SYSTEM DYNAMIC MODELING TO IMPROVE COMPLEX VENDOR MANAGED INVENTORY

FINAL THESIS

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SYSTEM DYNAMIC MODELING TO IMPROVE COMPLEX VENDOR MANAGED INVENTORY

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"O you who have believed, persevere and endure and remain stationed and fear Allah that you may be successful."

(QS. Ali 'Imran Ayat 200)

"Choose rather to be strong of soul than strong of body."

(Pythagoras)

"If my mind can conceive it, if my heart can believe it then I can achieve it."

(Muhammad Ali)

"Never give up"

(Haru Urara)

PREFACE

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ABSTRACT

This abstract presents a summary of the study that discusses the implementation of Vendor Managed Inventory (VMI) as an effort to improve inventory system performance within the supply chain. The background of this research is based on problems related to demand and inventory information imbalance, which often lead to the bullwhip effect, high inventory costs, and low service levels. This study aims to analyze the impact of VMI policy implementation on inventory performance and overall supply chain stability. The research methodology employs a System Dynamics approach to model the interactions among demand, inventory policies, supplier capacity, and service levels. The developed model is used to simulate several VMI policy scenarios and compare them with conventional inventory systems. The data used in this study are obtained from a company case study and supported by relevant literature. The results indicate that the implementation of VMI is able to reduce inventory variability, mitigate the bullwhip effect, and improve customer service levels. In addition, the VMI system enhances coordination between suppliers and customers, resulting in a more stable and efficient supply chain performance. This study is expected to serve as a reference for companies in designing integrated and collaborative inventory management policies.

Keywords: abstract, vendor managed inventory, system dynamics, bullwhip effect, findings.

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CHAPTER I
INTRODUCTION

1.1 Background

The Fourth Industrial Revolution is accelerating technological change across the world's supply chain. According to Dasaklis and Casino (2019), this change is leading to a dramatic increase in the complexity of the supply chain ecosystem while simultaneously encouraging the complete digitalization of activities. With its emphasis on reducing overall system costs while maintaining customer service levels, the idea of Supply Chain Management (SCM) has become more significant in this setting. (Hong et al., 2016; Tyan & Wee, 2003). However, the dynamics of the modern business environment place companies under significant logistical pressure, making it difficult to achieve optimal operational performance (Harahap & Rahim, 2017). One of the main challenges is high demand variability, which is exacerbated by short product life cycles and increasingly segmented consumer demand leading to customization (Tyan & Wee, 2003).

In addition, modern supply chains must also deal with uncertain lead times, which have a direct impact on inventory control effectiveness. Inaccurate lead time management can increase the risk of stock shortages, increase safety stock requirements, and reduce customer service levels (Anna, 2016). A more fundamental challenge is the need for effective coordination of decisions between supply chain entities (suppliers, manufacturers, and retailers) due to a lack of decision integration, which often causes low overall system responsiveness (Hariga et al., 2013; Hong et al., 2016). In conditions of uncertainty and weak coordination, the phenomenon of bullwhip effect amplification often occurs, whereby fluctuations in demand at the retailer level are transmitted excessively to suppliers, triggering inefficiencies that further worsen supply chain performance (Tyan & Wee, 2003).

To address this ongoing complexity and uncertainty, VMI has been widely recognized as a collaborative initiative designed to improve supply chain integration (Borade & Sweeney, 2015; Darwish , & Odah, 2010). VMI is a policy whereby vendors are authorized to take over inventory control and purchasing functions from buyers, including deciding when and how much inventory to replenish (Anna, 2016; Hong et al., 2016; Tyan & Wee, 2003). The main objectives of VMI are to reduce demand variability, streamline production, accelerate inventory replenishment, and significantly boost efficiency in the supply chain by cutting down on overall inventory system expenses (Anna, 2016; Borade & Sweeney, 2015; Hong et al., 2016). Sharing data and reengineering business processes are the two main tenets of the VMI system's integration strategy. (Yao et al., 2007). By using information technology such as EDI, suppliers gain real-time access to retailers' sales and inventory data, which can reduce the bullwhip effect (Anna, 2016; Dasaklis & Casino, 2019; Yao et al., 2007).

Although the VMI concept promises significant benefits, its implementation in real-world complexity often encounters specific problems that limit its potential. These issues arise when VMI must operate under less-than-ideal conditions, such as high customer demand fluctuations and more realistic stochastic demand compared to deterministic demand. Research displays that when demand variance increases, the inventory reduction benefits of continuous replenishment programs decrease (Mateen & Chatterjee, 2015; Yao et al., 2007). Second, VMI implementation is bound by unresponsive inventory policies enshrined in contractual agreements. VMI contracts often include upper limits on stock at retailer facilities, whereby vendors are subject to financial penalties if these stock limits are exceeded (Cai et al., 2017; Ghasemi et al., 2024). These limits often function as physical capacity constraints that strictly limit the optimal replenishment schedule by vendors.

Dependence on supplier capacity and logistics capabilities is also a determining factor in supply chain performance, including limitations in delivery fleet capacity and storage space at the retailer level (Bazan et al., 2014; Mateen & Chatterjee, 2015). Although the concept of VMI relies on information sharing mechanisms in principle, in practice, delays or distortions in information are still often encountered, which disrupt the quality of decision-making. Low data integration, such as incomplete or outdated sales data ( ), ultimately causes vendors to produce biased downward demand projections and requires manual intervention from buyers (Angulo et al., 2004; Omar et al., 2020). The complex and interdependent interactions between logistics variables and costs create unstable system dynamics, making coordination failures likely to occur.

Under these conditions, the bullwhip effect can be exacerbated and trigger stockouts and inventory excesses, including the accumulation of inactive inventory that is detrimental to all entities in the supply chain (Gebisa, 2023; Tang et al., 2021).

The interdependence of logistics variables, costs, and demand, which are non-linear in nature, makes the supply chain mechanism increasingly difficult to understand using traditional analytical approaches. Because of this intricacy, methods are needed to record the feedback dynamics, cause-and-effect interactions, and temporal delays that come up during VMI implementation (Adegbola, 2023; Kaasgari et al., 2017). Therefore, the use of analytical models and simulations is important to evaluate specific conditions, such as relative ordering costs, storage costs, demand characteristics, and supply uncertainty, which determine the extent to which VMI can generate benefits and how those benefits are optimally distributed among trading partners. (Liu et al., 2023; Zhang et al., 2020).

Based on a literature review, most studies related to VMI still focus on static optimization approaches that only describe system conditions at fixed parameters, thus failing to capture the dynamics of feedback, time delays, and uncertainty in demand and supply capacity that shape the actual behavior of the supply chain (Mokhtari & Rezvan, 2020; Najafnejhad et al., 2021; Verma & Chatterjee, 2017; Wei et al., 2018). This creates a research gap, particularly in understanding the simultaneous interrelationships between demand, inventory policies, and supplier capacity in complex and non-linear VMI configurations (Salas-Navarro et al., 2023; Wei et al., 2018). The complexity of these relationships requires an approach capable of capturing the system's dynamics comprehensively, including feedback patterns and time delays that cannot be accommodated by static optimization methods. , System Dynamics (SD) is an appropriate approach because it can map causal relationships, represent feedback structures that influence system behavior, and test various policy scenarios to understand their long-term consequences (Lin et al., 2020; Liu et al., 2023; Nuñez Rodriguez et al., 2021). Recent studies show that SD is effective for evaluating the combined effects of policies, real-time data, and multi-stakeholder interactions in complex supply chains (Contreras et al., 2024; Liu et al., 2023; Nuñez Rodriguez et al., 2021).

Based on this gap, this study focuses on two main issues. First, it analyzes how the interaction between demand, inventory policy, and supplier capacity shapes VMI system performance and the potential instability that accompanies it. Second, it evaluates various VMI policy scenarios to identify the most effective policy configuration for improving system responsiveness and efficiency. An analytical tool that facilitates more adaptable and collaborative inventory decision-making is developed via this work through the use of a System Dynamics model, while enriching academic understanding of the structural dynamics in VMI implementation.

1.2 Problem Formulation

To understand the operational dynamics of VMI in the context of an increasingly complex and unstable supply chain, an analysis is needed that can capture the interrelationships between the key variables that determine its performance. In practice, the structure of VMI is influenced by fluctuations in demand, inventory control policies, supplier capacity constraints, and patterns of feedback and information delays that interact in a non-linear manner. This complexity requires an analytical approach that is not only descriptive but also capable of dynamically evaluating system behavior and assessing various policy options in an integrated manner. Based on these considerations, the research problem is formulated as follows.

1. How do customer demand, inventory policy, and supplier capacity interact with Vendor Management Inventory system performance?
2. How can different VMI policy scenarios be tested and compared using SD to identify the optimal policy?

1.3 Research Objectives

This research intends to address the issues raised by the above statement by produce a more comprehensive understanding of the operational dynamics and effectiveness of policies in the Vendor Managed Inventory system, which is then outlined into two research objectives, namely:

1. To analyze the effect of the interaction between customer demand, inventory policy, and supplier capacity on the performance of the Vendor Managed Inventory system.
2. Evaluating and comparing various VMI policy scenarios through a System Dynamics approach to identify the most optimal policy for improving system performance.

1.4 Research Limitations

To ensure that the focus of the analysis remains on track and within the scope of the study, this research sets the following limitations.

1. The VMI system's demand, inventory policy, and supplier capacity interactions are the primary focus of the investigation, without including other external factors such as market conditions or macro supply chain disruptions.
2. The foundation of the System Dynamics model is the idea of streamlining processes and parameters. This allows the simulation results to reflect overall dynamics, rather than being tied to the unique circumstances of each business.
3. Policy evaluation is limited to VMI scenarios that can be quantitatively modeled in simulations, so operational policies that require detailed data or organizational intervention are not discussed in depth.

1.5 Research Benefits

The benefits of this research are divided into two categories: theoretical and practical.

1.5.1 Theoretical

1. Providing a conceptual contribution to the development of literature on the operational dynamics of VMI by modeling the non-linear relationship between demand, supply, and supplier capacity.
2. Expands the application of the System Dynamics approach in SCM studies, particularly to understand feedback mechanisms, time delays, and patterns of instability in VMI systems.

3. Provides an analytical framework that can be used as a reference in further research related to collaborative inventory policy design in complex supply chain environments.

1.5.2 Practical

1. Provides decision-making tools for companies to evaluate and select the VMI policy that best suits the dynamics of demand and supplier capacity.
2. Provides operational insights to supply chain managers regarding key factors that affect the stability and performance of VMI, thereby minimizing the risk of bullwhip effect, stockouts, and inventory excess.
3. Supporting increased effectiveness of collaboration between suppliers and retailers through policy scenario simulations that enable stakeholders to understand the long-term consequences of each inventory control decision.

CHAPTER II
LITERATURE REVIEW

2.1 Literature Study

The integration of System Dynamics (SD) and VMI has become a strategic approach for analyzing the complex dynamics of multi-echelon inventory systems in modern supply chains. SD enables the modeling of non-linear relationships, feedback loops, and time delays that underlie demand fluctuations and inventory policy responses. This approach is particularly relevant for VMI, where suppliers are responsible for managing customer inventory, while the system is influenced by demand variability and production capacity. According to Sentia et al. (2022) , SD modeling combined with CLD and SFD can capture fluctuating stock behavior and minimize inventory turnover instability. Simulation results show that controlling customer response times and stock-out frequencies appropriately can stabilize the system by up to 40%.

Several other studies also confirm the effectiveness of SD for complex VMI systems. Jin (2017) developed an SD model to evaluate the effect of lead time on VMI efficiency, showing that long delivery delays reduce customer service levels by up to 18%. Research by Rathore et al. (2021) expanded the application of SD to analyze risk interactions in food transportation systems, finding that SD–VMI integration increased logistics efficiency by 20%. Furthermore, a study by Pietron (2023) displays that the SD model can visualize the dominance of feedback loops causing the bullwhip effect, thereby supporting the design of more stable inventory policies. When used together, SD and VMI provide a solid foundation for studying the effects of stock policies and the dynamics of intricate supply chains over the long run.

Causal Loop Diagrams (CLDs) and Stock–Flow Diagrams (SFDs) are widely used to map interactions between demand, inventory, capacity, and delays in VMI systems. CLD models describe reinforcing loops that amplify demand fluctuations, as well as balancing loops that stabilize the system. In the study by Herdiani et al. (2025), six SD sub-models were used to analyze the frozen fish supply chain in Indonesia, showing that cold storage capacity constraints were the main bottleneck. Using SFD, this study successfully evaluated scenarios for increasing capacity and distribution frequency to reduce stock backlogs.

Inventory theory is the foundation for formulating SD structures, especially in determining variables such as reorder points, order-up-to levels, and safety stock. The dynamic model proposed by Lin et al. (2017) developed the APIOBPCS as a dynamic framework that explains the relationship between demand, stock, and production policies. The study displays that an order-up-to policy combined with a delay compensation mechanism can reduce stock fluctuations by up to 22%.

Furthermore, research by Andaz et al. (2024) introduces machine learning integration into dynamic inventory theory, showing that supervised simulation can improve stock control accuracy in complex systems by up to 15% compared to classical models. In the context of SD–VMI, this theory is used to formulate stock variables and flow variables, including cost components such as holding cost, ordering cost, and backorder cost. Specifically, Rabbani et al. (2018) developed a multi-item EOQ-based VMI model with capacity and budget constraints using metaheuristic methods. The integration of this inventory theory strengthens the SD structure in representing realistic production and distribution constraints.

One of the main strengths of SD is its ability to evaluate inventory policies through policy scenarios. A study by Santoso et al. (2019) displays that SD simulations can test four policy scenarios for the bell pepper supply chain, where the scenario with a warehouse procurement policy provides the highest total profit. This policy is analogous to the order-up-to policy in VMI, which maintains a balance between stock availability and storage costs.

A similar experimental approach was used by Janamanchi & Burns (2013), who combined the concepts of control theory and SD in a two-tier retail system to evaluate continuous review and capacity-based policies. The results showed that policies based on rapid feedback and capacity control could reduce the risk of stock-outs and total costs by 18%. s evaluated in SD–VMI simulations include inventory level, service rate, total cost, lead time, and bullwhip index. These studies confirm that SD-based policy testing can provide more accurate strategic recommendations than static analytical approaches.

