LOGISTIC REGRESSION-BASED CLASSIFICATION OF INVENTORY CONTROL SYSTEMS: A COMPARATIVE STUDY OF Q-SYSTEM AND P-SYSTEM IN BATIK RETAIL PRODUCTS

Submitted to the International Undergraduate Program in Industrial Engineering in Partial Fulfilment of Requirement for the Degree of Sarjana Teknik at the Faculty of Industrial Technology Universitas Islam Indonesia

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LOGISTIC REGRESSION-BASED CLASSIFICATION OF INVENTORY CONTROL SYSTEMS: A COMPARATIVE STUDY OF Q-SYSTEM AND P-SYSTEM IN BATIK RETAIL PRODUCTS

UNDERGRADUATE THESIS

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DEDICATION PAGE

Alhamdulillahirabbil'alamin
All praise and gratitude be to Allah SWT, whose mercy and blessings have guided me throughout the completion of this undergraduate thesis.
I dedicate this undergraduate thesis to my beloved parents, who never stopped asking how my thesis was progressing. Your persistent reminders became my unexpected source of motivation.
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Lastly, I dedicate this thesis to myself—for not giving up, for pushing through despite the doubts, for every sleepless night, and for believing that I could finish what I started. I thank myself for never quitting.

MOTTO

Fa inna ma'al 'usri yusra

"So, surely with hardship comes ease. "

Q.S Ash-Sharh (5)

PREFACE

Bismillahirrahmanirrahim

All praise is due to Allah SWT, who by His will and grace has allowed the author to complete this undergraduate thesis titled *"Logistic Regression-Based Classification of Inventory Control Systems: A Comparative Study of Q-System and P-System in Batik Retail Products."*. Salawat and greetings are also sent to the Prophet Muhammad SAW, who has brought us from darkness into the light of knowledge and faith

This thesis was written to fulfill one of the requirements for earning a Bachelor's degree in Industrial Engineering at Universitas Islam Indonesia. It explores a logistic regression-based approach to classifying inventory control methods, providing practical insight for inventory management within batik retail operations.

The author acknowledges that this work would not have been possible without the support, prayers, and encouragement from many individuals. Therefore, with great humility and gratitude, the author would like to thank:

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The author realizes that this thesis is far from perfect. Constructive feedback and suggestions are most welcome. It is hoped that this work may benefit future researchers and contribute to the advancement of data-driven inventory strategies in retail operations.

Yogyakarta, July 10th, 2025

Muhammmad Faadihilah

ABSTRACT

Inventory control plays a pivotal role in ensuring product availability and operational efficiency, especially within dynamic retail environments such as the Indonesian batik industry. Traditional systems like the Fixed Order Quantity (Q-System) and Fixed Order Period (P-System) are often selected based on managerial judgment, which may lead to suboptimal decisions due to the variability in demand and product characteristics. This study introduces a data-driven approach to classify inventory items into Q-System or P-System categories using logistic regression. Historical inventory data from a batik retail business in Pekalongan, encompassing demand, lead time, cost, and profitability for 15 high-performing products, was used to build and train the model. Each product's inventory control strategy was first evaluated based on total cost minimization, combining ordering cost, holding cost, and lost profit. The best strategy (Q or P) per product was determined and used as a classification label. Logistic regression was then applied, using normalized statistical and operational variables, to develop a predictive model. The model achieved perfect classification performance on training and testing datasets, with a Mean Squared Error (MSE) of 0, demonstrating its effectiveness. This approach enhances decision-making transparency, optimizes inventory costs, and bridges traditional inventory theory with modern predictive analytics. The findings offer practical implications for retailers aiming to adopt interpretable, data-informed inventory strategies.

Keywords: Inventory Management, Q-System, P-System, Logistic Regression

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CHAPTER I
INTRODUCTION

1.1 Background

Usually, inventory management for an item is determined subjectively by the inventory manager. For example, fast-moving item with low holding cost must be managed by the Q-system, but in some cases, the P-system may be more suitable, but is incorrectly replaced with the Q-system, leading to inefficiencies. Therefore, it should be determined which method is most effective in mitigating it. Inventory management is a critical aspect of retail operations, ensuring that products are available to meet customer demand while minimizing holding costs and avoiding stockouts. In the batik retail sector in Indonesia, characterized by a wide variety of products and fluctuating demand patterns influenced by cultural events, seasonal trends, and fashion cycles, effective inventory control is particularly challenging. Traditional inventory management methods, such as the Q-System (Fixed Order Quantity) and P-System (Fixed Order Period), have been widely used but often fall short in adapting to the dynamic nature of demand in such environments. The Q-System involves ordering a fixed quantity (Q) when the inventory level reaches a predetermined reorder point (R), making it suitable for items with stable demand. In contrast, the P-System reviews inventory at fixed intervals (T) and orders up to a target level (S), which is more appropriate for items with variable demand. However, selecting the optimal system for each inventory item remains a complex decision, often relying on managerial judgment or rule-of-thumb approaches that may not fully capture the underlying demand patterns. The batik retail sector faces unique challenges due to the high variety of products, each with distinct demand characteristics influenced by cultural significance, seasonal trends, and fashion preferences. This variability makes it difficult to apply a one-size-fits-all inventory control strategy, necessitating a more granular and data-driven approach to optimize inventory decisions. With the advent of big data and advanced analytics, there is an opportunity to leverage historical demand data to inform inventory decisions more accurately. Machine learning techniques, particularly classification algorithms, offer a promising avenue for automating and optimizing this process. Logistic regression, a well-established statistical method for binary classification, can be employed to predict whether an inventory item should be managed under the Q-System (coded as 0) or the P-System (coded as 1) based on its demand characteristics and other operational variables. Logistic regression is particularly suitable due to its interpretability, allowing managers to understand how different factors influence the choice of inventory system, which is crucial in business contexts. Studies such as (Dharani, Amrutha, Praveen, & Chakravarthi, 2022) demonstrate the use of classification techniques for multi-criteria inventory classification, while (Villegas-Ch, Navarro, & Sanchez-Viteri, 2024) highlight the application of machine learning to optimize inventory processes, suggesting logistic regression's potential in retail contexts.

This research introduces a method to determine the optimal inventory management strategy for batik retail products by applying logistic regression. Using historical data from Batik Retail Pekalongan, including daily demand volumes, stock levels, lead times, and cost structures, the proposed model will classify each inventory item into the most suitable control system. This approach not only promises to enhance operational efficiency by reducing overstocking and stockouts but also provides a transparent and interpretable framework for inventory decision-making, bridging the gap between traditional inventory theory and modern data-driven practices.

1.2 Problem Formulation

From the explanation of the research background above, the problem statement is:

Inventory management plays a vital role in ensuring product availability and operational efficiency. However, many companies still rely on traditional or manual inventory systems that are less responsive to fluctuations in demand or operational changes. These conventional approaches make it difficult to predict inventory management accurately, leading to overstocking or stockouts, which can impact service levels and increase operational costs.

In the era of data abundance, historical inventory data, demand records, and operational factors provide a valuable source for analysis. However, many businesses have not yet maximized the use of this data to predict inventory management. This research addresses the challenge of classifying inventory items into P-System or Q-System categories to optimize stock replenishment at Batik Retail Pekalongan. Therefore, this research focuses on applying logistic regression to analyse and classify inventory movement management, aiming to provide a predictive and interpretable model for decision-making in inventory management.

Based on the problem statement above, the research questions can be formulated as follows:

1. How can logistic regression classify inventory items into P-System or Q-System categories based on operational data?
2. How accurate and effective is the logistic regression model in analysing inventory behaviour?

1.3 Research Objective

The objective of this research is to analyse inventory management using logistic regression to support better inventory management decisions.

The specific objectives are:

1. To develop a logistic regression model that classifies inventory status on Q-System and P-System.
2. To identify and evaluate the significance of variables affecting inventory changes and the model's performance using appropriate evaluation metrics.

1.4 Research Benefit

The benefits obtained by this thesis are:

1. To contribute academically to the development of inventory management studies by demonstrating the application of logistic regression as a statistical classification method for predicting inventory management.

2. To provide a methodological reference for future research in the field of operations and supply chain management, especially those focusing on data-driven decision-making and inventory classification using interpretable models.

3. To offer empirical insights into the significant factors that influence inventory movement, which can be used as a foundation for developing more accurate and adaptive inventory control strategies in various business contexts.

1.5 Scope of Research

This research has a specific focus and is conducted within the following boundaries:

1. The inventory data analysed in this study is limited to historical records such as stock levels, demand transactions, and lead times obtained from a selected business case.
2. The method used in this research is logistic regression, specifically for classifying inventory management, determining P-System and Q-System.
3. The study is confined to the modelling and analysis phase; it does not include the development or implementation of the model into a live inventory management system or platform.

1.6 Systematic Writing

The systematic approach in writing this research is as follows:

CHAPTER I – INTRODUCTION
This chapter explains the background of the importance of inventory management in business operations, especially in supporting decision-making and minimizing stock-related risks. It highlights the limitations of traditional inventory models and introduces the use of logistic regression as a method to classify inventory management. This chapter also includes the formulation of problems, research objectives, research benefits, research scope, and systematic writing of the thesis.

CHAPTER II – LITERATURE REVIEW
This chapter contains a literature review of previous research related to inventory management and the application of logistic regression in classification problems. It includes supporting theories, such as inventory theory, classification methods, and data-driven decision-making frameworks, which serve as the foundation for the research.

CHAPTER III – RESEARCH METHODOLOGY
This chapter explains the research design, data sources, and variables used in the study. It also details the stages of data collection, preprocessing, and the development of the logistic regression model. Furthermore, it describes the evaluation methods used to assess model performance in classifying inventory movements.

CHAPTER IV – DATA COLLECTION AND PROCESSING

This chapter presents the process of collecting historical inventory data and preparing it for analysis. The data is then processed using logistic regression to classify inventory management. Model performance is evaluated using appropriate classification metrics, and the significance of influencing variables is analysed.

