$

$$else\ 0 \tag{28}$$

*Cumulative inaccuracy:* According to the explanations of the sales forecasting variables and the demand variable, by considering the long-term effect of sales forecasting, it is important to check the level of inaccuracy in the presentation of the previously announced forecasted sales compared to the actual market demand. For this reason, an index has been defined to present the cumulative amount of this non-compliance of the demand with the forecasted demand:

$$CI_t = \int_{t_0}^{t} DI_t dt \tag{29}$$

*Source(s):* Authors' own work

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