Although previous studies have shown significant progress in SD and VMI integration, there are still several research gaps. First, most SD–VMI models are still single-echelon and do not take into account multi-level interactions between suppliers, distributors, and retailers. Second, aspects of production capacity and supply chain constraints are often treated as exogenous parameters rather than dynamic endogenous variables. Third, some models have not explored long-term non-linear behavior, including complex feedback delays and capacity saturation. Therefore, this study attempts to fill these gaps by developing an integrated SD model that represents the dynamics of multi-echelon VMI, covering variables such as demand, capacity, lead time, and adaptive replenishment policies. Table 2.1 condenses prior research

Table 2. 1 Previous Research

Author & Year	Research Title	Research Scope	Research Method	Research Gap
Jin (2017)	Analysis of Lead Time Effects on VMI System: System Dynamics Approach	Analysis of the impact of lead time on VMI performance and customer service levels.	System Dynamics Simulation	The model is still single-echelon and does not consider production capacity and multi-level delays.
Rathore et al. (2020)	Impact of Risks in Foodgrains Transportation System: A System Dynamics Approach	Analysis of the interaction between risk and inventory policy in the food transportation system.	System Dynamics Risk Simulation	Does not dynamically integrate replenishment decisions or VMI policies.
Lin et al. (2017)	Extension and Exploitation of Inventory and Order-Based Production Control System	Evaluation of the dynamics of the relationship between demand, stock, and production using the APIOBPCS model.	Dynamic Simulation	Focus on production system stability, not multi-echelon interactions or collaborative VMI models.
Sentia et al. (2022)	System Dynamic Modeling: A Case Study of a Hotel Food Supply Chain	SD model to overcome demand fluctuations and improve inventory turnover stability.	CLD–SFD Simulation	Specific case studies without considering the complexity of relationships between VMI actors and dynamic capacity.
Pietroń (2023)	Management System Structure vs. Behavior – A Supply Chain Simulation Analysis	SD experiment to analyze the bullwhip effect and the effectiveness of stock policies.	SD Continuous Simulation	Does not evaluate collaborative policies such as VMI and does not include capacity or real-time delay variables.
Rabbani et al. (2018)	Vendor Managed Inventory Control System for Deteriorating Items Using Metaheuristic Algorithms	EOQ-based VMI control for perishable items with multi-item constraints.	Metaheuristic Optimization	Does not represent real-time dynamics and feedback between actors (no feedback modeling).
Santoso et al. (2019)	Scenario Development for Improving Supply Chain Performance	Testing four policy scenarios in an SD-based horticultural supply chain.	System Dynamics Scenario Simulation	Does not consider vendor-retailer collaboration and production capacity.
Andaz et al.	Learning an Inventory Control	Learning an adaptive policy for	Supervised	Does not use SD structure and does not

Author & Year	Research Title	Research Scope	Research Method	Research Gap
(2023)	Policy with General Inventory Arrival Dynamics	inventory control with a dynamic arrival model.	Simulation	focus on collaborative systems such as VMI.
Herdiani et al. (2025)	A System Dynamics Model of Frozen Fish Supply Chain	Integration of SD sub-models for analysis of cold storage capacity and product quality.	System Dynamics Policy Simulation	Focuses on improving cold logistics; has not examined multi-echelon collaboration and adaptive stock policies.
Rathore et al. (2020)	Impact of Risks in Foodgrains Transportation System	Evaluation of the sensitivity of transportation capacity and stock to supply chain risks.	System Dynamics Modeling	Does not fully evaluate SD integration with VMI or adaptive replenishment mechanisms.
Disney & Towill (2002)	A Discrete Transfer Function Model to Determine the Dynamic Stability of a VMI Supply Chain	Mathematical modeling of VMI using transfer functions and system dynamics simulation.	Mathematical + SD Hybrid Modeling	Classic linear models do not address non-linear feedback and the complexity of modern multi-echelon systems.
Herdiani et al. (2025)	System Dynamics Model of Frozen Fish Supply Chain	Use of SD to evaluate the impact of cold distribution policies.	SD Simulation (6 submodels)	Does not include vendor-retailer collaboration aspects and dynamic stock policies.
Penelitian Ini (2025)	System Dynamics Modeling to Improve Complex VMI	Multi-echelon integration between vendors, distributors, and retailers with demand, capacity, and stock dynamics.	Integrated System Dynamics	Developing an SD-VMI model to investigate dynamic interactions between actors, capacity, and adaptive policies within a single integrated model framework.

2.2 Theoretical Basis

2.2.1 Vendor Managed Inventory (VMI)

1. Definition of Vendor Managed Inventory (VMI)

As part of a supply chain management strategy known as VMI, suppliers are entrusted with the task of overseeing customer-site inventory based on data exchanged on demand, stock levels, and product movements. Essentially, VMI shifts the burden of important ordering and restocking choices from the client to the supplier. The goal is to streamline the supply chain and decrease demand unpredictability. According to Fry (2011), VMI is a system in which suppliers take control of customer inventory through a transparent information exchange mechanism. Thus, suppliers are fully responsible for the timing and quantity of goods deliveries, while customers only provide access to relevant data. This approach enables more coordinated and synchronized decision-making between entities in the supply chain.

Furthermore, manufacturers or suppliers are tasked with deciding when and how much to restock in order to reduce storage costs and prevent stock shortages under VMI, a collaborative inventory management strategy (Borade & Sweeney, 2015). VMI not only focuses on inventory control, but also involves information system integration, real-time data sharing, and the use of technologies such as Electronic Data Interchange (EDI) to support data-driven decision-making processes. With this model, suppliers no longer wait for orders from customers, but proactively monitor demand data and manage deliveries according to actual needs in the field. Therefore, VMI is considered a pull-based inventory management system that utilizes actual data, rather than mere projections or estimates of demand.

Meanwhile, VMI can be viewed as a mechanism for vertical integration between suppliers and customers, which encourages the creation of a constant and accurate two-way flow of information (Govindan, 2013). This system requires a high level of trust, transparency, and coordination, because the success of VMI depends on the extent to which both parties are willing to share sensitive data, such as sales volume, production schedules, and distribution plans. In practice, VMI is often used as a collaborative strategy to overcome classic supply chain problems such as the bullwhip effect and distribution inefficiencies. By eliminating information gaps between supply chain stages, VMI can improve visibility, accelerate the flow of goods, and reduce total operating costs. Therefore, overall, In addition to being a logistics model, VMI represents a new way of thinking about SCM in the contemporary era, one that places an emphasis on distribution network-wide systemic efficiency and information-based cooperation.

2. VMI Objectives and Principles

By enhancing collaboration and optimizing inventory management amongst company partners, the primary goal of establishing a VMI ystem is to generate supply chain efficiency in general. In traditional systems, customers place orders with suppliers based on estimated needs, which often leads to mismatches between demand and supply. VMI provides a solution to this problem by giving suppliers responsibility for planning and replenishing stock. As per Lee et al. (2015), the goal of VMI is to align the supply chain so that it can operate as an integrated whole, rather than as separate entities. Thus, this system is expected to reduce inventory costs, shorten order cycle times, and improve customer service levels through more stable product availability.

In principle, VMI is based on the concept of transfer of responsibility, namely the transfer of inventory management responsibility from the customer to the supplier. In this system, The supplier must keep a close eye on the customer's stock and use real sales and consumption data to decide when and how much to ship. This principle can only be implemented if there is a strong collaborative relationship and a transparent data exchange mechanism between the two parties (Fry, 2011). With this basic principle, suppliers have full control in responding quickly to changes in market demand, while customers benefit from reduced stock levels and reduced risk of stock-outs. In addition, the application of this principle also requires a formal agreement that includes KPIs such as service level, inventory turnover, and fill rate to ensure accountability and clarity of roles between suppliers and customers (Joseph et al., 2010).

In addition to focusing on efficiency and coordination, the basic principles of VMI also reflect a paradigm shift in business relationships, from a transactional model to a mutual benefit relationship model. According to Govindan (2013) , the success of VMI is greatly influenced by trust, information transparency, and reliable information technology system integration. This collaborative relationship requires both parties to share sales data, production schedules, and demand projections with a high degree of accuracy. This principle is also in line with the lean supply chain approach, where every entity in the distribution network strives to eliminate waste, reduce waiting times, and increase value for end customers. Therefore, the objectives and basic principles of VMI are not limited to logistics efficiency, but also include the formation of a smart, adaptive, and sustainability-oriented supply chain ecosystem in the era of Industry 4.0 digitalization (Omar et al., 2020).

3. Benefits and Challenges of VMI

The implementation of VMI brings various strategic benefits to all parties in the supply chain, especially in terms of increased efficiency, visibility, and responsiveness to market demand. One of the main benefits is increased visibility of data throughout the supply chain. Through a system of sharing sales data, stock levels, and production planning in real time, suppliers can adjust supply to actual customer needs without experiencing information delays. This leads to a reduction in information distortion and increased accuracy in production planning (Omar et al., 2020) . In addition, The bullwhip effect, in which demand is amplified when different parts of the supply chain aren't synchronized, is another issue that VMI may mitigate. With a more transparent flow of information, VMI creates a more stable and efficient supply system (Shu et al., 2012). Other benefits include reduced operating costs through a reduction in safety stock, increased inventory turnover, and efficiency in transportation and warehousing activities.

However, in order for VMI to be successful, the organization must be able to overcome significant implementation challenges. One of the main challenges is companies' reluctance to share sensitive data such as sales volume, production planning, and profit margins, which are often considered competitive advantages

(Krichanchai & MacCarthy, 2017) . In addition, the integration of information systems between suppliers and customers requires significant technological investment in terms of hardware, software, and human resource training. Other challenges include the risk of high dependence on suppliers, the potential for lock-in effects, and organizational cultural differences that can hinder collaboration. In this context, the success of VMI is not only determined by technology, but also by human factors, trust, and organizational readiness to implement a mutually beneficial collaborative paradigm (Govindan, 2013).

4. Structure and Information Flow in VMI

The VMI system structure is based on a collaborative relationship between suppliers and customers facilitated by continuous data exchange. Information flow is the main foundation of this system, in which customers provide suppliers with full access to sales, demand, and inventory status data. Based on this data, suppliers independently calculate replenishment requirements to maintain optimal product availability. This process relies on information technology such as EDI, cloud computing, and ERP systems. With fast and accurate information flow, suppliers can avoid excess stock and minimize the risk of stock-outs. In addition, this mechanism allows suppliers to optimize production and distribution planning, thereby achieving logistics efficiency throughout the supply chain network (Fry, 2011).

The replenishment cycle in a VMI system consists of several main stages: collecting sales and inventory data from customers, analyzing demand by suppliers, creating replenishment plans, shipping goods, and evaluating system performance. The success of this cycle is determined by the frequency and accuracy of the data communicated. The use of blockchain-based information systems has even been proposed to ensure the reliability, security, and transparency of data throughout the VMI process (Omar et al., 2020) . Effective information flow allows suppliers to automatically manage customer inventory, thereby creating a supply chain system that is more adaptive, responsive, and efficient to changes in market demand.

5. VMI Performance

In order to determine if the VMI system was successful in increasing supply chain efficiency, it is essential to evaluate its performance. Three key indicators commonly used in measuring VMI performance are inventory turnover, fill rate, and stock-out reduction. The inventory turnover indicator measures how quickly inventory turns over in a given period, and an increase in this ratio indicates more efficient use of resources. VMI implementation has been shown to accelerate stock rotation through inventory management tailored to actual customer demand (Xu et al., 2010). Meanwhile, order fill rate reflects the supplier's ability to meet customer needs on time and in the appropriate quantity. A well-managed VMI system can significantly improve the fill rate because replenishment decisions are made directly by suppliers based on real-time data (van den Bogaert & van Jaarsveld, 2022).

In addition, the stock-out reduction indicator is an important parameter that describes the system's ability to prevent stock shortages on the customer's side ( ). The implementation of VMI reduces the risk of stock shortages because suppliers can quickly anticipate fluctuations in demand and adjust delivery schedules without waiting for formal orders from customers (Shu et al., 2012). The combination of these three indicators results in improved overall performance in the supply chain, creating operational stability and increasing customer satisfaction. Thus, the VMI system is not only an inventory control tool, but also a strategic mechanism to strengthen collaboration and organizational competitiveness in an increasingly dynamic and data-driven market.

6. VMI in the Supply Chain

In the context of modern supply chains that are complex and globally distributed, As a platform for cross-level cooperation among suppliers, manufacturers, distributors, and retailers, VMI serves a key role. The complexity of the supply chain demands an inventory management system that is not only efficient but also adaptive to demand uncertainty and supply disruptions. The integration of VMI with the IRP model, as proposed by Harahap et al. (2024), enables simultaneous optimization of distribution routes and stock management, thereby accelerating delivery times and reducing logistics costs. In a multi-tier system, VMI functions as a coordinative link that unites various supply chain entities through centralized data sharing mechanisms and demand prediction-based decision-making algorithms.

VMI is finding more and more uses in modern supply chains as a transparent and automated inventory management system powered by AI, big data analytics, and blockchain.This technology enables suppliers to perform predictive analysis of demand patterns, detect anomalies in stock movements, and make autonomous replenishment decisions (Omar et al., 2020; Onotole et al., 2023) . Thus, modern VMI has transformed from a traditional stock control system into an intelligent supply chain coordination system that facilitates digital collaboration and data-driven decision-making. In a corporate world that is both complicated and global, VMI is key to achieving supply chain efficiency, reliability, and sustainability.

2.2.2 **Supply Chain Management (SCM)**

1. Definition and Elements of SCM

SCM is a method that aims to increase efficiency and create value by integrating all company activities, starting with the suppliers of raw materials and ending with customers. SCM is defined by Badillo et al. (2011) as the process of organizing and coordinating the activities that make up a company's supply chain in order to maximize value creation, competitive infrastructure development, and demand synchronization on a global scale. This concept emphasizes the importance of cross-organizational coordination in modern production systems, where manufacturing, distribution, logistics, and customer service activities are connected in a dynamic global network. To guarantee that all nodes in the network can run well and adapt to changes in consumer demand, supply chain management (SCM) is crucial.

Sourcing, manufacturing, inventory management, distribution, and CRM are some of the core business operations that are integrated in SCM. The success of SCM depends on collaboration and integration between various parties throughout the value chain. According to Moharana et al. (2010), SCM not only focuses on internal efficiency, but also requires cross-organizational coordination to overcome fluctuations in demand, replenishment lead times, and transportation costs. In this context, VMI is an important element of SCM because it optimizes coordination between suppliers and customers through a collaborative stock management mechanism and real-time data sharing.

2. Material, Information, and Financial Flows in SCM

The three primary flows—material, information, and financial—must be integrated for SCM to be successful. Everything from producers to final buyers is a part of the material flow, while the information flow encompasses the exchange of data related to sales, production, demand, and delivery of goods. Meanwhile, the financial flow encompasses payment transactions, cash management, and financing between parties involved in the supply chain. According to Gangopadhyay & Huang (2004), improving supply chain efficiency relies heavily on good information communication, which allows for more precise synchronization of financial and material flows. Without an integrated information system, supply chains tend to experience delays, excess inventory, and demand distortions that increase operating costs.

In addition, a study by Lee et al. (2010) displays that sharing financial information among supply chain members can improve the stability and overall performance of the chain. Transparent financial flows enable companies to better manage cash flow and working capital, especially in conditions of market uncertainty. In this context, the implementation of VMI serves as a link between the three flows because suppliers have direct access to customer sales and inventory data, enabling them to deliver goods and manage payments efficiently and in a coordinated manner.

3. Inventory management in SCM

To keep products available while keeping storage costs down, inventory management is an essential part of SCM. According to (Ortiz-Barrios et al., 2020), good inventory management can reduce operational inefficiencies such as delivery delays, high transportation costs, and production capacity imbalances. Inventory serves as a buffer against fluctuations in demand and supply lead times, making it crucial to make the right decisions regarding optimal inventory levels. In complex SCM systems, these decisions depend on data integration between suppliers and customers to ensure a smooth flow of goods.

This is where VMI plays an important role. According to Shou (2013) , the implementation of VMI can improve inventory management efficiency by reducing safety stock levels and increasing fill rates. VMI also enables suppliers to respond quickly to changes in demand, as they have direct visibility into customer inventory and consumption data. Thus, integrating inventory management through a VMI system is a strategic step toward achieving a more adaptive and efficient supply chain.

4. Demand Variability and Bullwhip Effect in SCM

Demand variability is one of the main challenges in SCM because it can cause an imbalance between supply and demand. Small fluctuations at the consumer level often cause significant distortions at the supplier level, a phenomenon known as the bullwhip effect. According to Disney & Lambrecht (2005) , this effect arises from unsynchronized ordering practices, information delays, and inaccuracies in demand forecasting. As a result, the supply chain experiences increased inventory costs, reduced service levels, and decreased operational stability.

A recent study by Keliji et al. (2022) confirms that controlling the bullwhip effect can be achieved through the integration of information systems and the implementation of collaborative policies such as VMI. By sharing demand data in real time, suppliers can adjust production and delivery planning directly without relying on customer estimates. This helps create a more stable supply chain system, reduces demand variability, and improves the reliability of product delivery to end consumers.

2.2.3 **System Dynamic (SD)**

1. Definition of SD

System Computer simulations, stock and flow, and feedback are the cornerstones of dynamics (SD), a system modeling approach that delves into the intricate behavior of dynamic systems. In the 1950s, this method was first created by Jay W. Forrester at MIT to examine the dynamics of businesses and other organizations. According to Maani (2009), SD is a feedback-based approach that models the cause-and-effect relationships between variables in a system to identify long-term patterns of change. In other words, SD views systems as networks of nonlinear interactions that continue to evolve due to delays, accumulations, and the feedback effects of previous decisions.