CHAPTER V – DISCUSSION

This chapter discusses the results obtained from the logistic regression model, including interpretation of coefficients, accuracy analysis, and implications for inventory decision-making. The findings are aligned with the research objectives, and insights are provided for practical application.

CHAPTER VI – CONCLUSION AND SUGGESTION

This chapter provides the conclusions drawn from the research and answers the formulated research questions. It also offers suggestions for further improvements and directions for future research in the area of predictive inventory analysis using statistical or machine learning approaches.

CHAPTER II
LITERATURE REVIEW

2.1. Theoretical Review

Inventory control continues to serve as a pivotal component in the operational success of manufacturing and retail enterprises, as it directly affects service level consistency, working capital optimization, and supply chain responsiveness. "In a dynamic retail environment characterized by product variety and fluctuating demand—such as the batik industry—effective inventory classification and replenishment systems are necessary to ensure product availability without incurring unnecessary holding costs. This pressing need has motivated numerous researchers to investigate both classical and modern inventory control approaches under conditions of uncertainty, perishability, and sustainability pressures.

Recent studies highlight the limitations of relying solely on deterministic inventory models, such as the Economic Order Quantity (EOQ) or Fixed Order Quantity (FOQ) systems, when demand volatility and lead time variability increase. Rizqi and Khairunisa (2021) propose the integration of probabilistic methods into deterministic frameworks, illustrating how demand forecasting combined with simulation methods can help balance the risks of overstock and stockout. Their findings emphasize the need for hybrid inventory models, particularly in environments with incomplete demand information or significant variability in customer orders. Similarly, Pulido-Rojano et al. (2020) provide evidence from a probabilistic cost minimization study that supports the redesign of reorder point policies based on statistical modeling of uncertainty.

Sustainability considerations are increasingly central to inventory theory. Utama et al. (2023) offer a comprehensive model that incorporates quality degradation, multi-material coordination, and carbon tax implications. Their mathematical formulation demonstrates how sustainability metrics—such as environmental penalties and deterioration thresholds—can be embedded into the decision variables of inventory models. This approach is echoed by Pattnaik et al. (2021), who conduct a systematic literature review and conclude that future inventory research must account for environmental performance, alongside traditional service-level and cost metrics.

Other scholars approach inventory classification challenges from the lens of clustering algorithms. Suraya et al. (2023) examine the use of K-means clustering to enhance ABC classification accuracy. Their experimental design confirms that clustering based on multi-variable analysis, including turnover rates and criticality indexes, yields a more granular classification of inventory items. This segmentation enables tailored replenishment strategies and policy differentiation across inventory classes, reducing blanket policies that often lead to inefficiencies. Complementary to this is the work by Zhu et al. (2021), who improve the accuracy of traditional K-means using distance-based enhancements, particularly in noisy and imbalanced datasets—a common condition in retail inventory data.

In parallel, the emergence of blockchain and digitized inventory technologies is reshaping supply chain visibility and authenticity. Chang et al. (2022) review blockchain applications in supply chain management and find that real-time ledger transparency significantly improves traceability and trust across distributed inventory systems. Their findings suggest that integrating blockchain with traditional inventory tracking systems can mitigate loss, theft, and manual record inconsistencies—benefits that are particularly critical in industries handling artisanal or regionally protected products like batik.

When it comes to classification modeling, logistic regression has garnered increasing attention for its transparency and suitability in handling binary or categorical predictions. In contrast to black-box machine learning methods, logistic regression offers explainable outputs and coefficient-based interpretation. As Pampel (2020) explains, the logistic function transforms a linear combination of predictors into a probability output, bounded between 0 and 1, making it ideal for risk classification and binary outcome prediction. In inventory contexts, this means logistic regression can be used to model the likelihood of a stockout, overstock, or normal stock levels, based on independent variables such as lead time, demand variability, and historical replenishment behavior.

The fundamental logistic regression model is mathematically expressed as:

$$\pi(x) = \frac{1}{1 + e^{-(\beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_n x_n)}} \tag{1}$$

Here, $\pi(x)$ represents the probability of an event occurring (e.g., a product being classified under a Q-system or P-system), and the log-odds are linearly related to the predictor variables. According to Hosmer et al. (2013), this formulation avoids the pitfalls of linear probability models, particularly the potential for predicting probabilities outside the 0–1 range. Furthermore, the exponentiated coefficients can be interpreted as odds ratios, providing actionable insights for inventory managers.

Table 2.1 Research Position

Author	**1**	**2**	**3**
Ahmed, Seraj, & Islam	√		
Chang, El-Rayes, & Shi	√	√	
Hosmer, Lemeshow, & Sturdivant			√
Mohammed, Melhum, & Ibrahim	√		
Montazeri, Sorourkhah, Marinković, & Lukovac	√	√	
Pampel			√
Panigrahi, Shrivastava, & Kapur	√		
Pattnaik, Nayak, Abbate, & Centobelli	√		
Pulido-Rojano, Gomez, Correa, & Saldarriaga	√		
Rizqi & Khairunisa		√	
Song, J.	√	√	
Utama, Santoso, Hendrawan, & Dania	√	√	
Vicente	√		
Zhang, Turan, Sarker, & Essam		√	

Zhu, Hua, Shi, Tang, & Miao		√	
Research	√	√	√

1. Inventory Control
2. P-Systems and Q-Systems
3. Logistic Regression

2.2. Theoretical Basis

2.2.1. Inventory Management

Inventory management encompasses the processes involved in ordering, storing, and utilizing an organization's inventory. This includes the management of raw materials, components, and finished products. Effective inventory management ensures that a company always has the right products in the right quantity for sale, at the right time. Failure in inventory management can result in excess inventory or stockouts, both of which have serious financial consequences (Song, 2022).

Modern inventory systems have evolved beyond simple stock replenishment models to dynamic, data-driven ecosystems. According to Rizqi and Khairunisa (2020), the use of hybrid systems, such as the integration of Monte Carlo simulations with Min-Max inventory policies, helps accommodate demand variability and reduce costs associated with overstocking and stockouts. These probabilistic methods are particularly useful in environments with perishable materials or products sensitive to quality degradation during storage. This is affirmed by Utama et al. (2020), who presented models that include tax penalties on carbon emissions and deterioration constraints in sustainable inventory planning.

Technology continues to reshape inventory practices. Blockchain, for instance, has been suggested as a transformative tool for enhancing transparency and traceability across the inventory lifecycle (El-Rayes & Shi, 2022). By maintaining tamper-proof records of transactions and stock levels, blockchain can mitigate issues like theft, misplacement, or fraudulent activities. Meanwhile, the adoption of cloud-based inventory systems offers scalability and real-time collaboration across global supply chains.

2.2.2 Inventory Control

Inventory control is a critical subset of inventory management that focuses on the regulation and oversight of inventory levels, movements, and usage to ensure operational efficiency, service level optimization, and cost minimization. It represents the tactical execution of inventory strategies by determining how much stock to hold, when to reorder, and in what quantity. Unlike inventory management, which may encompass broader planning and forecasting responsibilities, inventory control directly governs the day-to-day handling and replenishment of inventory within warehouses, distribution centers, or manufacturing facilities. Effective inventory control ensures that material flows align with demand signals, production schedules, and logistical constraints. As Pulido-Rojano et al. (2020) assert, the purpose of inventory control systems is to minimize costs while maintaining desired service levels under uncertain conditions, especially in probabilistic environments.

Classical inventory control systems traditionally relied on deterministic models, such as the Fixed Order Quantity (FOQ) and Fixed Order Interval (FOI) approaches, both of which operate under the assumptions of known and stable demand, fixed lead times, and constant unit costs. These methods remain foundational in inventory theory because of their simplicity and analytical clarity. However, deterministic models fall short when applied to real-world contexts involving high demand variability, supply disruptions, or product perishability. To address these limitations, researchers have developed probabilistic inventory control systems, which use statistical distributions to model demand and lead times, allowing for more adaptive safety stock calculations and reorder point strategies (Pulido-Rojano et al., 2020).

Hybrid models have emerged as a solution to combine the ease of deterministic policies with the realism of probabilistic approaches. For example, Rizqi and Khairunisa (2020) proposed an integration between deterministic Min-Max inventory control systems and Monte Carlo simulations to evaluate performance under demand uncertainty. Their model calculates reorder levels and order quantities using deterministic rules, but adjusts safety stock based on probabilistic modelling of demand variation. This hybrid approach offers a practical balance for organizations that lack the computational infrastructure to run fully probabilistic models but still need to account for demand uncertainty in their replenishment strategies.

Advancements in mathematical optimization have also strengthened inventory control theory. Vicente (2025) introduced a Mixed Integer Linear Programming (MILP) approach for inventory optimization in multi-echelon supply chains, where decisions at one location affect the performance of upstream and downstream nodes. This framework accommodates constraints such as capacity limits, service level agreements, and production schedules, yielding optimal inventory levels and replenishment timings across complex supply networks. Unlike simple reorder models, MILP formulations offer high flexibility and precision, but they require advanced data infrastructure and algorithmic expertise to implement effectively.

In the context of sustainability, modern inventory control theories now integrate environmental considerations into replenishment and disposal decisions. Pattnaik et al. (2021) noted that traditional inventory control models fail to account for environmental externalities such as carbon emissions and product obsolescence. In response, recent models now incorporate sustainability performance metrics alongside cost and service objectives. Utama et al. (2023) developed a sustainable inventory control framework that factors in quality degradation, environmental taxation, and multi-material coordination. This model prioritizes not only the availability of goods but also their lifecycle impact and associated environmental costs.

Technological integration is another defining feature of contemporary inventory control theories. Smart inventory systems use RFID, barcode scanning, and Internet of Things (IoT) sensors to provide real-time visibility of inventory status. This data supports continuous inventory monitoring, exception-based alerts, and predictive replenishment decisions. Vicente (2025) emphasized the use of digital twins and real-time analytics platforms that synchronize inventory control with upstream procurement and downstream distribution functions. These systems help organizations respond quickly to fluctuations in demand and disruptions in supply, reducing the bullwhip effect and improving inventory turnover.

2.2.3 Fixed Order Period System

The fixed order period system, also known as the periodic review system, is one of the foundational inventory control mechanisms used in supply chain management. This system operates on the principle that inventory levels are reviewed at consistent, pre-specified intervals—regardless of current stock status—and replenishment orders are placed to raise inventory to a target level. The interval between reviews remains fixed, making this system distinct from continuous review models in which inventory levels are constantly monitored. According to Pulido-Rojano et al. (2020), the key parameters in this system are the review period (T) and the order-up-to level (S), which together form the basis of the (T, S) policy structure. This type of system offers significant administrative simplicity, particularly in centralized purchasing environments or where supplier coordination is batched around calendar-based cycles.

From a theoretical perspective, fixed order period systems are most suitable for products with relatively predictable demand and low criticality. Their infrequent review nature can reduce monitoring and ordering costs, making them ideal for slow-moving or inexpensive items. Pattnaik et al. (2021) describe this system as being particularly relevant in industries with limited capacity to continuously monitor inventory or where procurement contracts stipulate periodic review cycles. The trade-off, however, lies in the system's responsiveness: since orders are only placed at fixed intervals, sudden demand surges between reviews can lead to stockouts unless safety stock is optimally calculated.

Inventory models under periodic review often rely on demand forecasting and statistical safety stock formulations. The stochastic nature of demand during the review period and lead time is typically modelled using probability distributions—commonly normal or Poisson distributions. As Utama et al. (2023) explain, determining the proper safety stock level is essential to maintain service levels, particularly when the review period (T) is long. The total demand variance during the review period and the subsequent lead time (T + L) becomes the basis for calculating the reorder quantity, ensuring sufficient coverage until the next replenishment arrives.

In sustainable inventory systems, the fixed order period system offers a structured approach to control logistics emissions and material waste. Periodic ordering can be aligned with transportation consolidation strategies, reducing delivery frequency and vehicle utilization costs. Pattnaik et al. (2021) emphasize the environmental benefit of synchronized ordering schedules across departments or supply chain tiers. By limiting the number of shipments and coordinating purchases, organizations can optimize their carbon footprint without significantly impacting inventory service levels.

However, one challenge frequently encountered in theoretical discussions is the need for high inventory buffers to mitigate demand variability during review intervals. Vicente

(2025) notes that in the presence of long lead times and unpredictable demand patterns, fixed review systems tend to require higher levels of safety stock than continuous review systems, resulting in increased holding costs. To address this, advanced periodic systems integrate probabilistic demand models and service-level constraints to balance cost efficiency and availability. The resulting (T, S) or (T, R, S) models, depending on whether order quantities are fixed or variable, offer flexible adaptation to real-world conditions.

In practice, fixed order period systems are often embedded within enterprise resource planning (ERP) software and integrated with purchasing modules. This digital integration allows firms to automate periodic review calculations, generate order proposals, and align them with budgetary or supplier timelines. As Utama et al. (2023) observe, the digitization of periodic systems enhances their responsiveness by coupling them with real-time data on demand, lead time, and supplier performance. This development bridges the gap between the theoretical simplicity of periodic reviews and the dynamic requirements of modern supply chains.

The role of periodic review systems in sustainable and resilient supply chains has expanded in recent theoretical discourse. According to Pattnaik et al. (2021), organizations are now seeking to balance operational efficiency with sustainability goals by adopting review intervals that minimize transportation emissions and packaging waste. Moreover, in volatile environments such as those disrupted by the COVID-19 pandemic, companies have modified their fixed review systems to include adaptive triggers, whereby the review interval (T) itself is revisited periodically to reflect environmental volatility (Vicente, 2025).

In addition to traditional applications, fixed-order-period systems are gaining traction in e-commerce and last-mile delivery contexts. Here, periodic review cycles are used to batch customer orders and optimize distribution center replenishment. Utama et al. (2023) highlighted the increasing use of review-based order generation in decentralized inventory models, where regional warehouses restock based on calendar schedules and demand aggregation algorithms.

Critically, theoretical models must acknowledge the limitations of periodic review systems in managing high-velocity items or products with high variability. In such contexts, reliance solely on periodic reviews may lead to either frequent stockouts or excessive inventory, depending on the accuracy of demand forecasts. This has led researchers to explore the fusion of periodic review logic with real-time alert systems, creating semicontinuous review models that maintain the simplicity of fixed schedules while allowing for emergency restocking when needed (Pulido-Rojano et al., 2020).

2.2.4 Fixed Order Quantity System

The fixed order quantity (FOQ) system, also referred to as the continuous review system, is one of the most foundational and widely implemented inventory control strategies in both theoretical and applied logistics. This model operates under the principle that an order of a predetermined, constant quantity (Q) is placed each time the inventory level falls to a specific reorder point (R) (Vicente, 2025). Unlike fixed order period systems that initiate replenishment at fixed time intervals, FOQ systems continuously monitor inventory levels and trigger replenishment based on real-time stock status. As such, the FOQ model is ideal in contexts where precise control over inventory availability is required and demand patterns can be reasonably forecasted or monitored (Pulido-Rojano et al., 2020).

The theoretical foundation of FOQ systems is deeply rooted in classical inventory models, particularly the Economic Order Quantity (EOQ) framework. EOQ models optimize order quantity by balancing the trade-off between ordering costs and holding costs, assuming constant demand and lead time. Although the EOQ assumes deterministic conditions, it forms the basis for fixed order quantity decisions in more complex, variable environments. Vicente (2025) demonstrated the application of FOQ systems in multi-echelon inventory models, using mixed integer linear programming to determine optimal reorder points and quantities across distributed networks.

A significant advantage of the FOQ system is its responsiveness to inventory depletion. Because inventory levels are monitored continuously, the system enables timely replenishment, thereby reducing the risk of stockouts, especially for high-demand or high-value items. This characteristic makes it highly suitable for A-class inventory in ABC classification systems, where tight control is required due to the high impact of stock unavailability. Pattnaik et al. (2021) emphasize that FOQ systems align closely with lean and just-in-time (JIT) manufacturing philosophies, which prioritize minimal buffer stock and high responsiveness.

The FOQ system’s reorder point (R) is generally determined based on lead time demand, which may be estimated using historical data or probabilistic distributions. In a deterministic environment, the reorder point is calculated as the product of average demand and lead time.

However, in a stochastic environment, safety stock is added to account for variability in either demand or lead time. According to Pulido-Rojano et al. (2020), proper calculation of safety stock is critical in ensuring service levels are maintained, especially in industries where delivery delays or demand fluctuations are common.

Probabilistic extensions of the FOQ model have been developed to improve its performance under uncertainty. These models replace constant demand assumptions with probability distributions such as normal, Poisson, or exponential, allowing for more robust reorder point and safety stock calculations. Utama et al. (2023) propose incorporating product deterioration and quality degradation into the FOQ framework, particularly for perishable or time-sensitive goods. Their model adjusts the reorder point dynamically based on the degradation rate and projected demand, enhancing the traditional FOQ structure to suit real-world inventory conditions.

Incorporating sustainability into FOQ models has become a subject of growing theoretical interest. Pattnaik et al. (2021) argue that frequent ordering in traditional FOQ systems may lead to increased transportation emissions and packaging waste. Consequently, sustainable FOQ models aim to balance the operational benefits of frequent replenishment with the environmental impact of logistics. Strategies include optimizing transportation batch sizes, using recyclable packaging, and coordinating orders across departments to minimize shipment frequency without compromising service levels.

In terms of classification and prioritization, FOQ systems are typically applied to high-velocity or high-criticality inventory items. For example, medical equipment, automotive parts, or electronics components often use FOQ policies to ensure availability. Conversely, items with low demand variability or low criticality may be managed using fixed period systems. Utama et al. (2023) discuss the application of FOQ systems in multi-material production environments, where each material may have unique degradation rates and procurement constraints. Their approach applies FOQ at the component level, ensuring synchronized replenishment in assembly operations.

Advanced formulations of FOQ models have explored hybrid control policies. For instance, Vicente (2025) integrates FOQ logic within MILP optimization frameworks to coordinate decisions across supply chain tiers. These hybrid systems consider not only local inventory levels but also upstream and downstream constraints, such as supplier lead times, production schedules, and customer delivery requirements. Such integration reflects the shift from isolated inventory control to network-wide inventory synchronization.

Despite its strengths, the FOQ system is not without limitations. Its reliance on accurate demand forecasting and real-time data monitoring can be problematic for firms with limited technological infrastructure or volatile demand environments. Moreover, the frequent ordering associated with FOQ policies may lead to higher ordering costs, especially if economies of scale in procurement or transportation are not leveraged. Pattnaik et al. (2021) point out that balancing order frequency with operational constraints is a key challenge in designing effective FOQ systems.

In response to these limitations, FOQ systems are increasingly supported by simulation-based validation and scenario analysis. Pulido-Rojano et al. (2020) use probabilistic simulations to test the sensitivity of reorder points and safety stock levels under various demand conditions. This helps inventory managers evaluate the robustness of FOQ policies and make data-informed adjustments to reorder parameters. Such theoretical advancements aim to improve the adaptability and resilience of inventory control in uncertain environments.

2.2.5 Logistic Regression

Based on Applied Logistic Regression and Logistic Regression: A Primer. Logistic regression (LR) is a fundamental statistical modeling technique used for predicting the probability of a binary or categorical outcome based on one or more independent variables. Unlike linear regression, which assumes a continuous dependent variable, logistic regression is designed for dichotomous outcomes, such as "increase vs. decrease" or "in-stock vs. out-of-stock." The theoretical formulation of logistic regression addresses the limitations of linear probability models by transforming the predicted values through the logit link function, thereby ensuring that the resulting probabilities fall within the valid [0,1] interval. According to Pampel (2021), the logistic regression model's ability to produce interpretable coefficients in terms of odds ratios makes it highly suitable for applied decision-making in operational fields like inventory control, risk classification, and supply chain analytics.