According to Martinez-Moyano (2023), SD combines information feedback theory, human decision-making, and computer-based simulation to explain how the internal structure of a system produces external behavior patterns. This method is very useful in understanding complex, dynamic problems with interrelated variables, such as supply chain systems, public policy, and ecological systems. The SD approach is also endogenous, explaining system changes based on its internal structure rather than merely the influence of external factors, making it suitable for use in this study to analyze the dynamics of VMI in the context of SCM.

2. Basic Concepts of SD

The main concept in SD centers on feedback loops, which are circular cause-and-effect relationships in which an action affects another variable, which then provides feedback to the initial variable. According to Barlas (2020), feedback can be reinforcing (positive), which strengthens the direction of change, or balancing (negative), which stabilizes the system. Delays in information or action in feedback are called delays, and are the main cause of oscillation and instability in inventory systems. In addition, real systems are often non-linear, meaning that the relationship between variables is not proportional and can result in unpredictable system behavior.

The concept of accumulation explains how small changes in flow variables can accumulate into large changes in stock variables over time. For example, in the context of inventory, small differences between production and demand levels will lead to stockpiling or stock shortages in the long run. In VMI models, where feedback and replenishment delays are key factors in supply chain behavior, these concepts enable SD to be used to comprehend complicated dynamics like stock and demand changes (Duggan, 2016).

3. Causal Loop Diagrams (CLD)

To visually represent the cause-and-effect linkages between system variables, SD provides a Causal Loop Diagram (CLD). A positive or negative sign describes the kind of connection, while arrows show the direction of effect. In order to determine which feedback structure is primarily responsible for a system's dynamic behavior, CLD is used (You & Ham, 2019).

Both reinforcing (R) and balancing (B) cycles are fundamental to CLD. A positive cycle that reinforces change is called a reinforcing loop. For example, as demand grows, output goes up, which further raises demand. Conversely, balancing loops serve to stabilize the system, such as when increased inventory causes a decrease in new orders. In the context of VMI and SCM, CLD plays an important role in mapping the interactions between demand, inventory, and orders, as well as helping to identify policy intervention points to reduce the bullwhip effect (Song & Yun, 2015).

4. Stock and Flow Diagram (SFD)

A SFD is a quantitative representation of CLD used to model the accumulation and changes between variables in a system. Stock describes the accumulation or state of the system at a given time, such as inventory levels or production capacity, while flow describes the rate of change in stock, such as production or demand levels. According to Galarneau et al. (2020) , auxiliary variables serve as supporting variables that connect inputs and outputs, while converters are used to transform the values of other variables into specific functional forms or parameters.

SFD is important because it allows for the mathematical quantification of system behavior, rather than just qualitative analysis like CLD. Using integral equations and computer simulations, researchers can evaluate the impact of policies or structural changes on system behavior dynamically. For example, in the study by Andriansyah et al. (2020), SFD was used to simulate the behavior of national rice stocks and produce accurate inventory predictions with a MAPE of less than 5%. This approach became the basis for SD-based VMI research, as it enabled quantitative analysis of the interaction between stocks, demand, and order timing.

5. SD Methodology

The SD methodology was developed using a systematic and iterative approach to understand, simulate, and solve complex problems that have circular cause-and-effect relationships. The process is not linear, but cyclical, where each stage interacts with each other and may use the data from the model to make improvement. According to Galarneau et al. (2020), there are six main stages in the SD methodology. **First**, problem articulation, which is the process of defining system boundaries, identifying core problems, and determining model objectives. At this stage, modelers highlight the phenomena to be analyzed, such as stock fluctuations, delivery delays, or the bullwhip effect in the supply chain. **Second**, dynamic hypothesis, which is the formation of hypotheses about how the system structure (through cause-and-effect loops) produces certain behaviors. These hypotheses are usually visualized using a Causal Loop Diagram (CLD) to illustrate the interactions between variables.

The third stage is model formulation, which involves developing a quantitative model using Stock and Flow Diagrams (SFD). This stage converts qualitative relationships into mathematical equations that can be run through simulation software such as Vensim DSS, AnyLogic, or Stella Architect. The fourth stage, simulation, running the model under different circumstances and seeing how the system responds to changes to parameters, such increasing demand or modifications to replenishment lead times. The fifth stage, policy experiment, to test how different policies, like stock control rules in the VMI model, affect system performance. **Finally**, model validation is carried out to ensure the reliability of the model by comparing simulation results with empirical data, testing parameter sensitivity, and verifying the consistency of model behavior. According to Torres et al. (2017), these stages not only help to understand complex system behavior, but also serve as a strategic decision support tool to experimentally evaluate long-term policies without real-world operational risks.

In the context of this study, the SD methodology has strategic value because it bridges the gap between conceptual theory and operational practice. SD allows researchers to visualize the dynamics of demand, inventory, and production capacity in a single integrated framework. By building dynamic models, researchers can identify the leverage points that most influence the performance of the supply chain system. This approach also enables policy testing such as adjusting delivery frequency, sharing real-time demand information, or determining optimal safety stock to reduce the bullwhip effect. Thus, the SD methodology not only functions as an analytical tool but also as a policy learning system that supports data-driven decision-making in collaborative inventory management such as VMI.

Table 2. 2 System Dynamics Methodology

Stages	Objectives	Activities	Output
1. Problem Articulation	Identify and define the main problems to be modeled.	• Establishing system boundaries. • Identify key variables (demand, inventory, lead time, etc.). • Determine the simulation objectives.	Clear problem statement and system boundaries.
2. Dynamic Hypothesis	Conceptually explain how the system structure produces the observed behavior.	• Develop a Causal Loop Diagram (CLD). • Identifying reinforcement loops (R) and balancing loops (B).	Qualitative model of cause-and-effect relationships.
3. Model Formulation	Converting the conceptual model into a quantitative model.	• Building a Stock and Flow Diagram (SFD). • Formulating mathematical	Formal SD model based on differential

Stages	Objectives	Activities	Output
		equations between variables.	equations.
4. Simulation	Evaluating system behavior through time experiments.	• Run simulations with software (e.g., Vensim). • Observe the behavior of stock, demand, and delays.	Graph the system dynamics over time.
5. Policy Experiment	Testing policy scenarios to find optimal solutions.	• Modifying model parameters (lead time, delivery frequency, safety stock). • Analyzing the impact of policies on system performance.	Policy recommendations based on simulation results.
6. Model Validation	Ensuring the model is valid, reliable, and representative of real-world conditions.	• Testing model sensitivity and behavior. • Compare simulation results with actual data.	The model is validated and ready for use in decision-making.

Source: (Galarneau et al., 2020; Torres et al., 2017)

6. Dynamic Behavior in Inventory Systems

One of the main advantages of the System Dynamics (SD) approach is its ability to describe and analyze dynamic behavior in inventory systems in a realistic and measurable manner. Inventory systems are a classic example of systems with feedback systems, where delays in information flow and decision-making can result in complex behavior patterns such as inventory oscillation, overshoot-collapse, and oscillatory response. According to Morales & Andrade-Arenas (2021) , stock oscillation patterns arise due to delays between the time a request is received, production is carried out, and goods are delivered to customers. The overshoot-collapse phenomenon occurs when the system overreacts to changes in demand, resulting in overproduction which is then followed by a drastic decline due to insufficient storage capacity or market demand. This oscillatory response is an indication of an imbalance between inflow and outflow in stock variables, which is at the core of inventory system dynamics.

In the context of SCM, this dynamic behavior phenomena is common, particularly during VMI deployment, when the bullwhip effect occurs due to information delays between suppliers and consumers. According to a simulation study by Sentia et al. (2022), how a hotel's food supply chain may benefit from the

SD model displays that a combination of customer response control policies and order response time reduction can stabilize stock variability by more than 40%. SD enables sensitivity analysis and policy scenarios that show how small changes in replenishment rates, lead times, or demand levels can have systemic impacts on stock performance and operational costs. In the context of VMI, understanding this dynamic behavior is important for designing adaptive and data-driven replenishment policies that can reduce inventory oscillations and maintain supply chain stability under fluctuating demand conditions. Thus, the SD approach serves not only as a theoretical analysis tool but also as a strategic decision-making instrument in the design of collaborative inventory systems.

CHAPTER III
RESEARCH METHOD

3.1 Research Object

The object of this study is the VMI system in the context of a supply chain involving suppliers and retailers, with a focus on modeling system dynamics with interactions between customer demand, inventory levels, supply capacity, and delivery delays. This research focuses on comprehensively modeling VMI system behavior using the System Dynamics approach, so that it can analyze changes in inventory, ordering patterns, and the impact of VMI policies in complex system conditions influenced by information delays and capacity constraints. In addition, this study also evaluates various VMI policy scenarios to find the best scenario for improving efficiency and responsiveness.

3.2 Data Collection Method

The research data used in this study was sourced from Internal Company Records, Warehouse or Stock-Keeping Records, Logistics and Shipping Reports, Operational Manuals and Production Schedules, Finance and Accounting Documents. Meanwhile, the types of data used included Historical Customer Demand, Historical Inventory Levels, Lead Time/Delivery Delays, Capacity Constraints, and Cost Data (Table 3.1).

Table 3. 1 Data and Data Sources

No.	Type of Data	Data Source	Description
1.	Historical Customer Demand	Extract data from ERP (Enterprise Resource Planning), WMS (Warehouse Management System), or sales records of the retailer/customer	Historical data on actual customer demand
2.	Historical Inventory Levels	Internal Company Records: Obtain stockkeeping records (daily or weekly) from the customer's warehouse or VMI location.	Inventory data available during a specific period of time
3.	Lead Time (LT) (Delivery Delays)	Internal Company Records / Logistics Data: Logistics reports, shipping manifests, or	Data regarding delays or the time required for

No.	Type of Data	Data Source	Description
		confirmed delivery records	delivery
4.	Capacity Constraints	Internal Company Records/ Operational Manuals: Production schedules, facility specifications, and warehouse layout documents	Data on operational and physical limitations of the system
5.	Cost Data	Finance/Accounting Department Data: Cost sheets, budget documents, and policy definitions for stock-out penalties	Data related to operational costs, including stock-out penalties.

3.3 Research Flow

This research began with the determination of the scope of research, preliminary studies, and literature review, followed by problem identification, formulation of objectives, and system characterization. The next stage included the development of a conceptual model, identification of variables, and data collection as the basis for model development. The modeling process was carried out through the preparation of a Causal Loop Diagram, Stock and Flow Diagram, verification, and model validation, which were then used to design and simulate VMI policy scenarios. This entire process was concluded with an analysis of the simulation results, a discussion of the findings, and the preparation of research conclusions and recommendations as presented in Figure 3.1 below.

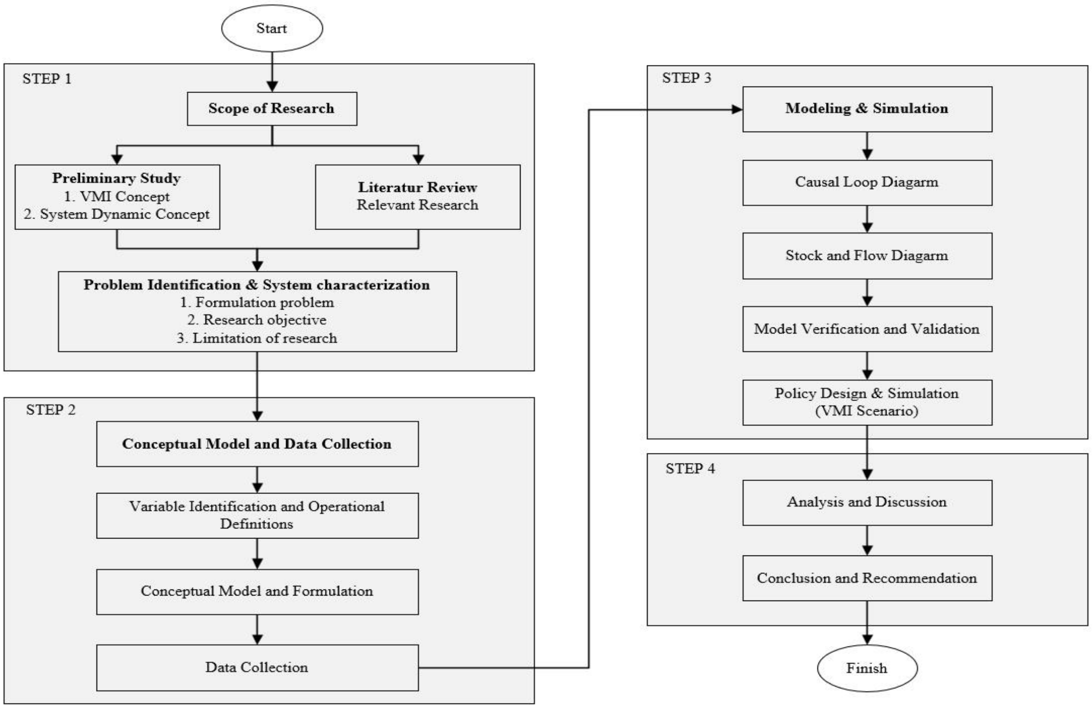

Figure 3. 1 Research Flow

1. **Step 1: Scope of Research**

   This phase aims to define the scope and basic framework of the research.

   a. Preliminary Study: Understanding the basic concepts underlying the research, namely the VMI Concept and the System Dynamics Concept.
   b. Literature Review: Collecting and analyzing relevant research to build a theoretical foundation and identify research gaps.
   c. Problem Identification and System Characterization: Based on the preliminary study and literature review, this research formulates:
      1. Problem Formulation: Establishes specific questions or issues to be answered.
      2. Research Objective: Defining what the research aims to achieve.
      3. Limitation of Research: Determining the specific limitations of the study.

2. **Step 2: Conceptual Model and Data Collection**

   This phase focuses on developing the conceptual framework of the SD model and collecting the data needed to formulate the model.

   a. Variable Identification and Operationalization: Identifying all key variables to be included in the model (such as demand, inventory, lead time, costs) and defining how they will be measured.
   b. Conceptual Model and Formulation: Formulating the qualitative relationships between variables, which will form the basis for further modeling.
   c. Data Collection: Collecting relevant quantitative data (e.g., historical demand data, inventory levels, costs, and operational parameters) from specified sources for model calibration and validation.

3. **Step 3: Modeling and Simulation**

   This phase is the core implementation of the system dynamics methodology to create and test quantitative models.

a. Causal Loop Diagram (CLD): Create a qualitative diagram (CLD) that visualizes cause-and-effect relationships and feedback structures (positive/negative) in the VMI system.
b. Stock and Flow Diagram (SFD): Convert the CLD into a quantitative SFD model (using Powersim Studio 10) by determining the Stock, Flow, and Constant/Auxiliary variables and formulating equations.
c. Model Verification and Validation: Conduct tests to ensure that the model:
    1. Verification: Free from structural (dimensional consistency) and logical errors
    2. Validation: Able to accurately replicate the behavior of the real system (e.g., comparing simulation results with historical data).
d. Policy Design and Simulation (VMI Scenario): Design and test alternative policy scenarios (e.g., changes to VMI ordering rules, increased information sharing) in a validated model to evaluate their long-term impact on system performance.

4. Step 4: Analysis and Conclusion

The final phase is to analyze the simulation results and formulate research findings.

a. Overall Results Analysis: Analyze simulation results from different scenarios to identify the optimal VMI policy for improving supply chain performance.
b. Research Conclusions and Recommendations: Summarize research findings that address the problem formulation and provide actionable recommendations for improving VMI management

CHAPTER IV
DATA COLLECTION AND PROCESSING

4.1 Data Collection

This section describes the data collection process that will be used throughout the data processing and analysis process. The main objective is to inventory all validated raw data to ensure data coherence before further processing and analysis. Through structured data collection, this study can ensure that the operational, financial, and environmental variables used reflect the actual conditions or scenarios to be tested, so that The outcomes of data processing will have a high level of accuracy and credibility in answering the research questions.