The basic formula for logistic regression, based on the Applied Logistic Regression book, is defined as follows:

$$\pi(x) = \frac{1}{1 + e^{-(\beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_n x_n)}} \tag{2}$$

Where:

$\pi(x)$ = The probability that the dependent variable equals 1, given values of the independent variables $x_1, x_2, \ldots, x_n$
e = Euler's number (the base of the natural logarithm)
β_0 = The intercept term; the predicted log-odds when all x values are zero
$\beta_1, \beta_2. \ldots, \beta_n$ = Coefficients representing the impact of each independent variable on the log-odds of the outcome
$x_1, x_2, \ldots, x_n$ = Independent Variables (predictors) used in the model
In a real case related to inventory management, the formula might be:

This logistic function is inherently nonlinear and sigmoidal in shape, which makes it well-suited to capturing threshold effects and saturation points often observed in real-world phenomena such as reorder behaviours or stock fluctuation probabilities (Pampel, 2021).

Logistic regression can be categorized into binary logistic regression (two outcome categories), multinomial logistic regression (more than two unordered categories), and ordinal logistic regression (ordered categories). In the context of inventory analysis, binary logistic regression is often used to predict stock status (e.g., in-stock vs. out-of-stock). According to Pampel (2021), the interpretability of the log-odds coefficients allows practitioners to assess how each predictor—such as demand variability, supplier lead time, or seasonality—affects the probability of a particular inventory outcome.

The assumptions of logistic regression are notably different from those of linear regression. Logistic regression does not require the residuals to be normally distributed, and it does not assume homoscedasticity. Instead, it assumes that the log-odds of the outcome are linearly related to the predictors. Additionally, multicollinearity among predictors should be minimized, and there should be a sufficient sample size in each category of the dependent variable to ensure reliable estimation (Pampel, 2021).

In inventory management, logistic regression is particularly useful for classification tasks. For example, Mohammed et al. (2023) applied logistic regression to medical data for stroke prediction, achieving high accuracy and demonstrating the technique's robustness in binary outcome modelling. Although their application domain is healthcare, the methodology directly parallels classification needs in inventory systems. Predicting whether inventory levels will fall below a safety threshold, or whether demand will exceed forecast expectations, are structurally equivalent classification problems. Mohammed et al. (2023) also incorporated data preprocessing techniques such as SMOTE (Synthetic Minority

Oversampling Technique) to handle class imbalance, and correlation-based feature selection to improve model efficiency—practices highly applicable in inventory datasets.

The theoretical use of logistic regression in inventory systems is increasingly supported by hybrid analytics models that combine classical inventory theories (e.g., EOQ, Min-Max) with predictive analytics. For instance, logistic regression can be used to model the likelihood of overstock or understock events based on historical consumption patterns, order cycles, supplier reliability, and lead time variability. When integrated into decision support systems or enterprise resource planning (ERP) software, LR models provide actionable insights, such as whether to trigger expedited replenishment or flag items for inventory policy review.

Moreover, logistic regression can support inventory classification systems by quantifying the probability of an item belonging to a particular criticality category (e.g., A vs. B vs. C class). While conventional ABC classification is based on simple consumption value sorting, integrating logistic regression allows for probabilistic classification that accounts for multidimensional predictors, such as lead time, price volatility, and customer order frequency. This theoretical extension helps inventory managers make more data-driven decisions when allocating control resources or defining replenishment policies.

Another advantage of logistic regression is its scalability and computational efficiency. Unlike some machine learning methods, logistic regression does not require large amounts of data or high computational power, which makes it practical for SMEs and real-time applications. It is also transparent and interpretable, enabling managers to explain decisions to stakeholders and auditors—an important consideration in regulated industries such as pharmaceuticals or aerospace inventory systems.

The limitations of logistic regression, however, are also acknowledged in the literature. One major drawback is its sensitivity to outliers and noise in the input data, which can distort coefficient estimates and mislead interpretations. Preprocessing techniques such as outlier detection, normalization, and feature transformation are therefore essential when applying LR in operational settings (Pampel, 2021). Furthermore, logistic regression assumes linearity in the logit space, which may not hold for all inventory relationships. In such cases, polynomial transformations or interaction terms may be added to improve model fit.

2.2.6. Supply Chain in Batik Retail

The batik retail industry operates within a complex supply chain network that involves multiple stakeholders from raw material suppliers to end consumers. Understanding Batik Retail Pekalongan's position within this network is crucial for effective inventory management strategy implementation, as supplier relationships and supply chain positioning directly influence inventory control decisions.

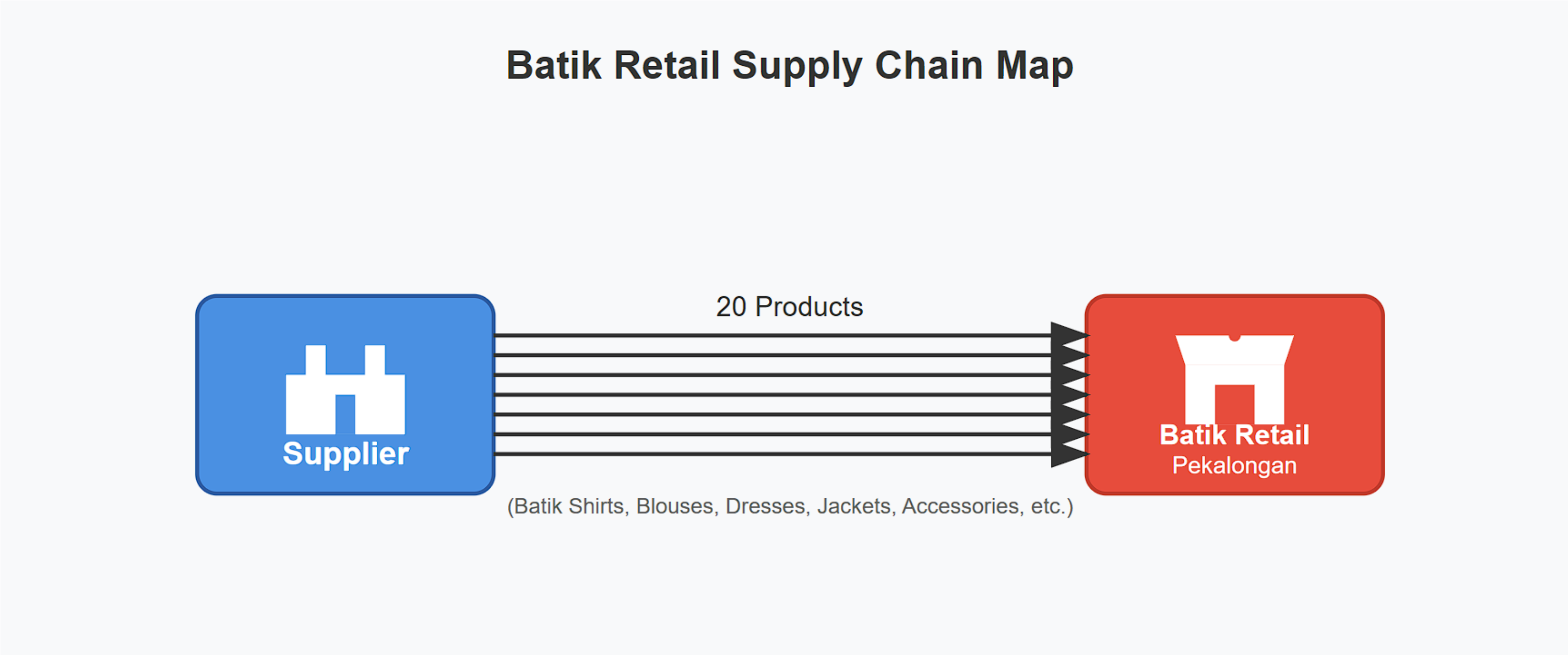

Figure 2.1 Batik Retail Supply Chain Map

Batik Retail Pekalongan operates as a downstream retailer in the batik supply chain, positioned strategically between three distinct supplier categories and end consumers. Based on operational data, the company maintains relationships with three primary suppliers, each with distinct characteristics:

This empirical supply chain analysis demonstrates that inventory control system selection depends not only on supplier relationships and lead times but also on product-specific demand patterns and cost structures, validating the need for the logistic regression classification approach developed in this study.

CHAPTER III
RESEARCH METHODOLOGY

3.1. Research Object

The subject of this research is Batik Retail at Pekalongan, a company engaged in the sale of batik and various garment products. The company operates in the fashion and textile industry, where demand fluctuations and product variety pose significant inventory management challenges. The object of this research is inventory management, specifically focused on how Batik Pekalongan classifies and controls its inventory to ensure efficient stock levels and minimize losses. The research involves analyzing primary and secondary data related to stock movement and product characteristics. Logistic regression will be applied to categorize inventory items and identify key factors influencing inventory classification. The goal is to enhance decision-making related to stock procurement, storage, and distribution.

3.2. Data Collection Method

3.2.1. Secondary Data

Secondary data is used to develop the theoretical and methodological foundation of this study. Sources include peer-reviewed journals, books, and academic conference papers. These sources support the conceptual framework for inventory control, fixed order systems, and logistic regression. In this research, secondary data is used to acquire demand data in Batik Retail for 3 years, which was acquired from third parties.

3.3 Research Instrument

This section presents the instruments utilized to collect and analyze data in this study. The selection of research instruments is critical in ensuring the accuracy, reliability, and relevance of the data obtained. In this research, the instruments are chosen to support quantitative analysis, especially inventory classification using clustering methods and predictive modeling through logistic regression. These instruments facilitate the acquisition of both primary and secondary data that reflect the inventory dynamics at Batik Retail, a company engaged in the sale of batik and other garment products. The research instruments used in this study include:

Research instruments are tools used to support the research process, including data collection, processing, analysis, and documentation. The instruments used in this study are as follows:

1. Laptop

   This device was used throughout the research process, including writing, storing files, data processing, and compiling the final thesis.

2. Microsoft Excel with Solver Add-in

   Microsoft Excel was utilized for data preprocessing and analysis. Basic tasks—such as cleaning raw inventory data, addressing missing values, and calculating descriptive statistics—were performed using Excel's standard functions. The Solver add-in played a key role in estimating the parameters of the logistic regression model.

3. Microsoft Word (Equation Editor)

   Used for documenting the research, including writing the logistic regression formulation using the built-in equation editor.

4. Diagrams.net

   This web-based tool was used to create flowcharts that visually explain the research process from data input to analysis and conclusion

3.4 Research Flow

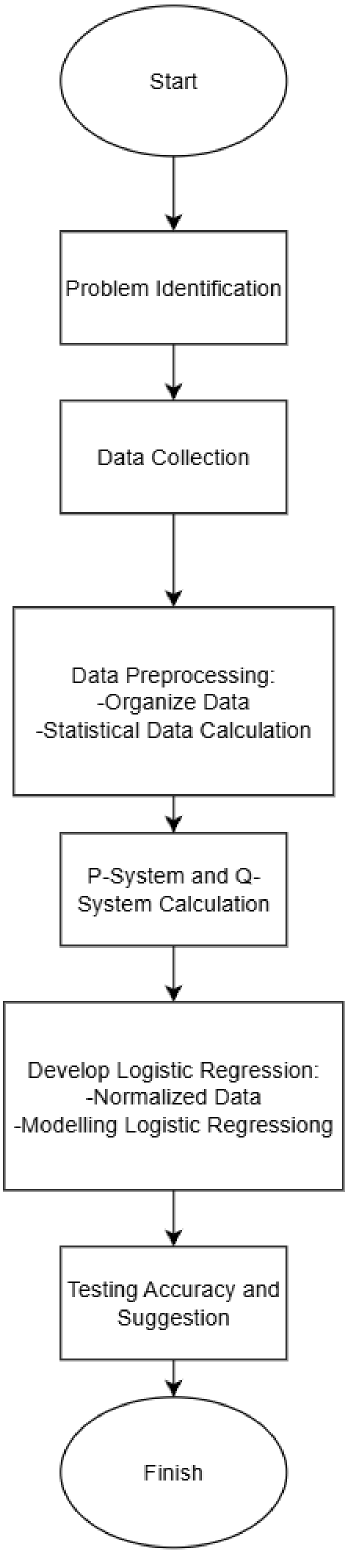

Figure 3. 1 Research Flowchart

The flowchart explanation is as follows:

1. Problem Identification

   Identify inefficiencies in current inventory strategies and explore the use of logistic regression for classification.

2. Data Collection

   Collect data from demand records and extract secondary sources for theoretical support.

3. Data Preprocessing

   Organize inventory data for each, for 15 products. The mean, standard deviation, lead time, holding cost, order cost, and profit for each product.

4. P-System and Q-System Calculation

   Calculating P-System and Q-System for each product, which are the lowest Total Cost using add-ins Solver in Microsoft Excel for each product that will determine the best method for each product whether it's P-System or Q-System.

5. Modelling with Logistic Regression

   Normalized the data using the formula:

$$X_{Normalized} = \frac{X - X_{min}}{X_{max} - X} \tag{3}$$

   And also use the Logistic Regression formula, as follows:

$$\pi(x) = \frac{1}{1 + e^{-(\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n)}} \tag{4}$$

   where the probability $\pi(x)$ predicts which inventory control method best applies to each product.

6. Testing Accuracy and Recommendation

   Use classification accuracy to assess the model's performance. Discuss how feature coefficients relate to inventory policy, and recommend improvements based on prediction insights.

CHAPTER IV
DATA COLLECTION AND PROCESSING

4.1. Data Collection

This study utilizes data collected from a batik retail business. A total of 15 products were selected for analysis. These products represent the top 15 best-selling items, identified based on total demand volume over a defined period. By focusing on high-performing products, the analysis ensures that improvements in inventory strategy will target the most critical contributors to overall performance. These variations reflect differences in demand patterns, cost structures, and profitability, making them ideal for evaluating inventory control strategies. To ensure the reliability of the model, only entries with complete data across key operational and demand-related features were retained. As a result, the final dataset used for logistic regression modeling consists of 15 complete entries with no missing values.
The variables selected for modelling include:

Table 4.1 Variable Data

No.	Variable Name	Description
1.	Monthly Demand	Demand sold per month (Jan–December)
2.	Holding Cost	Inventory holding cost per unit (Rp. 200 per piece per period)
3.	Order Cost	Cost incurred per order placed (Rp. 15.0000 per kilogram)
4.	Pcs/Kg	Unit weight (pieces per kilogram) – 4 pieces per kg
5.	Profit	Estimated gross profit per product

The data collected for each product includes:

a. Monthly demand for 3 years
b. Lead time
c. Holding cost
d. Ordering cost
e. Profit
f. Packaging density
g. Demand summary statistics (mean, standard deviation, min, max)

The key cost-related and logistical data for the 15 selected products are shown below:

Table 4.2 Product Data

No	Product	Ordering Cost	Holding Cost	Leadtime	Profit
1	Short sleeve standard batik shirt	15000	200	5	15000
2	Designer batik shirt	15000	200	5	30000
3	Long sleeve printed batik shirt	15000	300	4	25000
4	Premium printed batik shirt	15000	300	4	35000
5	Batik t-shirt	15000	200	5	15000
6	Limited edition batik jacket	15000	350	5	35000
7	Casual batik polo shirt	15000	250	5	15000
8	Modern batik blouse	15000	300	4	20000
9	Traditional batik dress	15000	200	4	20000
10	Stylish batik skirt	15000	200	5	20000
11	Batik scarf	15000	750	5	5000
12	Batik tie	15000	750	5	5000
13	Luxury batik jacket	15000	350	4	45000
14	Batik short	15000	150	4	15000
15	Batik pant	15000	200	5	15000

These features serve as independent variables to predict the optimal inventory control method for each product. The logistic regression model will classify each item into a P-system or Q-system based on the relationship between these features and the historical control.

4.1.1. Cost Components

Ordering Cost Structure: The ordering cost of 15,000 IDR represents the cost per kilogram of batik products ordered from suppliers. This cost structure is justified as follows:

a. Each kilogram of batik products contains approximately 4 pieces for standard items, and 3-4 pieces for specialized products
b. Therefore, the effective ordering cost per piece ranges from Rp. 3.750 to Rp. 5.000 depending on product type
c. This cost includes administrative expenses for purchase orders, supplier coordination,

transportation costs from suppliers to the retail location, and quality inspection processes

d. The per-kilogram basis reflects the supplier pricing structure commonly used in the Indonesian textile industry

Holding Cost: The holding cost has been set at Rp. 200-350 per piece per period, representing approximately 10-15% of the average selling price of batik products (2.000 IDR). This cost encompasses:

a. Warehouse rental and storage facility costs
b. Insurance coverage for stored inventory
c. Opportunity cost of capital tied up in inventory
d. Handling and maintenance expenses
e. Risk of obsolescence and damage during storage

This holding cost rate, for example, of Rp. 200 is based on retail industry standards and reflects conservative storage and carrying costs. The rate accounts for the relatively stable nature of batik products, which have cultural significance and maintain their value over time.

4.2 Data Preprocessing

Preprocessing is a critical step in ensuring the quality and integrity of the data before modeling. This stage involves cleaning missing values, engineering relevant features, converting categorical variables, and normalizing where necessary to prepare the dataset for logistic regression classification.

4.2.1 Demand Data

Prior to analysis, the dataset was reviewed for completeness and consistency. The original dataset contained monthly demand, cost components, and product attributes for 15 batik products. All incomplete records were excluded. The dataset comprised 15 complete product records, each containing demand for 3 years. And these are the data:

Table 4.3 Product Demand Data

Product ID	Product Name	Jan	Feb	Mar	Apr	May	Jun	…	Dec
1	Short sleeve standard batik shirt	128	98	111	115	125	111	…	108
2	Designer batik shirt	6	0	6	10	2	5	…	10
3	Long sleeve printed batik shirt	87	75	81	100	70	96	…	86
4	Premium printed batik shirt	36	31	0	0	36	31	…	27
5	Batik t-shirt	46	52	59	55	41	41	…	55
6	Limited edition batik jacket	11	18	22	20	11	22	…	11
7	Casual batik polo shirt	36	56	49	49	41	40	…	45
8	Modern batik blouse	92	81	66	89	82	73	…	69
9	Traditional batik dress	163	141	130	143	118	143	…	155
10	Stylish batik skirt	27	19	16	19	13	21	…	26
11	Batik scarf	4	1	2	3	4	6	…	6
12	Batik tie	3	4	3	3	7	2	…	3
13	Luxury batik jacket	5	3	4	6	6	4	…	4
14	Batik short	54	54	51	58	62	42	…	56
15	Batik pant	21	19	17	29	20	17	…	21

4.2.2 Statistical Feature Calculation

To summarize demand behavior and prepare input for modeling, statistical measures were calculated from the monthly demand data of each product:

a. Mean:
   The average monthly demand.
b. Standard Deviation:
   A measure of demand variability. A high standard deviation implies fluctuating demand, which may require more responsive inventory control.
c. Minimum Value:
   The lowest monthly demand figure provides insight into demand dips and potential stockout periods.
d. Maximum Value:
   The highest observed monthly demand, reflecting peak demand conditions and safety stock requirements.