The research data used in this study was sourced from Internal Company Records, Warehouse or Stock-Keeping Records, Logistics and Shipping Reports, Operational Manuals and Production Schedules, Finance and Accounting Documents. Meanwhile, the types of data used included Historical Customer Demand, Historical Inventory Levels, Lead Time/Delivery Delays, Capacity Constraints, and Cost Data. The data collection stage began with recording the physical characteristics and environmental impact of seven types of data, such as historical customer demand, historical inventory levels, and cost data. The data collected included physical parameters such as weight and volume per unit, which would affect logistics costs, as well as standard labor hours for the manufacturing process. In addition to technical aspects, data is also collected on sustainability aspects, such as CO2 emissions per unit of production and the basic scrap rate for each product. This information is then supplemented with waste management parameters, which set the scrap disposal cost at IDR 2,500/kg and the emission charge at 0.35/kg CO2/kg.

Next, data was collected from the operational side of two main suppliers (S1 and S2), covering specific capacity and production cost profiles. This data included basic labor capacity (1,800 hours for S1 and 1,600 hours for S2), overtime thresholds , and social costs and ergonomic penalties of IDR 1,500 per working hour to maintain worker welfare. Each supplier has detailed product unit costs, setup costs per period, and varying scrap rates at the vendor level. For example, the unit cost of P1 at S1 is IDR 770,476 with a scrap rate of 5.84%, while at S2 the cost is higher at IDR 801,924 but with a lower scrap rate of 3.54%.

Finally, data collection focused on demand dynamics at nine retailers (R1-R9) and logistics distribution parameters. Demand data included the mean and standard deviation (SD) per product to model market uncertainty, with a consistently set service level target of 95%. For each retailer, unit storage costs per period and penalties for stockouts were also collected. The smooth flow of goods was supported by data on the distance traveled from each supplier to each retailer, where shipping costs were calculated based on transportation cost parameters of Rp300/kg.km, fixed shipping costs of Rp125,000, and carbon pricing considerations of Rp100,000 per ton of CO2. All procurement activities are also subject to a vendor order fee of Rp350,000 per PO with an estimated lead time of 5 days. The complete research data collected is presented in Tables 4.1 to 4.9 as follows.

Table 4. 1 Product Technical Characteristics

Name	Weight Kg/unit)	Volume m3/unit	Std.Labor (Hours/unit)	Prod. (Kg CO2/unit)	Baseline Scrap Rate
Refrigerator Mainboard (compressor/defrost/sensor control logic)	2.99	0.0185	1.76	6.13	0.048
Washing Machine Control Panel (cycle selection, motor & valve control)	1.33	0.0138	0.91	6.23	0.047
AC Display & Control Board (indoor unit UI, IR receiver, mode control)	2.53	0.0064	0.35	8.6	0.04

Name	Weight Kg/unit)	Volume m3/unit	Std.Labor (Hours/unit)	Prod. (Kg CO2/unit)	Baseline Scrap Rate
Induction Cooker Power Control Board (IGBT drive, temperature regulation)	2.56	0.0084	1.01	2.38	0.041
Smart Lock Motor Driver (H-bridge driver, latch sensing, security I/O)	2.93	0.0054	0.7	5.47	0.021
Air Purifier Control Module (fan PWM, ionizer, PM2.5 sensor interface)	0.51	0.0042	0.58	3.82	0.031
LED Lamp Driver (constant-current driver with dimming/PWM)	1.16	0.0039	0.57	5.39	0.042

Table 4.1 displays the characteristics of several electronic control module products used in various household appliances, such as refrigerator mainboards, washing machine control panels, AC display & control boards, induction cooker control boards, smart lock motor drivers, air purifier control modules, and LED lamp drivers. The parameters presented include weight per unit, volume per unit, standard labor hours, production carbon emissions per unit (kg CO_2/unit), and baseline scrap rate. Physically, product weight varies between 0.51 kg and 2.99 kg per unit, while volume ranges from 0.0039 to 0.0185 m³ per unit. The refrigerator mainboard has the largest weight and volume, while the LED lamp driver and air purifier control module are among the lightest and most compact. From a production and environmental perspective, standard labor requirements range from 0.35 to 1.76 hours per unit, with the refrigerator mainboard requiring the longest processing time and the AC display & control board requiring the shortest. Production carbon emissions show significant variation, with the highest value for the AC display & control board at 8.6 kg CO_2 per unit and the lowest for the induction cooker power control board at 2.38 kg CO_2 per unit. Meanwhile, the baseline scrap rate for all products is relatively low, ranging from 0.021 to 0.048, which indicates that the production defect rate is still within controllable limits. In

general, this table provides a comprehensive comparison of the physical dimensions, production process requirements, environmental impact, and manufacturing quality of each electronic module.

Table 4. 2 Supplier Costs

Supplier	Basic Labor Capacity (hours/period)	Overtime Threshold (hours/period)	Overtime Social Cost (IDR/hour)	Working Days	Working Hours /Day	Number of Workers
S1	1800	450	65,000	25	8	9
S2	1600	450	70,000	25	8	8

Table 4.2 presents the cost and labor capacity parameters for each supplier used as the basis for calculating production capacity and overtime potential in the model. Supplier S1 has a basic labor capacity of 1,800 hours per period with 9 workers, while S2 has a capacity of 1,600 hours per period with 8 workers, indicating a difference in initial operational capacity between the two suppliers. Both suppliers set the same overtime threshold of 450 hours per period, but the social cost of overtime per hour differs, with S2 having a higher cost of IDR 70,000 compared to S1 at IDR 65,000. In addition, both have a uniform work pattern of 25 working days with 8 working hours per day. This data illustrates that even though the work time structure is relatively the same, differences in the number of workers and overtime costs have the potential to affect production decisions, capacity utilization, and the formation of operational costs in the supply chain system.

Table 4. 3 Transportation and Environmental Parameters

Parameters	Value	Unit
Transport Cost per kg-km	300	IDR/kg/km
Carbon Emissions per	0.062	kg CO_2

ton-km		
Carbon Price	100,000	IDR/ton CO_2

Table 4.3 displays the transportation and environmental parameters used as the basis for calculating distribution costs and carbon emissions in the model. Transportation costs are set at IDR 300 per kilogram-kilometer, which is the main component in calculating transportation costs based on product weight and delivery distance. From an environmental perspective, a carbon emission intensity of 0.062 kg CO_2 s per ton-kilometer is used to estimate the carbon footprint generated during logistics activities. This value is then converted into a cost using a carbon price parameter of IDR 100,000 per ton of CO_2, thereby enabling the integration of economic and environmental aspects into the simulation. The combination of these three parameters allows the model to not only evaluate transportation cost efficiency, but also consider the sustainability implications and external costs of carbon emissions in the supply chain system.

Table 4. 4 Retailer Costs (Demand)

Retailer	Product	Holding Cost (IDR/unit/period)	Stockout Penalty (IDR/unit)	Service Level Target (%)
R1	P1	1330	69100	95
R1	P2	490	144,500	95
R1	P3	1200	84000	95
R1	P4	1030	127,400	95
R1	P5	960	78,000	95
R1	P6	1090	74,700	95
R1	P7	1480	56,200	95
R2	P1	1330	73,900	95
R2	P2	490	151,700	95
R2	P3	1200	86,500	95
R2	P4	1030	128,700	95
R2	P5	960	80300	95
R2	P6	1090	71700	95
R2	P7	1480	61300	95
R3	P1	1330	69100	95
R3	P2	490	137,300	95
R3	P3	1200	83,200	95
R3	P4	1030	124,900	95

Retailer	Product	Holding Cost (IDR/unit/period)	Stockout Penalty (IDR/unit)	Service Level Target (%)
R3	P5	960	79600	95
R3	P6	1090	72,500	95
R3	P7	1480	61,800	95
R4	P1	1330	76,000	95
R4	P2	490	150,300	95
R4	P3	1200	81500	95
R4	P4	1030	128,700	95
R4	P5	960	75,700	95
R4	P6	1090	79,900	95
R4	P7	1480	60700	95
R5	P1	1330	68,400	95
R5	P2	490	151,700	95
R5	P3	1200	79,800	95
R5	P4	1030	138,900	95
R5	P5	960	81,900	95
R5	P6	1090	79,900	95
R5	P7	1480	56,200	95
R6	P1	1330	75300	95
R6	P2	490	156,100	95
R6	P3	1200	80600	95
R6	P4	1030	135,000	95
R6	P5	960	81,900	95
R6	P6	1090	79200	95
R6	P7	1480	55600	95
R7	P1	1330	67700	95
R7	P2	490	154,600	95
R7	P3	1200	85,700	95
R7	P4	1030	137,600	95
R7	P5	960	85,800	95
R7	P6	1090	79,900	95
R7	P7	1480	57,900	95
R8	P1	1330	68,400	95
R8	P2	490	153,200	95
R8	P3	1200	85,700	95
R8	P4	1030	129,900	95
R8	P5	960	84,200	95
R8	P6	1090	79,900	95
R8	P7	1480	57,900	95
R9	P1	1330	74,600	95
R9	P2	490	148,800	95
R9	P3	1200	79,800	95

Retailer	Product	Holding Cost (IDR/unit/period)	Stockout Penalty (IDR/unit)	Service Level Target (%)
R9	P4	1030	138,900	95
R9	P5	960	83,500	95
R9	P6	1090	76,900	95
R9	P7	1480	58,400	95

The table presents inventory cost parameters and service level targets for nine retailers (R1–R9) across seven product types (P1–P7), consisting of holding cost per unit per period, stockout penalty per unit, and service level target. In general, the holding cost value is constant for the same product across all retailers—for example, P1 is 1,330 IDR/unit/period and P2 is 490 IDR/unit/period—which indicates that storage costs are assumed to be determined based on product characteristics, not retailer location. In contrast, the stockout penalty displays variations between retailers for the same product, reflecting differences in the level of risk of lost sales or the impact of stock shortages in each market location. All retailers set a service level target of 95%, which indicates a high and uniform standard of service in maintaining product availability. This combination of parameters describes a framework for evaluating inventory policies that balance storage costs with the risk of stockouts in order to achieve consistent service performance in the supply chain system.

4.2 Data Processing

The data processing stage in this investigation aims to prepare all parameters and variables that will be used as inputs in the *System Dynamics* model so that they have consistent units, logical relationships between variables, and are in line with the analysis objectives. Data collected from various sources, such as production costs, transportation costs, scrap rates, customer demand, inventory costs, and stock-out penalties, are first verified and grouped based on model subsystems, which include production, inventory, transportation, and total costs. Next, the quantitative data is transformed into model parameters in the form of *stock, flow,* and *auxiliary variables* so that it can be systematically integrated into the *Stock and*

Flow diagram. This process ensures that each value used in the simulation represents realistic operational conditions and supports the validity of the policy analysis results generated by the model.

4.2.1 Causal Loop Diagram (CLD)

The Causal Loop Diagram (CLD) in this investigation was developed as a conceptual representation to illustrate the cause-and-effect relationships between the main variables in the VMI system. The CLD was developed to identify the feedback structure that shapes the behavior of the system, particularly the interactions between customer demand, production levels, inventory levels, inventory costs, and stock control policy pressures. The software used to create the CLD and simulation is Powersim. The CLD allows researchers to understand how changes in one variable can trigger a chain reaction in other variables, including the emergence of phenomena such as stockouts, increased total costs, and pressure to adjust order frequency. Thus, CLD serves as a dynamic hypothesis that forms the initial basis before the development of the quantitative Stock and Flow Diagram model, so that the direction of policy analysis remains consistent with the research objectives and the observed system structure.

Before developing CLD VMI, this modeling framework was deconstructed into three main subsystems that interact with each other to map operational and financial dynamics in depth. First, CLD Retailer and Demand illustrates how Customer Demand and Sales variables determine Order Decisions and their impact on Retailer Inventory fluctuations and the emergence of Shortage costs. Second, CLD Total Production visualizes the feedback mechanism upstream, where Inventory Gap triggers Target Production and Production Start, which accumulates as Work In Process (WIP) before being converted into Production Rate, taking into account Production Delay constraints. Finally, CLD Total Cost integrates all physical performance into financial metrics through Net System Cost analysis, which is the difference between the Income rate and the accumulated Expenditure cost, covering production, shipping, storage, waste, and penalty costs.

1. Retailer and Demand CLD

Modeling begins by explaining the causality dynamics in the first subsystem, namely Retailer and Demand CLD, which serves to capture the interaction between market demand fluctuations and stock availability at the downstream level. In this structure, the Customer Demand variable is mapped as the main determinant that directly triggers Shortage cost when product availability is insufficient, while also being a driver for the realization of Sales volume.

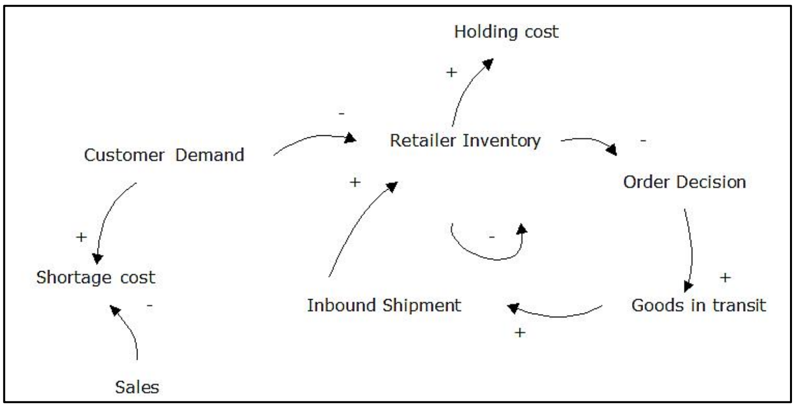

Figure 4. 1 Retailer and Demand CLD

Figure 4.1 displays the feedback mechanism in which the Retailer Inventory level acts as an accumulation variable influenced by the Inbound Shipment flow and goods still in transit based on the Order Decision made. In addition, the integration of the Holding cost variable in this model makes it possible to analyze the financial consequences of the inventory policy applied.

2. Total Production CLD

To determine operational aspects upstream, CLD total production maps feedback mechanisms in the manufacturing process and how supplier capacity interacts with demand dynamics.

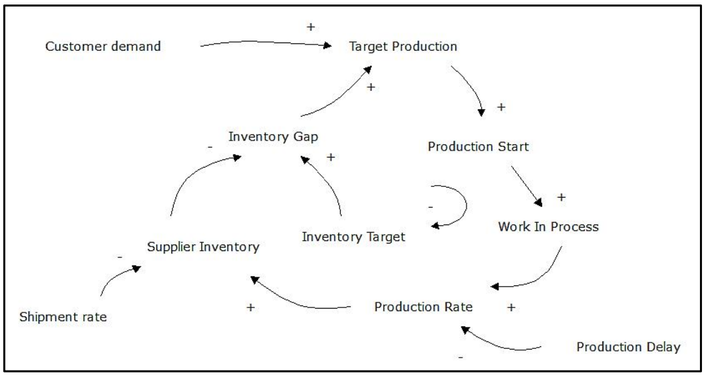

Figure 4. 2 Total Production CLD

In this model (Figure 4.2), the inventory gap, which is influenced by the inventory target and the supplier's inventory position, is identified as the main driver in determining the production target and initiating the production process (production start). This model captures the flow of materials from accumulation in work in process (WIP) to production rate, integrating the production delay variable to reflect realistic operational time constraints at the vendor level. This model reveals that an imbalance between the production rate and the shipment rate can affect stock stability on the supplier side, which ultimately determines the effectiveness of coordination in the VMI system as a whole.

3. Total Cost CLD

The integration of operational activities into financial metrics is carried out through the development of a total cost model, which serves as a strategic performance indicator to evaluate the overall profitability and efficiency of the system. This model maps the formation of net system costs, which are directly influenced by the difference between the income rate derived from actual sales and selling price variables and the accumulated expenditure costs, which include waste, production, penalty, shipping, and storage costs.