These values were computed directly from the raw monthly demand data. They formed part of the feature set used both in clustering and later in the logistic regression model. The purpose of including these measures was to translate raw demand history into operational patterns that influence inventory strategy decisions. So, these are the calculations for the mean and standard deviation for products:

Table 4.4 Monthly Demand Product 1

No	Product Name	Jan	Feb	Mar	Apr	May	Jun	…	Dec	Sum
1.	Short sleeve standard batik shirt	128	98	111	115	125	111	…	108	4049

With the sum of 4049 for product 1 after 36 months, we round up the result of the mean and standard deviation. Thus, the mean and standard deviation for product 1 is:

a. Mean: 112
b. Standard Deviation: 11

So, these are the statistical data for the 15 products:

Table 4.5 Statistical Data

No	Product	Mean	Standard Deviation	Min. Value	Max Value
1	Short sleeve standard batik shirt	112	11	92	128
2	Designer batik shirt	6	2	0	12
3	Long sleeve printed batik shirt	80	15	49	119
4	Premium printed batik shirt	30	12	0	45
5	Batik t-shirt	49	6	39	59
6	Limited edition batik jacket	15	4	6	22
7	Casual batik polo shirt	44	8	27	62
8	Modern batik blouse	78	9	51	93
9	Traditional batik dress	138	11	118	163
10	Stylish batik skirt	20	4	12	32
11	Batik scarf	4	2	1	11
12	Batik tie	3	2	0	8
13	Luxury batik jacket	5	2	2	9
14	Batik short	56	6	42	69
15	Batik pant	21	5	12	31

4.3 P-System and Q-System Calculation

To determine the most cost-efficient inventory control method for each product, the total cost of inventory was calculated under two classical systems: the Q-System (Fixed Order Quantity) and the P-System (Fixed Order Period). The objective was to identify which system minimized the total cost, defined in this study as the sum of three components:

1. Ordering Cost: based on how frequently inventory is replenished and the cost incurred per order.
2. Holding Cost: representing the cost of storing inventory over time, and
3. Lost Profit: representing the opportunity cost from unmet demand due to stockouts.

To ensure accuracy and optimality in cost estimation, this total cost was minimized using the Solver add-in in Microsoft Excel. Solver was employed to optimize decision variables (such as order quantity and review period) under system-specific constraints for each product. This process allowed the model to identify the parameter values that resulted in the lowest possible total cost for both systems.

a. In the Q-System, the Solver optimized order quantity to minimize the frequency and cost of replenishment while balancing inventory levels against demand.
b. In the P-System, the Solver optimized the review period and target order-up-to level, accounting for variability in demand and lead time.

By optimizing each system independently and calculating total cost as a unified function of ordering, holding, and lost profit, a fair and consistent comparison was made across all products. The system with the lower total cost was selected as the most appropriate inventory control method and used as the classification label in the logistic regression model. In this research, Solver add-ins in Microsoft Excel are used to determine the lowest cost possible; thus, the reorder point (r), Q, and P are determined by the Solver. These are examples of the calculation for product 2:

Table 4.6 Q-System Calculation Product 2

				Q	2				
				r	1				
t	Beginning Inventory	Demand	Ending Inventory	Order Status	Order Received	Lost Sales	Ordering Cost	Holding Cost	Lost Profits
1	5	0	5	0	0	0	0	1000	0
2	5	0	5	0	0	0	0	1000	0
3	5	0	5	0	0	0	0	1000	0
4	5	0	5	0	0	0	0	1000	0
5	5	0	5	0	0	0	0	1000	0
6	5	0	5	0	0	0	0	1000	0
7	5	0	5	0	0	0	0	1000	0
8	5	0	5	0	0	0	0	1000	0
9	5	0	5	0	0	0	0	1000	0
10	5	0	5	0	0	0	0	1000	0
11	5	0	5	0	0	0	0	1000	0
12	5	1	4	0	0	0	0	800	0
13	4	0	4	0	0	0	0	800	0
14	4	0	4	0	0	0	0	800	0
15	4	0	4	0	0	0	0	800	0
16	4	0	4	0	0	0	0	800	0
…		…	…	…	…	…	…	…	…
60	1	0	1	0	0	0	0	200	0
						Total	90000	25200	90000

Total Cost	205.200

Table 4.7 P-System Calculation Product 2

				P	26				
				R	5				
t	Beginning Inventory	Demand	Ending Inventory	Order Status	Order Received	Lost Sales	Ordering Cost	Holding Cost	Lost Profits
1	5	0	5	0	0	0	0	1000	0
2	5	0	5	0	0	0	0	1000	0
3	5	0	5	0	0	0	0	1000	0
4	5	0	5	0	0	0	0	1000	0
5	5	0	5	0	0	0	0	1000	0
6	5	0	5	0	0	0	0	1000	0
7	5	0	5	0	0	0	0	1000	0
8	5	0	5	0	0	0	0	1000	0
9	5	0	5	0	0	0	0	1000	0
10	5	0	5	0	0	0	0	1000	0
11	5	0	5	0	0	0	0	1000	0
12	5	1	4	0	0	0	0	800	0
13	4	0	4	0	0	0	0	800	0
14	4	0	4	0	0	0	0	800	0
15	4	0	4	0	0	0	0	800	0
16	4	0	4	0	0	0	0	800	0
…	…	…	…	…	…	…	…	…	…
60	4	0	4	0	0	0	0	800	0
						Total	45000	25800	240000

Total Cost	310.800

So, these are the total costs for Q-system and P-system based on the calculation:

Table 4.8 Total Cost

No	Product Name	Q-System	P-System
1.	Short sleeve standard batik shirt	1.149.000	978.000
2.	Designer batik shirt	205.200	310.800
3.	Long sleeve printed batik shirt	1.113.000	1.083.000
4.	Premium printed batik shirt	515.000	533.000
5.	Batik t-shirt	647.000	476.000
6.	Limited edition batik jacket	345.500	312.500
7.	Casual batik polo shirt	425.000	442.500
8.	Modern batik blouse	417.000	513.000
9.	Traditional batik dress	1.166.000	1.091.000
10.	Stylish batik skirt	381.000	339.000
11.	Batik scarf	146.000	121.000
12.	Batik tie	126.250	109.500
13.	Luxury batik jacket	507.000	412.500
14.	Batik short	205.500	217.500
15.	Batik pant	351.000	295.000

4.4 Inventory Clustering Based on Total Cost Minimization

Following the total cost optimization for both the Q-System and P-System, each product was evaluated based on which system yielded the lowest overall cost, incorporating ordering cost, holding cost, and lost profit. This comparative analysis formed the foundation for assigning the most appropriate inventory control strategy to each product. The system with the minimum total cost was selected as the optimal inventory method for that product. This decision was then formalized into a binary classification label for use in the logistic regression model:

a. 1 = P-System (Fixed Order Period)
b. 0 = Q-System (Fixed Order Quantity)

This label served as the target variable in the classification process, representing a cost-based inventory policy choice grounded in data-driven optimization rather than subjective managerial judgment. The binary format enables the use of supervised classification algorithms to predict system assignment from operational characteristics. Only products with complete cost information and valid optimization results were retained in the final dataset. After filtering, a total of 15 complete product records were included for model development.

Table 4.9 Inventory Clustering

No	Product	Best Method	Decision
1	Short sleeve standard batik shirt	P-System	1
2	Designer batik shirt	Q-System	0
3	Long sleeve printed batik shirt	P-System	1
4	Premium printed batik shirt	Q-System	0
5	Batik t-shirt	P-System	1
6	Limited edition batik jacket	P-System	1
7	Casual batik polo shirt	Q-System	0
8	Modern batik blouse	Q-System	0
9	Traditional batik dress	P-System	1
10	Stylish batik skirt	P-System	1
11	Batik scarf	P-System	1
12	Batik tie	P-System	1
13	Luxury batik jacket	P-System	1
14	Batik short	Q-System	0
15	Batik pant	P-System	1

4.5 Data Linearity

To assess linearity, the relationship between each normalized independent variable and the log-odds of the outcome was examined. The analysis of the normalized variables reveals several non-linear patterns:

a. Mean Demand vs. System Selection: The relationship between normalized mean demand and system selection shows non-linear characteristics. Products with very low demand (Designer batik shirt, Batik scarf, Batik tie) and very high demand (Traditional batik dress, short sleeve standard shirt) both tend toward P-System, while moderate demand products show mixed classifications. This suggests a U-shaped or quadratic relationship rather than linear.

b. Standard Deviation vs. System Selection: The relationship between demand variability and system selection exhibits non-linear behavior. Products with both very low variability (Batik scarf, Batik tie, Designer shirt) and high variability (Long sleeve printed shirt) favor P-System, while moderate variability products show diverse classifications.

c. Lead Time and Holding Cost Interactions: The interaction between lead time and holding cost creates non-linear decision boundaries. The classification boundary is not simply determined by linear combinations of these variables but appears to involve interaction effects and threshold behaviors.

d. The identified non-linear relationships suggest that while logistic regression provides interpretable results and achieves perfect classification accuracy on the current dataset, the underlying data structure exhibits non-linear characteristics. This finding supports the recommendation for future research to explore non-linear classification methods such as Artificial Neural Networks (ANN), which can better capture complex interaction effects and non-linear decision boundaries.

However, for the current study's objectives of providing an interpretable and implementable classification system, logistic regression remains appropriate due to its transparency.

4.6 Develop the Logistic Regression Dataset

To support a data-driven classification of inventory control systems, this study developed a binary logistic regression model. The objective of the model is to predict whether a product should be managed under the P-System or the Q-System, using operational and demand-based characteristics.

Before constructing the model, the input variables were normalized to a uniform scale using the min-max normalization method. This step ensures that features measured on different units or scales do not disproportionately influence the regression output. The normalized data was manually appended to the lower section of the dataset and used as the input for model training.

The logistic regression model estimates the probability that a product should be classified under the P-System, based on its normalized attributes. Model coefficients were estimated using the Solver add-in in Microsoft Excel, which minimized the log-loss function to achieve the best parameter fit. Once the coefficients were obtained, the model was used to calculate $\pi(x)$ for each product.