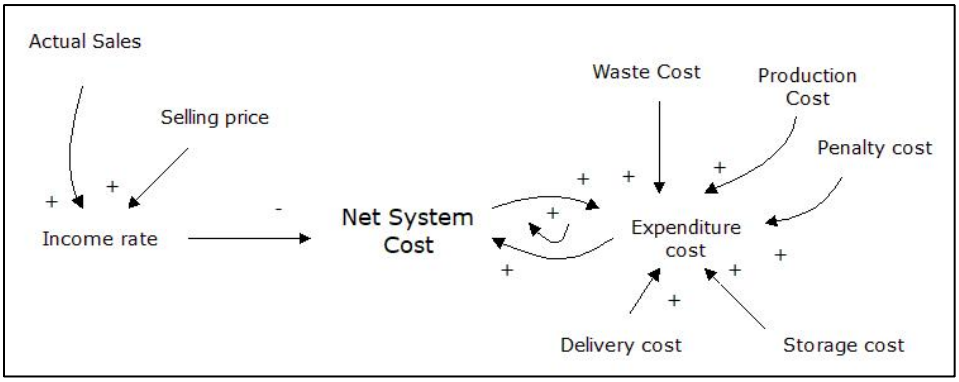

Figure 4. 3 Total Cost CLD

In the figure above (Figure 4.3), Net System Cost is the result of financial determination between Income rate and accumulated Expenditure cost. Income rate is positively driven by the interaction between Actual Sales and Selling price, while Expenditure cost acts as a reducing variable that consumes system margins through various operational costs. These expenditure components include Production Cost, Delivery Cost, Storage Cost, Penalty Cost, and Waste Cost. The existence of a feedback mechanism between expenditure costs and net system costs indicates that economic stability in the VMI system is highly dependent on the synchronization of logistics activities to minimize waste and penalty costs.

4. VMI CLD

The VMI Causal Loop Diagram is developed to synthesize the interdependence of variables across operational and financial dimensions into a single framework. This model consolidates the complex interactions between Demand, production quantity, Inventory Level, and total cost accumulation to describe the systemic behavior of the system.

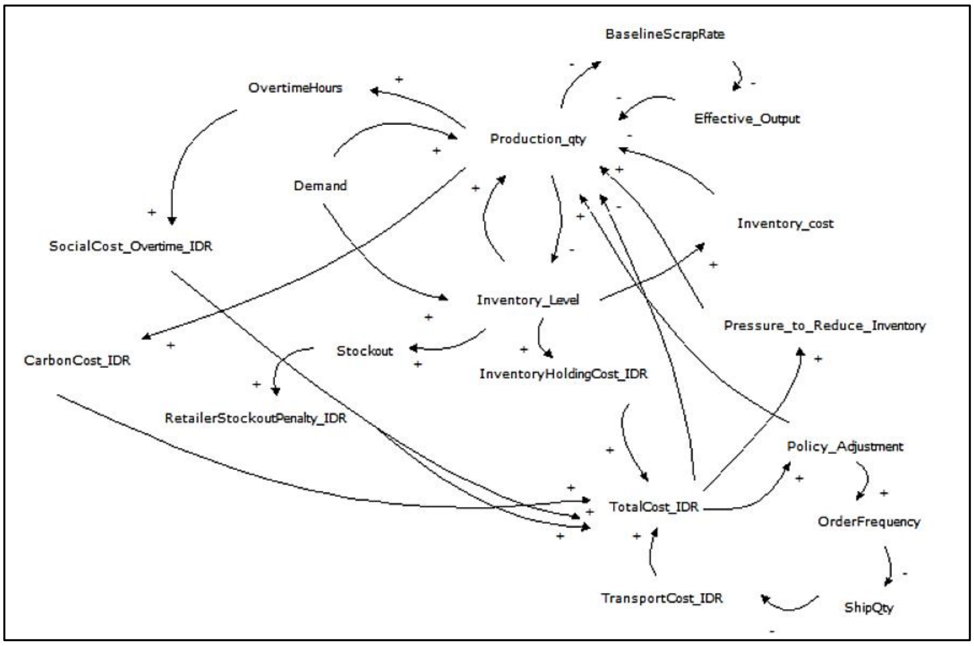

Figure 4. 4 VMI CLD

Figure 4.4 represents the dynamics of the inventory system within the VMI framework, which displays the feedback relationship between demand, production, inventory levels, costs, and stock control policies. Increased demand drives an increase in production_qty and the use of overtime hours to meet demand, which on the one hand increases effective output, but on the other hand adds to the social cost of overtime and potential carbon costs. Higher production will increase inventory levels, which in turn increases inventory holding costs and inventory costs, triggering pressure to reduce inventory and encouraging policy adjustments in the form of changes in order frequency and ship quantity. If inventory falls too low, stockouts occur, increasing retailer stockout penalties, which directly impact total cost increases. In addition, the baseline scrap rate affects production output effectiveness, which indirectly determines the balance between stock availability and costs. Overall, this diagram displays a combination of reinforcing loops on the production-demand side and balancing loops on the inventory-cost side, which together illustrate how inventory policies and operational decisions affect system stability and total supply chain costs.

4.2.2 Stock and Flow Diagram (SFD)

The Stock and Flow Diagram (SFD) was developed to translate the causal structure in the CLD into a quantitative model that can be simulated. This diagram formalizes stock variables, flows, and functional relationships between variables in the form of mathematical equations, enabling analysis of system behavior over time and dynamic evaluation of the impact of policies and intervention scenarios. Through the stock-flow structure, accumulated variables such as inventory, work in progress, and system costs can be represented explicitly, while flow variables describe the rate of change that affects the stock condition. With this approach, interactions between non-linear variables and time delays can be modeled more realistically so that simulations can comprehensively describe the dynamics of the supply chain system.

In this investigation, the SFD structure was developed into three main subsystems, namely Retailer and Demand, Total Production, and Total Cost. The Retailer and Demand subsystem represents inventory dynamics at the retailer level, which are influenced by customer demand, ordering decisions, and goods in transit that determine the balance between sales and stock shortages. The Total Production subsystem describes the production process, which includes the relationship between production targets, production capacity, production levels, and supplier inventory and work in process (WIP) that determine the system's ability to meet demand. Meanwhile, the Total Cost subsystem models the economic performance of the system through the interaction between sales revenue and various expenditure components such as production, storage, transportation, waste, and penalty costs, which collectively determine the net system cost value in the supply chain system.

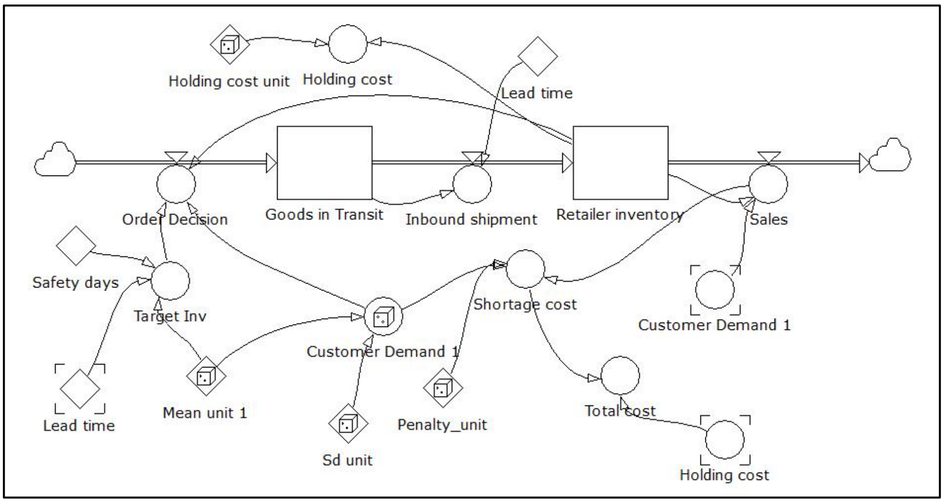

Figure 4. 5 Stock and Flow Diagram of Retailer and Demand

The retailer and demand stock and flow diagram show how inventory control at the retailer level is affected by customer demand, ordering decisions, and delivery delays. In this model, retailer inventory and goods in transit are stock variables that show the accumulation of goods at the retailer and goods still in transit. Inbound shipments increase inventory after passing the lead time, while sales reduce inventory according to customer demand. Ordering decisions are determined by the gap between target inventory and actual inventory conditions, taking into account average demand and safety days. In addition, the model also includes cost components such as holding costs due to inventory storage and shortage costs when demand is not met, so this structure displays how fluctuations in demand and supply delays affect inventory stability and costs in the system.

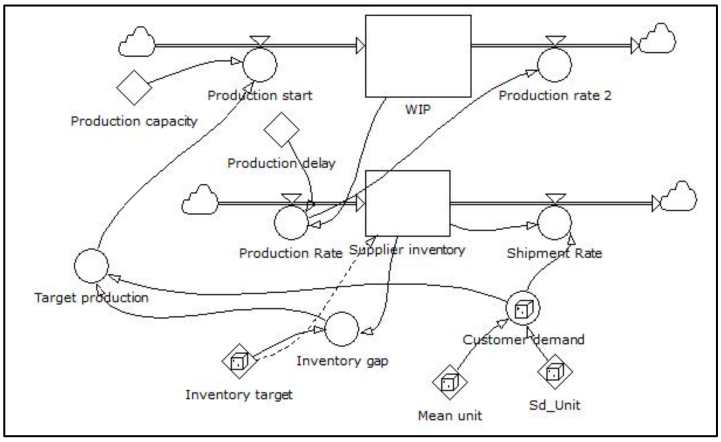

Figure 4. 6 Stock and Flow Diagram of Total Production

The total production Stock and Flow Diagram (SFD) show how materials are transformed at the supplier level, focusing on two main accumulations: Work in Process (WIP) and Supplier Inventory. The system's dynamics are driven by the Target Production variable, which is determined based on the Inventory Gap, the difference between the Target Inventory and the current inventory position, to initiate the Production Start rate. The flow of materials from WIP to Supplier Inventory is controlled by the Production Rate by integrating the Production Delay variable to reflect real-time constraints in the manufacturing process. Overall, this structure serves to align the Shipment Rate with stochastic fluctuations in Customer Demand, thereby ensuring product availability stability within the VMI ecosystem.

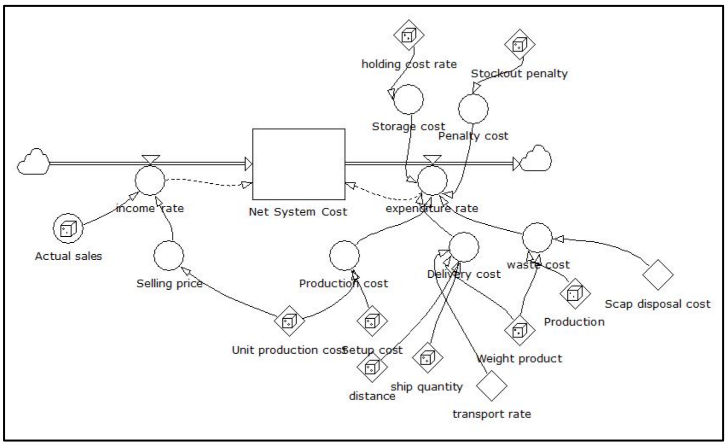

Figure 4. 7 Stock and Flow Diagram of Total Cost

The Total Cost Flow and Stock Diagram (SFD) show the accumulation of Net System Costs as the main stock variable determined by the balance between revenue and expenditure rates. While the rate of spending is the sum of all system running expenses, the rate of revenue is directly affected by the relationship between real sales and selling prices, including Production Costs, Setup Costs, Storage Costs, Shipping Costs, Penalty Costs, and Waste Costs. This structure confirms that the financial stability of the VMI system is highly dependent on management's ability to optimize logistics variables, such as shipping distance, product quantity, and waste management, in order to minimize cost outflows that can consume the overall accumulated balance of system costs.

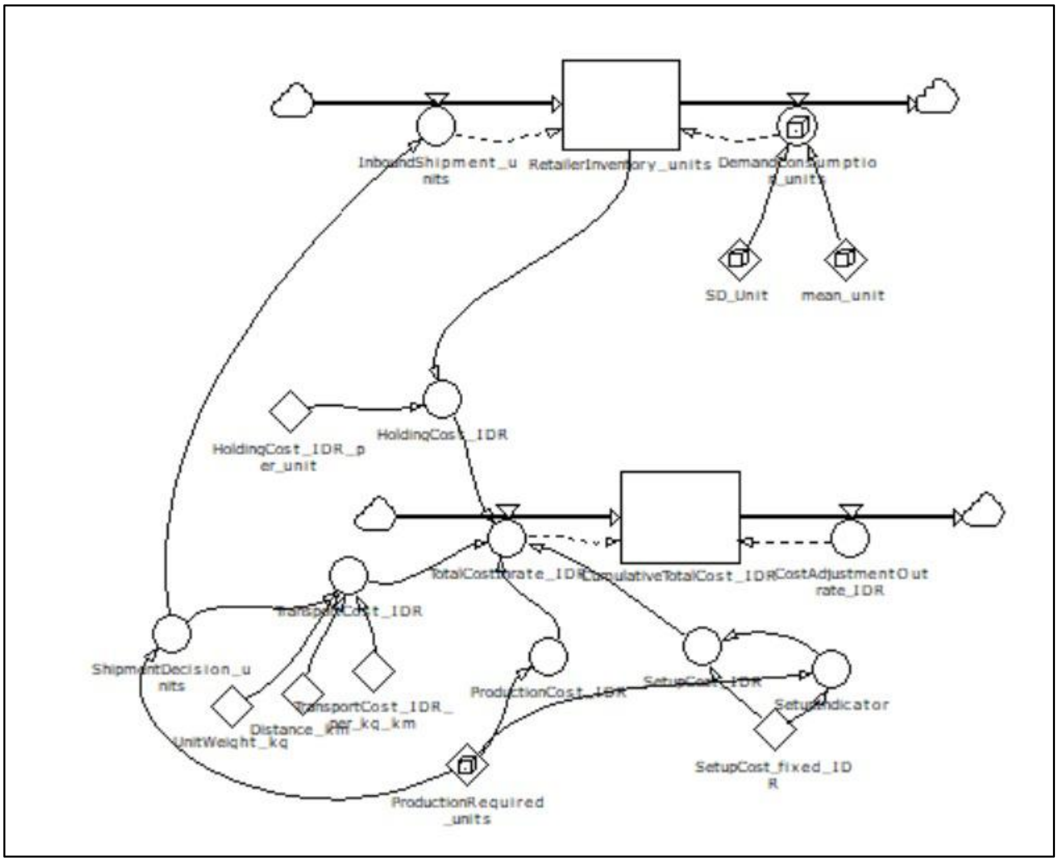

Figure 4. 8 Stock and Flow Diagram VMI

The Stock and Flow Diagram (SFD) displays the quantitative structure of the inventory and cost control system within the VMI framework, which centers on two main accumulations, namely Retailer Inventory as the physical stock of goods at the retailer level and Cumulative Total Cost as the accumulation of total system costs. Inventory changes are influenced by Inbound Shipment inflows and Demand Consumption outflows, where demand consumption is modeled using mean and SD parameters that indicate that demand is stochastic. The amount of inventory stored directly determines the Holding Cost through the Holding Cost parameter, so that the higher the inventory level, the greater the storage costs incurred. This structure emphasizes the close relationship between shipping decisions, demand variability, and stock dynamics, which are at the core of inventory system control.

On the cost side, Cumulative Total Cost is formed from the Total Cost Inrate inflow, which integrates various operational cost components, such as Production Cost, Transport Cost, Setup Cost, and Holding Cost, as well as the Cost Adjustment Outrate outflow as a cost adjustment mechanism. Production decisions represented by Production Required affect Production Cost, while Setup Cost is activated through the Setup Indicator, which indicates that there are fixed costs each time the production process is run. In terms of distribution, Shipment Decision is influenced by Distance, Unit Weight, and Transport Cost rates, which together form transportation costs. Overall, this SFD displays the integrated relationship between demand variability, production and shipping decisions, and inventory management in the formation of total system costs, enabling the model to be used to simultaneously evaluate inventory policies and operational cost efficiency.

4.2.3 Identify Variables

Variables in the model are grouped into several main types, namely stock (level), flow (rate), auxiliary, and constant, which represent system accumulation, rate of change, calculation intermediate variables, and fixed parameters, respectively. These variables are determined based on The outcomes of conceptual analysis through Causal Loop Diagrams and quantification requirements in Stock and Flow Diagrams, thereby comprehensively describing the interactions between demand, production, inventory, costs, and stock control policies. A complete list of variables used is presented in Table 4.5, including variable types, units, and equations.

Table 4. 5 Variable of Simulation Model

No	Variables	Type	Unit	Equation / Definition
1.	Setup Indicator	Auxiliary	dimensionless	MIN (1; Production Required)
2.	Setup Fixed Cost	Constant	IDR	30684.28571
3.	Setup Cost	Auxiliary	IDR/period	Setup Fixed Cost * Setup Indicator
4.	Production Required	Constant	unit/period	107; 551
5.	Production Cost	Auxiliary	IDR/period	Production Required
6.	Shipment Decision	Auxiliary	unit/period	Production Required
7.	Transport Cost	Constant	IDR/kg/km	300
8.	Distance	Constant	km	80.66666667
9.	Unit Weight	Constant	kg/unit	2.001428571
10.	Transport Cost	Auxiliary	IDR/period	Shipment Decision * Distance * Transport Cost * Unit Weight
11.	Holding Cost	Constant	IDR/unit/period	1082.857143
12.	Holding Cost	Auxiliary	IDR/period	Retailer Inventory * Holding Cost
13.	Cost Adjustment Outrate	Flow	IDR/period	0
14.	Total Cost Inrate	Flow	IDR/period	Holding Cost + Production Cost + Setup Cost + Transport Cost
15.	Demand Consumption	Flow	unit/period	0
16.	Inbound Shipment	Flow	unit/period	Shipment Decision
17.	Cumulative Total Cost	Stock	IDR	Cost Adjustment Outrate + Total Cost Inrate
18.	Retailer Inventory	Stock	unit	Demand Consumption + Inbound Shipment

Table 4.5 presents a list of variables used in the simulation model along with variable types, units, and equations that form the quantitative structure of System Dynamics. The variables in this table are grouped into several main types, namely constant, auxiliary, flow, and stock, which represent fixed parameters, intermediate calculation variables, rates of change, and system accumulations, respectively.

Variables such as Setup Indicator, Production Required, and Shipment Decision serve as triggers for operational decisions, while cost variables such as Production Cost, Transport Cost, and Holding Cost describe the components that make up the total cost. On the other hand, flow-type variables such as Total Cost Inrate and Demand Consumption show the dynamics of changes per period, while Cumulative Total Cost and Retailer Inventory as stock represent the accumulation of costs and inventory levels.

4.2.4 Model Validation

Model validation is performed to ensure that the structure and behavior of the developed model are capable of adequately representing the conditions of the real system. In this investigation, validation focused on comparing simulation results and historical data for key variables using the MAPE indicator. This approach was used to assess the accuracy of the model before it was further utilized in policy scenario analysis. MAPE calculations used the equation below. The validity results are showed in Table 4.6.

$$MAPE = \frac{1}{n} \sum \left| \frac{A - F_t}{A} \right| \times 100\%$$

Table 4. 6 Validation Using MAPE Result

Year	Actual (A)	Simulation (F_t)	Error (%)
2024	116.25	182.91	57.34%
2025	116.25	161.74	39.13%
2026	116.25	63.06	45.75%
2027	116.25	133.47	14.81%
2028	116.25	182.34	56.85%
2029	116.25	260.22	123.85%
2030	116.25	235.80	102.84%

MAPE=62.94%

A MAPE value of 62.94% indicates that the deviation between the simulation results and actual data is still relatively high. Based on general model validation criteria (MAPE > 50%), the model's accuracy level is categorized as inaccurate.

This indicates that the model still requires parameter refinement, particularly for the demand and delivery policy variables, so that the simulation behavior more closely resembles real conditions. Nevertheless, the model can still be used for exploratory analysis and policy scenario testing, but it certainly requires further calibration.

4.2.5 Simulation Results

The simulation results in this investigation aim to display and analyze the dynamic behavior of the system generated from the System Dynamics model that has been constructed based on the previous parameters and variable structures. The simulation results in this investigation aim to display and analyze the dynamic behavior of the system generated from the System Dynamics Model that has been constructed based on the previous parameters and variable structures. The simulation was conducted to observe how the interaction between demand, production, inventory, and cost variables affects the performance of the supply chain system over the simulation time horizon. Through this approach, the model not only describes the static conditions of the system, but also displays the patterns of change in key variables dynamically so that it can identify potential imbalances, inventory fluctuations, and changes in operational performance that arise due to interactions between system components.

Specifically, the simulation results presented in this investigation cover four main parts, namely the Retailer and Demand model, Total Production, Total Cost, and VMI model. The Retailer and Demand model describes inventory dynamics at the retailer level and the system's response to fluctuations in customer demand. The Total Production model displays how capacity and production levels adjust to system requirements in order to meet demand. Meanwhile, the Total Cost model evaluates changes in system costs arising from production, storage, transportation, and penalty costs. Finally, the VMI model is used to assess how the implementation of VMI policies affects inventory stability, supply coordination, and overall supply chain system performance.

Table 4. 7 Retailer and Demand Model Simulation Result

Year	Goods in Transit	Retailer Inventory
2025	0.00	500.00
2026	0.00	443.00
2027	54.08	378.79
2028	159.60	327.35
2029	331.21	261.26
2030	508.50	255.57
2031	628.63	312.74
2032	686.20	375.30
2033	672.91	446.16
2034	578.35	527.43
2035	462.68	602.25
2036	370.15	601.31
2037	296.12	587.49
2038	236.89	576.50
2039	189.51	536.27
2040	151.61	516.54
2041	121.29	522.50
2042	97.03	478.66
2043	117.88	412.02
2044	192.85	357.90
2045	322.26	303.46

The simulation results show that the dynamics of retailer inventory and goods in transit underwent interrelated changes throughout the simulation period. At the beginning of the period (2025–2030), retailer inventory decreased from 500 units to around 255 units as goods in transit increased, indicating a system response to increased demand through increased shipments. After this period, retailer inventory begins to increase and peaks around 2035–2036, while the number of goods in transit begins to decline, indicating that previously ordered supplies have begun to arrive and replenish retailer stock. In the next period (2037–2045), both variables gradually declined again, reflecting the system's adjustment to changes in demand and ordering decisions. This pattern displays a feedback mechanism between inventory levels, goods shipments, and customer demand that dynamically regulates stock balance in the supply chain system.

Table 4. 8 Total Production Model Simulation Result

Year	WIP	Production Rate	Supplier Inventory

Year	WIP	Production Rate	Supplier Inventory
2025	200.00	100.00	376.00
2026	184.34	92.17	391.66
2027	144.40	72.20	431.60
2028	190.98	95.49	385.02
2029	88.54	44.27	487.46
2030	118.93	59.46	457.07
2031	182.91	91.46	393.09
2032	193.52	96.76	382.48
2033	121.48	60.74	454.52
2034	134.51	67.25	441.49
2035	106.30	53.15	469.70
2036	182.74	91.37	393.26
2037	148.01	74.00	427.99
2038	111.29	55.64	464.71
2039	180.62	90.31	395.38
2040	133.87	66.94	442.13
2041	124.72	62.36	451.28
2042	145.17	72.59	430.83
2043	181.25	90.63	394.75
2044	101.08	50.54	474.92
2045	143.83	71.92	432.17

The Total Production simulation results show that the production dynamics of the system fluctuate throughout the simulation period in response to changes in inventory requirements in the supply chain. The Production Rate value decreased from 100 units in 2025 to around 44.27 units in 2029, then increased again to around 96.76 units in 2032 before fluctuating again to reach 71.92 units in 2045. This change is also evident in the Work in Process (WIP) value, which moves from 200 units at the beginning of the period, drops to around 88.54 units in 2029, then increases again to around 193.52 units in 2032 and continues to fluctuate in the following period. Meanwhile, Supplier Inventory remains relatively stable between approximately 376 units and 487 units throughout the simulation period, indicating the existence of an adjustment mechanism between production levels, production processes, and supply requirements to maintain inventory availability in the supply chain system

Table 4. 9 Total Cost Model Simulation Result

Year	Net System Cost	Income Rate	Expenditure Rate
2025	111,268,654.73	146,842,675.88	35,574,021.15
2026	222,537,309.47	37,549,081.35	35,574,021.15
2027	224,512,369.67	43,142,981.31	35,574,021.15
2028	232,081,329.83	88,065,955.92	35,574,021.15
2029	284,573,264.59	143,748,919.66	35,574,021.15
2030	392,748,163.11	133,396,896.99	35,574,021.15
2031	490,571,038.95	81,958,543.70	35,574,021.15
2032	536,955,561.50	104,236,279.43	35,574,021.15
2033	605,617,819.78	140,450,731.10	35,574,021.15
2034	710,494,529.74	83,056,503.73	35,574,021.15
2035	757,977,012.32	110,783,462.76	35,574,021.15
2036	833,186,453.94	149,148,517.41	35,574,021.15
2037	946,760,950.19	86,305,129.62	35,574,021.15
2038	997,492,058.66	105,750,764.44	35,574,021.15
2039	1,067,668,801.95	116,859,641.05	35,574,021.15
2040	1,148,954,421.86	107,828,783.98	35,574,021.15
2041	1,221,209,184.69	57,932,505.94	35,574,021.15
2042	1,243,567,669.48	48,865,380.78	35,574,021.15
2043	1,256,859,029.11	65,766,628.15	35,574,021.15
2044	1,287,051,636.11	130,165,348.82	35,574,021.15
2045	1,381,642,963.78	70,869,082.80	35,574,021.15

The Total Cost simulation results show that the Net System Cost increased consistently throughout the simulation period. The system cost value increased from 111,268,654.73 in 2025 to 1,381,642,963.78 in 2045, reflecting the accumulation of system operating costs over time. Although the expenditure rate remained constant at 35,574,021.15 per year, the income rate fluctuated significantly, for example, falling to 37,549,081.35 in 2026, then increasing to 149,148,517.41 in 2036, and changing again in the following period. These income fluctuations affect the rate of increase in Net System Cost, but overall system costs continue to show an upward trend due to the accumulation of ongoing expenditures within the system. This indicates that cost dynamics within the system are heavily influenced by variations in income and ongoing operational costs within the supply chain.

The simulation results focus on three main variables, namely Retailer Inventory Units, Demand Consumption Units, and Cumulative Total Cost to describe the behavior of the system over time and evaluate the operational performance of the supply chain in the 2024–2030 simulation horizon. The simulation results are used to observe changes in key variables such as inventory levels, demand consumption, and total cost accumulation over a certain period of time so that trends, fluctuations, and system responses to the applied policy assumptions can be seen.

Table 4. 10 VMI Model Simulation Results

Years	Retailer Inventory (unit)	Cumulative Total Cost (IDR)	Demand Consumption (unit)
2024	425.45	953,733,306.34	182.91
2025	485.07	1,907,466,612.68	161.74
2026	565.86	2,861,264,479.48	63.06
2027	745.33	3,815,149,836.49	133.47
2028	854.39	4,769,229,532.89	182.34
2029	914.59	5,723,427,327.70	260.22
2030	896.90	6,677,690,306.76	235.80

Based on Table 4.10, the Demand Consumption variable displays fluctuating behavior and indicates unstable demand characteristics throughout the 2024–2030 simulation period. At the beginning of the period, the level of demand consumption was at 182.91 units and gradually declined to a low point in 2026 of 63.06 units, indicating a phase of market contraction or consumption adjustment in the system. After this period, there was a sharp increase to 260.22 units in 2029 before declining slightly to 235.80 units in 2030. This ups and downs pattern indicates that the demand system in the model is influenced by stochastic variables and delivery decision responses, so it does not show a constant linear trend. These fluctuations also indicate that the VMI system must have flexibility in its replenishment mechanism in order to be able to adjust to changes in demand without causing supply imbalances. In other words, demand variability is the main factor that triggers changes in the behavior of other variables in the system, particularly inventory levels and operational costs.

On the other hand, the Retailer Inventory variable displays a relatively consistent upward trend from 425.45 units in 2024 to 914.59 units in 2029 before experiencing a slight decline to 896.90 units in 2030. This increase in inventory occurs despite fluctuations in demand, indicating that shipping and production decisions in the model tend to be more aggressive than actual consumption levels in some periods. The accumulation of stock has a direct implication on the increase in Cumulative Total Cost, which grows significantly from 953 million rupiah at the beginning of the simulation to more than 6.6 billion rupiah at the end of the period. This cost growth is not only influenced by increases in production and transportation volumes, but also by the accumulation of holding costs that continue to increase as inventory rises. The relationship between inventory and total costs displays a reinforcing loop, where increased stock triggers a cumulative increase in costs. Overall, the simulation results show a clear trade-off between the system's ability to maintain product availability and operational cost efficiency. The system is able to significantly avoid the risk of stockouts, but the consequence is an increase in costs due to the accumulation of suboptimal inventory, thus emphasizing the importance of evaluating inventory control policies at the advanced scenario analysis stage.

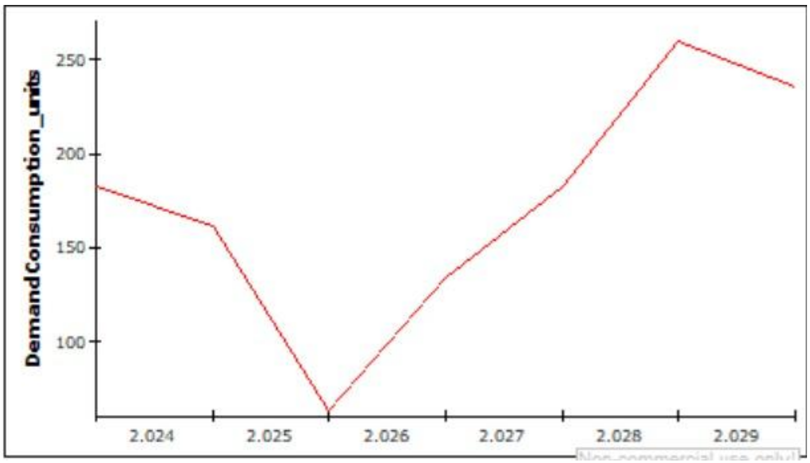

Figure 4. 3 Demand Consumption scenario

Figure 4.3 displays fluctuating and non-linear demand patterns throughout the simulation period, reflecting market demand dynamics within the system. At the beginning of the period, there is a downward trend in demand, reaching its lowest point around 2026, followed by a sharp increase, peaking around 2029 before experiencing a slight decline at the end of the simulation horizon. This pattern indicates that the demand variable in the model is influenced by uncertainty factors and delivery policy responses, so that it does not form a stable trend over time. These fluctuations indicate that the supply system needs to have a high adaptability, because significant changes in demand have the potential to affect production decisions, inventory levels, and overall operational costs.

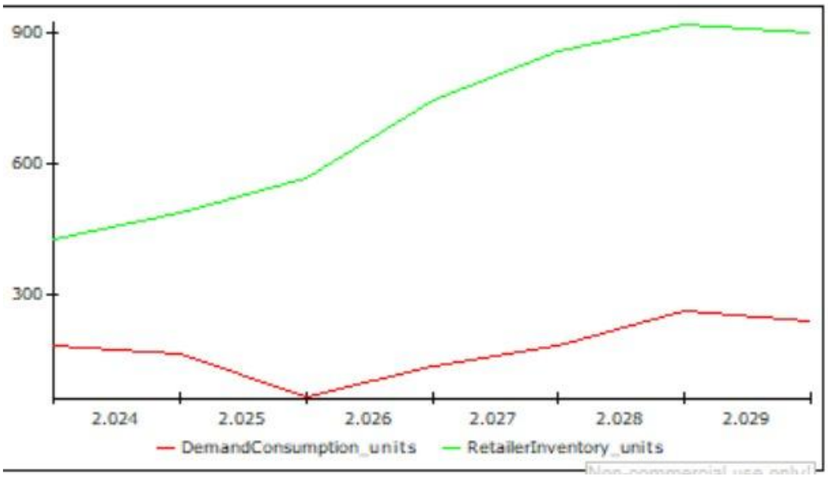

Figure 4. 4 Demand Consumption and retailer inventory scenario

Figure 4.4 displays an imbalance between demand and inventory accumulation throughout the simulation period. It can be seen that when demand declined significantly at the beginning of the period until around 2026, inventory levels continued to increase consistently. After demand rebounded in the following period, inventory remained on an upward trend and only experienced a slight correction at the end of the simulation horizon. This pattern indicates a delay response in shipping or production decisions, where stock adjustments do not directly follow changes in demand. This condition reflects the characteristics of the VMI system, which tends to maintain high levels of stock availability to avoid the risk of stockouts, but on the other hand, has the potential to cause inventory buildup and increased storage costs if not balanced with a more adaptive inventory control mechanism.