A classification threshold of 0.5 was applied:

a. If $\pi(x) \geq 0{,}5$, the product was classified as P-System.

b. If $\pi(x) < 0{,}5$, the product was classified as Q-System.

These predicted classifications represent the proposed inventory control strategy under the logistic regression model. In the next phase, these assignments were used to recalculate the total cost of managing each product and compare it with the existing uniform strategy assumption. For the normalized products calculation, we refer to Table 4.5 for the mean, standard deviation of each product, so these are the calculation for products normalized calculation:

Table 4.10 Normalized Calculation Product 1

Product	Mean	Standard Deviation	Leadtime	Holding Cost	Decision
Short sleeve standard batik shirt	0,8	0,69	1	0,45	1

Thus, the normalized data is as follows:

Table 4.11 Normalized Data

Product ID	Product Name	Mean(x_1)	St. Dev (x_2)	Leadtime (x_3)	Hold. Cost (x_4)	Decision (x_5)
1	Short sleeve standard batik shirt	0,8	0,69	1	0,45	1
2	Designer batik shirt	0,02	0	1	0,45	0
3	Long sleeve printed batik shirt	0,57	1	0	0,81	1
4	Premium printed batik shirt	0,2	0,77	0	0,81	0
5	Batik t-shirt	0,34	0,3	1	0,45	1
6	Limited edition batik jacket	0,08	0,15	1	1	1
7	Casual batik polo shirt	0,3	0,46	1	0,63	0

8	Modern batik blouse	0,56	0,53	0	0,81	0
9	Traditional batik dress	1	0,69	0	0,45	1
10	Stylish batik skirt	0,13	0,15	1	0,45	1
11	Batik scarf	0,01	0	1	0	1
12	Batik tie	0	0	1	0	1
13	Luxury batik jacket	0,01	0	0	1	1
14	Batik short	0,39	0,3	0	0,27	0
15	Batik pant	0,13	0,23	1	0,45	1

After the normalized data is calculated and obtained, after logistic regression is developed to compare decisions on clustered and logistic regression. The coefficient/intercept terms are determined by the solver add-in the results are:

a. β_0= -42,95

b. β_1= -48,54

c. β_2= 21,75

d. β_3= 25,69

e. β_4= 12,1

f. β_5= 94,96

Then, an example calculation for logistic regression for product 1 is developed, as follows:

	β_0	β_1	β_2	β_3	β_4	β_5	
	-42,95	-48,54	21,75	25,69	12,1	94,96	
No.	Product Name	Mean	Standard Deviation	Leadtime	Holding Cost	Decision	Prediction
1	Short sleeve standard batik shirt	0,8	0,69	1	0,45	1	1

So, in product 1, since the result of logistic regression is ≥ 0,5. Then, the prediction will be P-system or in binary is 1. The following is the result of logistic regression for each product:

Table 4.12 Logistic Regression

	β_0	β_1	β_2	β_3	β_4	β_5		
	-42,95	-48,54	21,75	25,69	12,1	94,96		
Product ID	Product Name	Mean	St. Dev	Leadtime	Hold. Cost	Decision	Prediction	SE
1	Short sleeve standard batik shirt	0,8	0,69	1	0,45	1	1	0
2	Designer batik shirt	0,02	0	1	0,45	0	0	0
3	Long sleeve printed batik shirt	0,57	1	0	0,81	1	1	0
4	Premium printed batik shirt	0,2	0,77	0	0,81	0	0	0
5	Batik t-shirt	0,34	0,3	1	0,45	1	1	0
6	Limited edition batik jacket	0,08	0,15	1	1	1	1	0
7	Casual batik polo shirt	0,3	0,46	1	0,63	0	0	0
8	Modern batik blouse	0,56	0,53	0	0,81	0	0	0
9	Traditional batik dress	1	0,69	0	0,45	1	1	0
10	Stylish batik skirt	0,13	0,15	1	0,45	1	1	0
11	Batik scarf	0,01	0	1	0	1	1	0
12	Batik tie	0	0	1	0	1	1	0
13	Luxury batik jacket	0,01	0	0	1	1	1	0
14	Batik short	0,39	0,3	0	0,27	0	0	0
15	Batik pant	0,13	0,23	1	0,45	1	1	0
							MSE	0

CHAPTER V
RESULTS AND DISCUSSION

5.1. System Accuracy Testing

This section evaluates the classification performance of the logistic regression model developed in Chapter 4 by testing it on 5 new products that were not part of the original training dataset. The goal is to assess how accurately the system can predict whether a product should be managed under the P-System or Q-System.

5.1.1. Testing Methodology

The logistic regression model was trained using 15 top-selling products with known cost-optimized inventory method labels (P or Q). To test its generalization ability, 5 new products were selected and processed using the same steps. And these are the data for 5 products for 3 years:

Table 5.1 Testing Data

No	Product	Ordering Cost	Holding Cost	Leadtime	Profit
1	Batik vest	15000	2000	5	15000
2	Urban batik polo	15000	1500	4	25000
3	Batik kimono	15000	3000	5	40000
4	Batik cardigan	15000	3000	4	30000
5	Batik bomber jacket	15000	3000	4	30000

Table 5.2 Demand for Testing Data

Product ID	Product Name	Jan	Feb	Mar	Apr	May	…	Dec
1	Batik vest	31	31	23	31	35	…	26
2	Urban batik polo	94	96	56	74	69	…	63
3	Batik kimono	30	23	22	26	23	…	29
4	Batik cardigan	33	34	36	15	31	…	34
5	Batik bomber jacket	16	6	10	6	16	…	10

These values were computed directly from the raw monthly demand data. They formed part of the feature set used both in clustering and later in the logistic regression model. The statistical features calculated in the next step:

Table 5.3 Statistical Calculation Product Testing 1

No	Product Name	Jan	Feb	Mar	Apr	May	…	Dec	Sum	Mean	St.Dev
1.	Batik vest	31	31	23	31	35	…	26	1018	28	5

Table 5.4 Statistical Feature on Testing Data

No	Product	Mean	Standard Deviation	Min. Value	Max Value
1	Batik vest	28	5	19	42
2	Urban batik polo	75	10	56	96
3	Batik kimono	27	4	18	37
4	Batik cardigan	30	7	15	38
5	Batik bomber jacket	8	3	4	16

The next is the P-system and Q-system calculation. To ensure accuracy and optimality in cost estimation, this total cost was minimized using the Solver add-in in Microsoft Excel. Solver was employed to optimize decision variables (such as order quantity and review period) under system-specific constraints for each product. These are the calculations for product 1 testing data:

Table 5.5 Q-System Calculation Product Testing 1

					Q	4			
					r	4			
t	Beginning Inventory	Demand	Ending Inventory	Order Status	Order Received	Lost Sales	Ordering Cost	Holding Cost	Lost Profits
1	5	0	5	0	0	0	0	10000	0
2	5	0	5	0	0	0	0	10000	0
3	5	0	5	0	0	0	0	10000	0
4	5	0	5	0	0	0	0	10000	0
5	5	1	4	0	0	0	0	8000	0
6	4	1	3	0	0	0	0	6000	0
7	3	1	2	0	0	0	0	4000	0
8	2	1	1	1	0	0	15000	2000	0
9	1	1	0	0	0	0	0	0	0
10	0	1	0	0	0	1	0	0	15000
11	0	1	0	0	0	1	0	0	15000
12	0	1	0	0	0	1	0	0	15000
13	0	1	3	0	4	0	0	6000	0
14	3	1	2	0	0	0	0	4000	0
…		…	…	…	…	…	…	…	…
60	0	1	0	0	0	1	0	0	15000
						Total	120.000	152.000	285.000
						Total Cost	557.000		

Table 5.6 P- System Calculation Product Testing 1

P	4
R	4

t	Beginning Inventory	Demand	Ending Inventory	Order Status	Order Received	Lost Sales	Ordering Cost	Holding Cost	Lost Profits
1	5	0	5	0	0	0	0	10000	0
2	5	0	5	0	0	0	0	10000	0
3	5	0	5	0	0	0	0	10000	0
4	5	0	5	1	0	0	-15000	10000	0
5	5	1	4	0	0	0	0	8000	0
6	4	1	3	0	0	0	0	6000	0
7	3	1	2	0	0	0	0	4000	0
8	2	1	1	1	0	0	15000	2000	0
9	1	1	0	0	-1	1	0	0	15000
10	0	1	0	0	0	1	0	0	15000
11	0	1	0	0	0	1	0	0	15000
12	0	1	0	1	0	1	15000	0	15000
13	0	1	2	0	3	0	0	4000	0
14	2	1	1	0	0	0	0	2000	0
…		…	…	…	…	…	…	…	…
60	1	1	0	1	0	0	15000	0	0
						Total	180000	230000	135000

Total Cost	545.000

So, these are the total costs for Q-system and P-system for the testing data based on the calculation, and after that, the logistic regression is developed by normalizing the testing data first:

Table 5.7 Total Cost of Testing Data

No	Product Name	Q-System	P-System	Decision
1.	Batik vest	557.000	545.000	1
2.	Urban batik polo	843.500	888.500	0
3.	Batik kimono	872.000	1.027.000	0
4.	Batik cardigan	1.077.000	1.044.000	1
5.	Batik bomber jacket	717.000	651.000	1

Table 5.8 Normalized Testing Data

Product ID	Product Name	Mean(x_1)	St. Dev (x_2)	Leadtime (x_3)	Hold. Cost (x_4)	Decision (x_5)
1	Batik vest	0,3	0,29	1	0,33	1
2	Urban batik polo	1	1	0	0	0
3	Batik kimono	0,28	0,14	1	1	0
4	Batik cardigan	0,33	0,57	0	1	1
5	Batik bomber jacket	0	0	0	1	1