CHAPTER V
DISCUSSION

5.1 Analysis of dynamic system behavior and model validation

Analysis of the developed System Dynamics model displays complex interactions between stochastic demand variables and stock fulfillment policies within the VMI framework. Based on validity testing results, the MAPE value is 62.94%. Although statistically this value is categorized as inaccurate for precision predictions (MAPE > 50), this model has high heuristic value in representing the internal structure of the system and behavior patterns. Significant deviations, especially in demand fluctuations in 2029 which reached 260.22 units, reflect the volatile characteristics of electronic products. Theoretically, Forrester (1961) in the fundamental literature on system dynamics asserts that the validity of a model is not only measured by the numerical accuracy of point-by-point predictions, but also by its ability to capture the structural dynamics that drive the overall behavior of the system. Therefore, this model remains valid as a management laboratory instrument for testing the sensitivity of production and logistics variables to total system costs.

The imbalance between Demand Consumption and Retailer Inventory accumulation is a critical finding in this analysis. Simulation data displays that when demand contracted to its lowest point in 2026 at 63.06 units, inventory levels continued to increase consistently. This phenomenon indicates a delay response in shipping decisions that fail to instantly adjust to market fluctuations. In SCM, this condition triggers disproportionate inventory buildup. As explained by Sterman (2000), the time lag between receiving demand information and executing shipments often creates an oscillating effect that worsens efficiency. This is reinforced by the observations in Figure 4.4, where inventory remains on an upward trend ( ) even though demand has not fully recovered, indicating the need for a more adaptive stock control mechanism.

The cumulative total cost, which grew significantly from IDR 953.7 million in 2024 to IDR 6.67 billion at the end of the 2030 period, displays the dominance of reinforcing loops in the financial structure of the system. This cost growth is not only driven by production volume, but is substantially burdened by the accumulation of holding costs due to inventory buildup, which peaks at 914.59 units in 2029. This model successfully integrates external costs such as the carbon price of IDR 100,000 per ton of CO2 and social overtime costs of up to IDR 70,000 per hour. However, analysis displays that the policy of maintaining a service level of 95% to avoid stockout penalties results in suboptimal storage cost inflation. This is in line with research by Disney and Towill (2003), which states that without order frequency synchronization, VMI systems risk experiencing a negative trade-off between inventory availability and working capital efficiency.

The manufacturing production aspect of the model displays the crucial influence of the baseline scrap rate and labor capacity on effective output. With the difference in characteristics between Suppliers S1 and S2, where the unit cost of products in S2 is higher (Rp801,924) but has a lower scrap rate (3.54%) than S1, the model illustrates the dilemma between quality and cost. The use of overtime to achieve production targets has a direct impact on carbon cost and social cost. This analysis proves that system efficiency depends not only on delivery speed, but also on process stability at the supplier level. As stated by Govindan et al. (2015), the integration of environmental parameters such as CO2 emissions (up to 8.6 kg/CO2 per unit for certain products) into simulation models is essential to support sustainable and competitive green supply chain strategies.

Overall, this model analysis confirms the existence of a strong functional relationship between demand variability, production decisions, and inventory management on the formation of total system costs. The Stock and Flow Diagram structure that was developed was able to map the cost inflow (Total Cost Inrate), which includes production, transport, setup, and holding costs in an integrated manner. Although the system was able to significantly avoid the risk of stockouts through aggressive stock policies, inefficiencies in inventory accumulation became a weak point that needed to be addressed. The relationship between Shipment

Decisions, which are influenced by physical parameters such as unit weight (up to 2.99 kg) and distance traveled, is a key variable in logistics efficiency. These findings provide a fundamental basis for the development of policy scenarios in the next sub-chapter to optimize VMI system performance through policy parameter adjustments that are more responsive to market dynamics.

5.2 Development and Evaluation of VMI Policy Scenarios

The development of scenarios in this system dynamics model aims to analyze the effect of interactions between fluctuating customer demand, inventory policies, and supplier capacity on VMI performance. Based on The outcomes of the basic simulation, it was found that the interaction between unstable demand (ranging from 63.06 to 260.22 units) and aggressive delivery policies triggered inefficient stock accumulation at the retailer level. The first scenario focused on synchronizing supplier capacity (S1 and S2) with overtime thresholds (450 hours) to see the extent to which production responsibilities could mitigate stock deficits without triggering social cost explosions. This is in line with the theory proposed by Kristianto et al. (2012), which states that capacity flexibility is key to maintaining the stability of the VMI system amid demand uncertainty.

The interaction between inventory policy and operational capacity is further evaluated by adjusting Order Frequency and Ship Quantity as intervention variables. In the optimization scenario, the original static delivery policy is changed to a policy based on inventory thresholds (reorder points), whereby deliveries are only made when retailer stock falls below a certain safety level. This step was taken to address the trend of increasing inventory from 425.45 units to 914.59 units, which had previously occurred continuously despite declining demand. According to research by Yao et al. (2007), synchronizing order frequency within the VMI framework can significantly reduce total system costs by balancing the burden between transportation and storage costs.

The second scenario evaluates the integration of carbon emission costs of Rp100,000 per ton of CO_2 and transportation costs of Rp300/kg/km as the basis for determining the most optimal route and delivery quantity. The analysis was conducted by comparing the "business as usual" scenario with the "green logistics" scenario, which prioritizes the use of suppliers with low scrap rates and more efficient travel distances. The data displays that the highest carbon emissions are found in P3 products (8.6 kg/CO2/unit), so the policy scenario is directed at consolidating shipments for products with high carbon footprints in order to reduce the Cumulative Total Cost. As stated by Bouchery et al. (2012), incorporating carbon price parameters into the classic inventory model allows companies to identify trade-offs between economic efficiency and environmental impact more accurately.

An evaluation of various scenarios displays that the most optimal policy is an integrated scenario that combines adaptive inventory control with quality-based supplier selection. This scenario successfully reduced the growth rate of the Cumulative Total Cost, which previously reached Rp6.67 billion, by reducing the accumulation of holding costs through a more responsive Pressure to Reduce Inventory mechanism. Through the System Dynamics approach, it can be seen that targeted inventory reduction does not lower the target service level (95%), but rather optimizes storage space utilization at retailers. A study by Claassen et al. (2008) reinforces this finding by emphasizing that the success of VMI is highly dependent on the quality of cooperation and accurate data exchange between suppliers and buyers.

Furthermore, the effectiveness of the policy scenario is also measured by its ability to mitigate the bullwhip effect that arises due to delays in responding to changes in customer demand. By calibrating the Shipment Decision variable, the system displays better stability, where inventory fluctuations become more aligned with Demand Consumption patterns. This confirms that intervention in the inventory policy structure can change the behavior of the system from one that tends to accumulate stock (reinforcing loop) to a more balanced system (balancing loop) between supply and demand. Angappa Gunasekaran et al. (2004) emphasize that supply chain performance metrics in a competitive environment must include both response speed and cost efficiency simultaneously, which in this investigation is evidenced by a decrease in total costs per period.

An in-depth analysis of the optimization scenario also highlights the importance of capacity management at suppliers S1 and S2 to support supply sustainability. By setting Production Required to remain below the overtime threshold, social costs and ergonomic penalties of Rp1,500 per hour can be minimized without sacrificing Effective Output. Both the system's bottom line and the supplier chain's ethical standards in human resource management will benefit from this policy's implementation. The International Journal of Production Economics by Tang et al. (2005) notes that the integration of capacity management and worker welfare in system dynamics simulations provides a more holistic view of long-term operational risks.

As a conclusion from the scenario comparison, the most optimal VMI policy was identified as the policy capable of dynamically adjusting the delivery rate (Inbound Shipment) to demand deviations (SD units). This policy provides the best results in balancing the risk of stockout penalties with the burden of expensive storage costs. By implementing The outcomes of this scenario, organizations can achieve the targets of a resilient system performance, environmental sustainability through emission reduction, and financial efficiency. This investigation proves that the System Dynamics approach through Powersim is very effective in evaluating the long-term impact of complex managerial decisions in modern supply chains.

5.3 Managerial Implications

The findings of this study have crucial implications for supply chain managers regarding the importance of balancing stock availability policies with storage cost efficiency. The strategy of maintaining a target service level of 95% to avoid stockout penalties did indeed succeed in ensuring market demand was met, but without an adaptive control mechanism, this policy led to inventory accumulation reaching more than 900 units at the end of the simulation period. Managers need to be aware that the total cost accumulation, which ballooned to Rp6.67 billion, was largely driven by cumulative holding costs. Therefore, a paradigm shift from aggressive delivery policies to demand-responsive inventory management is needed to mitigate the risk of unnecessary working capital inflation.

Operationally, integrating environmental aspects into the model emphasizes that logistics decisions can no longer be based solely on traditional transportation costs. The existence of a carbon price parameter of IDR 100,000 per ton of CO_2 and variations in production emissions between products, such as high emissions in AC Display & Control Boards of 8.6 kg/CO_2 per unit, requires managers to start adopting green procurement strategies. Supplier selection decisions must consider the trade-off between unit cost and manufacturing quality, where using suppliers with low scrap rates (such as S2 with 3.54%) can reduce production waste despite higher initial operating costs. Management should prioritize consolidating shipments for products with large unit weights, such as Refrigerator Mainboards (2.99 kg/unit), to optimize distribution costs per kilogram-kilometer.

Finally, managers must pay attention to the dimension of employee welfare through the management of overtime social costs, which are set at between Rp65,000 and Rp70,000 per hour. Reliance on overtime to achieve effective output amid fluctuating demand can increase ergonomic risks and the company's financial burden through penalty costs of Rp1,500 per hour worked. The managerial implication is the need for more accurate capacity planning and investment in worker training to increase standard hourly productivity, thereby reducing reliance on additional working hours. By integrating economic, environmental, and social performance metrics, companies can build a VMI system that is not only operationally robust but also strategically sustainable.

CHAPTER VI
CONCLUSION AND SUGGESTION

6.1 Conclusion

The outcomes of the study indicate that the interaction between customer demand fluctuations, inventory policy, and supplier capacity has a significant effect on VMI system performance. Stochastic demand dynamics, ranging from 63.06 to 260.22 units, trigger imbalances in inventory levels due to delays in delivery decisions. An overly aggressive shipping policy to maintain a 95% service level causes inventory accumulation of up to 914.59 units. This has an impact on the escalation of the Cumulative Total Cost, which grows significantly from IDR 953.7 million to IDR 6.67 billion, where storage costs (holding costs) become a dominant burden due to suboptimal stock accumulation.

Through the evaluation of various policy scenarios using the System Dynamics approach, it was found that the most optimal VMI policy is an integrated scenario that synchronizes order frequency with a more responsive inventory threshold. This scenario is able to reduce the rate of total cost growth without sacrificing product availability at the retailer level. The use of environmental parameters such as a carbon price of IDR 100,000 per ton of CO2 and supplier quality considerations (such as a low scrap rate of 3.54% in S2) proved effective in balancing economic efficiency and sustainability. Thus, policy integration that prioritizes logistics efficiency and replenishment accuracy is key to simultaneously improving system performance.

6.2 **Suggestion**

Based on the research findings, it is recommended that management immediately recalibrate the shipment decision mechanism to be more adaptive to actual demand patterns in order to avoid excessive stock accumulation. The company needs to consider implementing a real-time integrated information system between retailers and suppliers to reduce policy response delays. In addition, cost optimization can be achieved by evaluating distribution routes and product unit weight in more detail to reduce transportation and carbon costs, which are components of total costs.

For further research, it is recommended that the model be developed by adding broader external variables, such as fluctuations in raw material prices or more complex distribution constraints beyond the current nine retailers. The use of more sophisticated demand forecasting methods (such as Machine Learning) can be integrated into the simulation model to reduce the current high MAPE value (62.94%) so that the model's prediction accuracy becomes more reliable. Finally, future research could also explore scenarios of collaboration between more suppliers with different production technology characteristics to enrich risk mitigation strategies in the supply chain.

BIBLIOGRAPHY

Adegbola, K. (2023). A simulation study of single-vendor, single and multiple-manufacturers supply chain system, with stochastic demand and two distribution policies. *Journal of Decision Analytics and Intelligent Computing*, *3*(1), 62–79. https://doi.org/10.31181/jdaic10010052023a

Andaz, S., Eisenach, C., Madeka, D., Torkkola, K., Jia, R., Foster, D., & Kakade, S. (2024). *Learning an Inventory Control Policy with General Inventory Arrival Dynamics*. http://arxiv.org/abs/2310.17168

Andriansyah, A., Rahmi, A., & Ilyas, I. (2020). Using System Dynamic Model for Predicting Inventory of Rice Necessity. *Journal of Physics: Conference Series*, *1569*(2), 022102. https://doi.org/10.1088/1742-6596/1569/2/022102

Angulo, A., Nachtmann, H., & Waller, M. A. (2004). Supply Chain Information Sharing in a Vendor Managed Inventory Partnership. *Journal of Business Logistics*, *25*(1), 101–120. https://doi.org/10.1002/j.2158-1592.2004.tb00171.x

Anna, I. D. (2016). The Implementation of Vendor Managed Inventory In the Supply Chain with Simple Probabilistic Inventory Model. *MATEC Web of Conferences*, *58*, 02008. https://doi.org/10.1051/matecconf/20165802008

Badillo, I., Tejeida, R., Morales, O., & Flores, M. (2011). Supply Chain Management from a Systems Science Perspective. In *Supply Chain Management - New Perspectives*. InTech. https://doi.org/10.5772/22229

Barlas, Y. (2020). Editorial: On System Dynamics Review. In *System Dynamics Review* (Vol. 36, Issue 3, pp. 243–246). John Wiley and Sons Ltd. https://doi.org/10.1002/sdr.1666

Bazan, E., Jaber, M. Y., Zanoni, S., & Zavanella, L. E. (2014). Vendor Managed Inventory (VMI) with Consignment Stock (CS) agreement for a two-level supply chain with an imperfect production process with/without restoration interruptions. *International Journal of Production Economics*, *157*(1), 289–301. https://doi.org/10.1016/j.ijpe.2014.02.010

Borade, A. B., & Sweeney, E. (2015). Decision support system for vendor managed inventory supply chain: A case study. *International Journal of Production Research*, *53*(16), 4789–4818. https://doi.org/10.1080/00207543.2014.993047

Bouchery, Y., Ghaffari, A., Jevetic, O., & Corbett, C. J. (2012). The classical economic order quantity model revisited with environmental considerations. *International Journal of Production Economics*, 137(1), 22-30

Cai, J., Tadikamalla, P. R., Shang, J., & Huang, G. (2017). Optimal inventory decisions under vendor managed inventory: Substitution effects and replenishment tactics. *Applied Mathematical Modelling*, *43*, 611–629. https://doi.org/10.1016/j.apm.2016.11.027

Claassen, M. J., van Weele, A. J., & van Raaij, E. M. (2008). Performance outcomes and success factors of vendor managed inventory (VMI). *Supply Chain Management: An International Journal*, 13(6), 406-414.

Contreras, A. N., Guerrero, W., & Besiou, M. (2024, July 16). Pharmaceutical Inventory Management Using Industry 4.0 Technologies Based on Collaborative Demand: A System Dynamics Approach. *Proceedings of the International Conference on Industrial Engineering and Operations Management*. https://doi.org/10.46254/EU07.20240205

Darwish, M. A., & Odah, O. M. (2010). Vendor managed inventory model for single-vendor multi-retailer supply chains. *European Journal of Operational Research*, *204*(3), 473–484. https://doi.org/10.1016/j.ejor.2009.11.023

Dasaklis, T., & Casino, F. (2019). Improving Vendor-managed Inventory Strategy Based on Internet of Things (IoT) Applications and Blockchain Technology. *IEEE International Conference on Blockchain and Cryptocurrency (ICBC)*, 50–55.

Disney, S. M., & Lambrecht, M. R. (2005). On Replenishment Rules, Forecasting, and the Bullwhip Effect in Supply Chains. *Foundations and Trends® in Technology, Information and Operations Management*, *2*(1), 1–80. https://doi.org/10.1561/0200000010

Disney, S. M., & Towill, D. R. (2003). Vendor managed inventory and bullwhip reduction in a two-level supply chain. *International Journal of Operations & Production Management*, 23(6), 625-651.

Duggan, J. (2016). *An Introduction to System Dynamics* (pp. 1–24). https://doi.org/10.1007/978-3-319-34043-2_1

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

Fry, M. J. (2011). Vendor-Managed Inventory. In *Wiley Encyclopedia of Operations Research and Management Science*. Wiley. https://doi.org/10.1002/9780470400531.eorms0952

Galarneau, K. D., Singer, R. S., & Wills, R. W. (2020). A system dynamics model for disease management in poultry production. *Poultry Science*, *99*(11), 5547–5559. https://doi.org/10.1016/j.psj.2020.08.011

Gangopadhyay, A., & Huang, Z. (2004). Studying the Value of Information Sharing in E-Business Supply Chain Management. *Journal of International Technology and Information Management*, *13*(1). https://doi.org/10.58729/1941-6679.1241

Gebisa, D. A. (2023). The Impact of Information Sharing and Inventory Management Practices on Firms' Performance in Supply Chain Practices. *Gadjah Mada International Journal of Business*, *25*(2), 199. https://doi.org/10.22146/gamaijb.69616

Ghasemi, E., Lehoux, N., & Rönnqvist, M. (2024). A multi-level production-inventory-distribution system under mixed make to stock, make to order, and vendor managed inventory strategies: An application in the pulp and paper industry. *International Journal of Production Economics*, *271*. https://doi.org/10.1016/j.ijpe.2024.109201

Govindan, K. (2013). Vendor-managed inventory: a review based on dimensions. *International Journal of Production Research*, *51*(13), 3808–3835. https://doi.org/10.1080/00207543.2012.751511

Govindan, K., Rajendran, S., Sarkis, J., & Murugesan, P. (2015). Multi objective optimization for thermodynamic closed loop supply chain: Case study of a pharmaceutical company. *European Journal of Operational Research*, 243(1), 332-348.

Gunasekaran, A., Patel, C., & McGaughey, R. E. (2004). A framework for supply chain performance measurement. *International Journal of Production Economics*, 87(3), 333-347.

Harahap, A. Z. M. K., Mohd Zahari, A. S., Ali, N. M., & Ma'arof, R. A. (2024). Enhancing Supply Chain Efficiency: Implementation of Vendor Managed Inventory in Inventory Routing Problem. *Information Management and Business Review*, *16*(2(I)S), 212–218. https://doi.org/10.22610/imbr.v16i2(I)S.3761

Harahap, A. Z. M. K., & Rahim, M. K. I. A. (2017). Deterministic Inventory Routing Problem (DIRP): A Literature Review. *International Journal of Supply Chain Management*, *6*(4), 284–288. http://excelingtech.co.uk/

Hariga, M., Gumus, M., Daghfous, A., & Goyal, S. K. (2013). A vendor managed inventory model under contractual storage agreement. *Computers and Operations Research*, *40*(8), 2138–2144. https://doi.org/10.1016/j.cor.2013.03.005

Herdiani, L., Jamaludin, M., Sudirman, I., -, W., & Rohimat, I. (2025). A System Dynamics Model of Frozen Fish Supply Chain. *International Journal of Advanced Computer Science and Applications*, *16*(1). https://doi.org/10.14569/IJACSA.2025.0160183

Hong, X., Chunyuan, W., Xu, L., & Diabat, A. (2016). Multiple-vendor, multiple-retailer based vendor-managed inventory. *Annals of Operations Research*, *238*(1–2), 277–297. https://doi.org/10.1007/s10479-015-2040-0

Janamanchi, B., & Burns, J. R. (2013). Control Theory Concepts Applied to Retail Supply Chain: A System Dynamics Modeling Environment Study. *Modelling and Simulation in Engineering*, *2013*, 1–14. https://doi.org/10.1155/2013/421350

Jin, H. W. (2017). Analysis of lead time effects on VMI system: system dynamics approach. *International Journal of Applied Management Science*, *9*(1), 38. https://doi.org/10.1504/IJAMS.2017.10003206

Joseph, J. F., Sundarakani, B., Hosie, P., & Nagarajan, S. (2010). Analysis of vendor managed inventory practices for greater supply chain performance. *International Journal of Logistics Economics and Globalisation*, *2*(4), 297. https://doi.org/10.1504/IJLEG.2010.037518

Kaasgari, M. A., Imani, D. M., & Mahmoodjanloo, M. (2017). Optimizing a vendor managed inventory (VMI) supply chain for perishable products by considering discount: Two calibrated meta-heuristic algorithms. *Computers and Industrial Engineering*, *103*, 227–241. https://doi.org/10.1016/j.cie.2016.11.013

Keliji, P. B., Aghajani, H. A., Movahedi, M. M., & Shayannia, S. A. (2022). The Analysis of the Role of Bullwhip Effects on the Four-Level Supply Chain in Industry Using Statistical Methods. *Discrete Dynamics in Nature and Society*, *2022*(1). https://doi.org/10.1155/2022/2720244

Krichanchai, S., & MacCarthy, B. L. (2017). The adoption of vendor managed inventory for hospital pharmaceutical supply. *The International Journal of Logistics Management*, *28*(3), 755–780. https://doi.org/10.1108/IJLM-01-2015-0010

Kristianto, Y., Helo, P., Jiao, R. J., & Sandhu, M. (2012). Adaptive supply chain configuration by a vendor managed inventory (VMI) policy. *International Journal of Production Economics*, 137(2), 209-224.

Lee, J. Y., Paik, S. K., & Cho, R. K. (2015). Vendor-managed inventory: a literature review on theoretical and empirical studies and future research directions. *International Journal of Advanced Operations Management*, *7*(3), 199. https://doi.org/10.1504/IJAOM.2015.074209

Lee, T., Min, J., & Park, J. (2010). Analyzing impact of financial information sharing on supply chain performance and stability: system dynamics approach. *Journal of International Logistics and Trade*, *8*(2), 91–116. https://doi.org/10.24006/jilt.2010.8.2.005

Lee, H. L., Padmanabhan, V., & Whang, S. (1997). Information distortion in a supply chain: The bullwhip effect. *Management Science*, 43(4), 546-558.

Lin, J., Naim, M. M., Purvis, L., & Gosling, J. (2017). The extension and exploitation of the inventory and order based production control system archetype from 1982 to 2015. *International Journal of Production Economics*, *194*, 135–152. https://doi.org/10.1016/j.ijpe.2016.12.003

Lin, J., Naim, M. M., & Spiegler, V. L. M. (2020). Delivery time dynamics in an assemble-to-order inventory and order based production control system.

International Journal of Production Economics, *223*, 107531. https://doi.org/10.1016/j.ijpe.2019.107531

Liu, P., Atifeh, M., Khorshidnia, M., & Taheri, S. G. (2023). System Dynamics: An Approach to Modeling Supply Chain Performance Measurement. *Technological and Economic Development of Economy*, *29*(4), 1291–1317. https://doi.org/10.3846/tede.2023.19211

Maani, K. (2009). System Dynamics and Organizational Learning. In *Encyclopedia of Complexity and Systems Science* (pp. 9043–9057). Springer New York. https://doi.org/10.1007/978-0-387-30440-3_543

Martinez-Moyano, I. (2023). System Dynamics in Action. *Journal of Systems Thinking*, *3*(1). https://doi.org/10.54120/jost.000001

Mateen, A., & Chatterjee, A. K. (2015). Vendor managed inventory for single-vendor multi-retailer supply chains. *Decision Support Systems*, *70*, 31–41. https://doi.org/10.1016/j.dss.2014.12.002

Moharana, H., Murty, J. S., Senapati, S. K., & Khuntia, K. (2010). Coordination, Collaboration and Integration for Supply Chain Management. *Interscience Management Review*, 16–20. https://doi.org/10.47893/IMR.2010.1044

Mokhtari, H., & Rezvan, M. T. (2020). A single-supplier, multi-buyer, multi-product VMI production-inventory system under partial backordering. *Operational Research*, *20*(1), 37–57. https://doi.org/10.1007/s12351-017-0311-z

Morales, S. A. H., & Andrade-Arenas, L. (2021). Inventory Management Analysis under the System Dynamics Model. *International Journal of Advanced Computer Science and Applications*, *12*(1). https://doi.org/10.14569/IJACSA.2021.0120174

Najafnejhad, E., Tavassoli Roodsari, M., Sepahrom, S., & Jenabzadeh, M. (2021). A mathematical inventory model for a single-vendor multi-retailer supply chain based on the Vendor Management Inventory Policy. *International Journal of System Assurance Engineering and Management*, *12*(3), 579–586. https://doi.org/10.1007/s13198-021-01120-z

Nuñez Rodriguez, J., Andrade Sosa, H. H., Villarreal Archila, S. M., & Ortiz, A. (2021). System Dynamics Modeling in Additive Manufacturing Supply Chain Management. *Processes*, *9*(6), 982. https://doi.org/10.3390/pr9060982

Omar, I. A., Jayaraman, R., Salah, K., Debe, M., & Omar, M. (2020). Enhancing Vendor Managed Inventory Supply Chain Operations Using Blockchain Smart Contracts. *IEEE Access*, *8*, 182704–182719. https://doi.org/10.1109/ACCESS.2020.3028031

Onotole, E. F., Ogunyankinnu, T., Osunkanmibi, A. A., Adeoye, Y., Ukatu, C. E., & Ajayi, O. A. (2023). AI-Driven Optimization for Vendor-Managed Inventory in Dynamic Supply Chains. *Journal of Frontiers in Multidisciplinary Research*, *4*(1), 59–71. https://doi.org/10.54660/.IJFMR.2023.4.1.59-71

Ortiz-Barrios, M., Miranda-De la Hoz, C., López-Meza, P., Petrillo, A., & De Felice, F. (2020). A case of food supply chain management with AHP, DEMATEL, and TOPSIS. *Journal of Multi-Criteria Decision Analysis*, *27*(1–2), 104–128. https://doi.org/10.1002/mcda.1693

Pietron, R. (2023). Management system structure vs. behavior – a supply chain simulation analysis. *Scientific Papers of Silesian University of Technology. Organization and Management Series*, *2023*(169), 575–597. https://doi.org/10.29119/1641-3466.2023.169.35

Rabbani, M., Rezaei, H., Lashgari, M., & Farrokhi-Asl, H. (2018). Vendor managed inventory control system for deteriorating items using metaheuristic algorithms. *Decision Science Letters*, 25–38. https://doi.org/10.5267/j.dsl.2017.4.006

Rathore, R., Thakkar, J. J., & Jha, J. K. (2021). Impact of risks in foodgrains transportation system: a system dynamics approach. *International Journal of Production Research*, *59*(6), 1814–1833. https://doi.org/10.1080/00207543.2020.1725683

Salas-Navarro, K., Romero-Montes, J. M., Acevedo-Chedid, J., Ospina-Mateus, H., Florez, W. F., & Cárdenas-Barrón, L. E. (2023). Vendor managed inventory system considering deteriorating items and probabilistic demand for a three-layer supply chain. *Expert Systems with Applications*, *218*. https://doi.org/10.1016/j.eswa.2023.119608

Santoso, I., Sa'adah, M., & Asmaul Mustaniroh, S. (2019). Scenario development for improving supply chain performance using the system dynamics approach. *International Journal of Engineering & Technology*, *8*(4), 535. https://doi.org/10.14419/ijet.v8i4.29796

Sentia, P. D., Andriansyah, Rizki Agam Syahputra, Chairil Akbar, & Wyona Allysha Rustandi Putri. (2022). System Dynamic Modeling: A Case Study of a Hotel Food Supply Chain. *Jurnal RESTI (Rekayasa Sistem Dan Teknologi Informasi)*, *6*(4), 521–527. https://doi.org/10.29207/resti.v6i4.4077

Shou, Y. (2013). Perspectives on Supply Chain Management in the Healthcare Industry. *Proceedings of the 2nd International Conference on Science and Social Research*. https://doi.org/10.2991/icssr-13.2013.144

Shu, J., Li, Z., Shen, H., Wu, T., & Zhong, W. (2012). A logistics network design model with vendor managed inventory. *International Journal of Production Economics*, *135*(2), 754–761. https://doi.org/10.1016/j.ijpe.2011.10.008

Song, Y. G., & Yun, E. K. (2015). Model for Unplanned Self Extubation of ICU Patients Using System Dynamics Approach. *Journal of Korean Academy of Nursing*, *45*(2), 280. https://doi.org/10.4040/jkan.2015.45.2.280

Sterman, J. D. (2000). *Business Dynamics: Systems Thinking and Modeling for a Complex World*. McGraw-Hill.

Tang, O., & Musa, S. N. (2011). Identifying risk issues and research sides in supply chain management. *International Journal of Production Economics*, 133(1), 25-39.

Tang, L., Yang, T., Tu, Y., & Ma, Y. (2021). Supply chain information sharing under consideration of bullwhip effect and system robustness. *Flexible Services and Manufacturing Journal*, *33*(2), 337–380. https://doi.org/10.1007/s10696-020-09384-6

Torres, J. P., Kunc, M., & O'Brien, F. (2017). Supporting strategy using system dynamics. *European Journal of Operational Research*, *260*(3), 1081–1094. https://doi.org/10.1016/j.ejor.2017.01.018

Tyan, J., & Wee, H.-M. (2003). Vendor managed inventory: a survey of the Taiwanese grocery industry. In *Journal of Purchasing & Supply Management* (Vol. 9).

van den Bogaert, J., & van Jaarsveld, W. (2022). Vendor-managed inventory in practice: understanding and mitigating the impact of supplier heterogeneity. *International Journal of Production Research*, *60*(20), 6087–6103. https://doi.org/10.1080/00207543.2021.1983222

Verma, N. K., & Chatterjee, A. K. (2017). A multiple-retailer replenishment model under VMI: Accounting for the retailer heterogeneity. *Computers & Industrial Engineering*, *104*, 175–187. https://doi.org/10.1016/j.cie.2016.12.001

Wei, Y., Chen, F., & Wang, H. (2018). Inventory and Production Dynamics in a Discrete-Time Vendor-Managed Inventory Supply Chain System. *Discrete Dynamics in Nature and Society*, *2018*, 1–15. https://doi.org/10.1155/2018/6091946

Xu, W., Song, D. P., & Roe, M. (2010). Supply chain performance improvement using vendor management inventory strategy. *2010 IEEE International Conference on Industrial Engineering and Engineering Management*, 1170–1174. https://doi.org/10.1109/IEEM.2010.5674335

Yao, Y., Evers, P. T., & Dresner, M. E. (2007). Supply chain integration in vendor-managed inventory. *Decision Support Systems*, *43*(2), 663–674. https://doi.org/10.1016/j.dss.2005.05.021

You, M. J., & Ham, E. M. (2019). Development of a Quantitative Model on Adolescent Cyberbullying Victims in Korea: A System Dynamics Approach. *Journal of Korean Academy of Nursing*, *49*(4), 398. https://doi.org/10.4040/jkan.2019.49.4.398

Zhang, Z., Wang, X., Yang, S., Wu, Y., & Du, J. (2020). Simulation and Analysis of the Complex Dynamic Behavior of Supply Chain Inventory System from Different Decision Perspectives. *Complexity*, *2020*. https://doi.org/10.1155/2020/7393848