After the normalized data is calculated and obtained, later logistic regression is developed to compare decision on clustered and logistic regression. For the coefficient/intercept terms (β_n) which are determined by solver add-ins, these are the results:

g. β_0= -42,95
h. β_1= -48,54
i. β_2= 21,75
j. β_3= 25,69
k. β_4= 12,1
l. β_5= 94,96

So, the logistic regression is applied:

Table 5.9 Logistic Regression on Testing Data

	β_0	β_1	β_2	β_3	β_4	β_5		
	-42,95	-48,54	21,75	25,69	12,1	94,96		
Product ID	Product Name	Mean	St. Dev	Leadtime	Hold. Cost	Decision	Prediction	SE
1	Batik vest	0,3	0,29	1	0,33	1	1	0
2	Urban batik polo	1	1	0	0	0	0	0
3	Batik kimono	0,28	0,14	1	1	0	0	0
4	Batik cardigan	0,33	0,57	0	1	1	1	0
5	Batik bomber jacket	0	0	0	1	1	1	0
							MSE	0

5.1.2. Accuracy Measurement

For each test product, the true optimal method was determined through total cost minimization, as done in Chapter 4. The model's prediction was compared to the true label. The classification results are summarized below:

Table 5.10 Testing Data Summarized

No	Product Name	Actual Method	Predicted Method
1	Batik vest	P	P
2	Urban batik polo	Q	Q
3	Batik kimono	Q	Q
4	Batik cardigan	P	P
5	Batik bomber jacket	P	P

The system achieved an accuracy of 100% on the test set, indicating that the logistic regression model can generalize well to new data. This suggests the system is suitable for assisting decision-making in selecting inventory control strategies for products not included in the original dataset. Misclassification may occur in cases where product characteristics lie close to the classification threshold or where subtle cost differences are not fully captured by the model. Nonetheless, the results support the model's operational relevance in reducing total inventory cost through correct system assignment.

5.2. Suggestion for Future Improvement

While the logistic regression model developed in this study performed well, with a testing accuracy of 100% there remains significant potential to enhance both classification performance and model sophistication through the integration of more advanced machine learning methods.

5.2.1 Adoption of Artificial Neural Networks (ANN)

One promising alternative to logistic regression is the use of Artificial Neural Networks (ANN) for inventory classification. Unlike logistic regression, which is linear, ANN can model non-linear relationships and complex interactions between variables, such as the interaction of lead time and demand variability in determining the most suitable inventory method.

Neural networks can automatically capture patterns in historical inventory data, making them highly suitable for larger, more diverse product datasets or datasets with hidden nonlinearities. For instance, a multi-layer perceptron (MLP) model could be trained using the same features (mean demand, standard deviation, lead time, holding cost) but may uncover patterns that logistic regression fails to detect due to its linear assumptions.
However, while ANN can offer higher predictive accuracy, it lacks the interpretability of logistic regression. Therefore, it is recommended for use when prediction performance is prioritized over transparency, or when used in conjunction with explainable AI methods such as SHAP to interpret the output.

5.2.2. Practical Implementation and ERP Integration

The logistic regression-based classification system developed in this study offers significant potential for integration into Enterprise Resource Planning (ERP) systems, providing automated and data-driven inventory strategy selection for retail operations.

The classification module can be embedded within existing ERP inventory management modules through the following implementation approach:

Automated Classification Module: The logistic regression model can be programmed as a classification engine within the ERP system's inventory management module. When new products are added to the system, the module automatically:

1. Data Collection: Extracts relevant product characteristics (mean demand, standard deviation, lead time, holding cost) from historical sales and procurement data stored in the ERP database
2. Feature Normalization: Applies the min-max normalization formula developed in this study to ensure consistent input scaling
3. Classification Processing: Executes the logistic regression equation with the optimized coefficients (β_0 = -42.95, β_1 = -48.54, β_2 = 21.75, β_3 = 25.69, β_4 = 12.1, β_5 = 94.96) to determine the optimal inventory control method
4. System Assignment: Automatically assigns P-System or Q-System parameters and triggers appropriate reorder policies

Integration Benefits:

a. Elimination of Manual Decision-Making: Reduces reliance on subjective managerial judgment in inventory system selection

b. Consistent Application: Ensures standardized application of cost-optimization principles across all product categories

c. Real-time Adaptation: Enables dynamic reclassification as product characteristics evolve over time

d. Cost Reduction: Systematic application of the optimized classification can reduce total inventory costs by ensuring each product uses its most cost-efficient control method

Implementation Considerations: For successful ERP integration, the classification module requires:

a. Regular model validation using updated historical data

b. User interface for monitoring classification decisions and manual overrides when necessary

c. Integration with existing procurement and warehouse management modules

d. Audit trail functionality to track classification changes and their impact on inventory performance

This automated approach transforms the research findings into a practical tool that can enhance inventory efficiency in real-world retail operations, particularly beneficial for companies managing diverse product portfolios like Batik Retail Pekalongan.

CHAPTER VI
CONCLUSION AND SUGGESTION

6.1 Conclusion

This study aimed to improve inventory control decision-making in the batik retail sector by using a data-driven classification approach to determine whether each product is more cost-efficiently managed under a Q-System (Fixed Order Quantity) or a P-System (Fixed Order Period). The conclusions drawn are based on the two stated research objectives:

1. The research successfully developed a logistic regression model using product features such as mean demand, demand variability (standard deviation), lead time, and holding cost. The dependent variable was the most cost-efficient inventory system, determined through total cost analysis (ordering cost, holding cost, and lost profit) using Solver optimization in Excel. The model achieved an accuracy of 100% on the test dataset of 5 new products, confirming its ability to generalize well to unseen data. This model enables inventory classification not by intuition or static rules but through quantitative analysis, improving accuracy and cost efficiency.
2. The model revealed that certain variables, especially mean demand**,** standard deviation**,** and lead time, significantly influence the inventory control decision. Products with stable and high demand tended to benefit more from the Q-System, while those with irregular or lower demand patterns performed better under the P-System. The logistic regression model's coefficients, obtained through Solver, quantitatively illustrated each variable's impact on the classification outcome. The model was evaluated using a confusion matrix and testing accuracy metric, confirming its validity and predictive performance.

6.2 Suggestion

According to the findings and process of this study, several important insights were gained that may be beneficial for future research and practical applications. The following suggestions are offered:

1. Future research is encouraged to explore more advanced classification models such as Artificial Neural Networks (ANN) or ensemble methods. These models may provide improved prediction accuracy, especially when dealing with more complex or non-linear inventory behavior across different product types.

2. It is important that future studies consider including additional variables that may influence inventory decisions, such as seasonality, trend changes, and external supply chain factors. Lack of relevant variables may limit the performance of the model and reduce its applicability in more dynamic environments.
3. Companies are recommended to adopt data-driven techniques like the logistic regression model used in this study as part of their decision-making tools. This approach can enhance the accuracy and efficiency of inventory control, especially in retail environments where product diversity and demand variability are high.
4. It is recommended that future studies conduct sensitivity analysis to evaluate the robustness of the logistic regression coefficients under different market conditions and demand scenarios. This analysis would help determine the stability of the classification model when key parameters such as lead times, costs, or demand patterns change due to external factors such as economic conditions, seasonal variations, or supply chain disruptions.

REFERENCES

Ahmed, M., Seraj, R., & Islam, S. S. (2020). The k-means algorithm: A comprehensive survey and performance evaluation. *Electronics*, 1295.

Chang, A. (., El-Rayes, N., & Shi, J. (2022). Blockchain technology for supply chain management: A comprehensive review. *Fintech*, 191-205.

Hosmer, D. W., Lemeshow, S., & Sturdivant, R. X. (2013). *Applied logistic regression.* New Jersey: Wiley.

Mohammed, M. G., Melhum, A. I., & Ibrahim, A. L. (2022). Optimizing accuracy of stroke prediction using logistic regression. *Journal of Theoretical and Applied Information Technology, 100(4)*, 41-47.

Montazeri, F. Z., Sorourkhah, A., Marinković, D., & Lukovac, V. (2024). Robust-fuzzy-probabilistic optimization for a resilient, sustainable, and circular supply chain network design under uncertainty. *Big Data and Computing Visions, 4(2)*, 146-163.

Pampel, F. C. (2020). *Logistic regression: A primer.* California: SAGE Publications.

Panigrahi, R. R., Shrivastava, A. K., & Kapur, P. K. (2023). Impact of inventory management practices on the operational performances of SMEs: Review and future research directions. *Journal of Global Operations and Strategic Sourcing*, 74-99.

Pattnaik, S., Nayak, M. M., Abbate, S., & Centobelli, P. (2021). Recent Trends in Sustainable Inventory Models: A literature review. *Sustainability*, 11756.

Pulido-Rojano, A., Gomez, A., Correa, Y., & Saldarriaga, J. F. (2020). An optimization approach for inventory costs in probabilistic inventory models: A case study. *Revista chilena de ingeniería*, 384-395.

Rizqi, Z. U., & Khairunisa, A. (2021). Integration of deterministic and probabilistic inventory methods to optimize the balance between overstock and stockout. *IOP Conference Series: Materials Science and Engineering*, 1-6.

Song, J.-S. J. (2022). *Research handbook on inventory management.* Cheltenham: Edward Elgar Publishing.

Utama, D. M., Santoso, I., Hendrawan, Y., & Dania, W. P. (2023). Sustainable production-inventory model with multi-material, quality degradation, and probabilistic demand: From bibliometric analysis to a robust model. *Indonesian Journal of Science & Technology*, 172-196.

Vicente, J. J. (2025). Optimizing Supply Chain Inventory: A Mixed Integer Linear Programming Approach. *Systems, 13(1)*, 33.

Zhang, D., Turan, H. H., Sarker, R., & Essam, D. (2024). Robust optimization approaches in inventory management: Part A—The survey. *IISE Transactions*, 818-844.

Zhu, A., Hua, Z., Shi, Y., Tang, Y., & Miao, L. (2021). An Improved K-Means Algorithm Based on Evidence Distance. *Entropy, 23(11)*, 1550.