CHAPTER I
INTRODUCTION

This chapter presents the foundation for conducting the research, encompassing the background, research questions, research objectives, research contributions, and research limitations to clarify the focus, direction, and scope of the study. This section provides the basis for understanding the research problem and the direction of the study's development. Through this chapter, the rationale and boundaries of the research are established before the theoretical foundations and related studies are discussed in the following chapter.

1.1 Background

In the retail sector, inventory management is subject to pressure arising from fluctuating demand and product distribution across multiple points of sale. These conditions make forecasting accuracy an essential factor in maintaining a balance between stock availability and market demand. Inaccurate predictions may increase the risks of stockouts and overstocks, which can affect customer satisfaction, operational costs, and the efficiency of inventory planning [1][2][3]. Therefore, an approach capable of predicting demand more accurately is required as a basis for inventory decision-making.

Demand forecasting serves as the foundation of inventory control because forecast results are used to determine procurement quantities and regulate stock levels to support more optimal inventory planning [4][5]. When forecasting accuracy declines, an imbalance between demand and product availability Therefore, selecting an appropriate forecasting method is an important factor in supporting more systematic inventory management, particularly under operational conditions that are not yet supported by a structured forecasting system.

In practice, daily sales data often exhibit unstable characteristics, particularly when analysed at the product level, because transactions do not necessarily occur every day. Consequently, the data contain numerous zero values and form intermittent or lumpy demand patterns. These conditions make the data sparse and complicate the identification of trend and seasonal patterns, thereby reducing forecasting model performance. This issue has been widely discussed in studies concerning irregular demand data and infrequent transactions [7][8]. One approach used to address this condition is temporal aggregation, which involves changing the data frequency from daily observations to a higher-level period, such as weekly data. This approach has been shown to reduce noise, improve pattern stability, and clarify data characteristics for the forecasting process [9][10][11]. In the context of the Grand Optic case study, the use of weekly data is also based on operational requirements, as stock evaluation and management are conducted periodically on a weekly basis. In addition, the daily data indicate that several products have days without transactions, making them less representative for direct use in forecasting. Therefore, the data are aggregated from daily to weekly frequency to produce more stable patterns while aligning the analysis with Grand Optic's inventory-planning requirements.

Statistical methods such as the Autoregressive Integrated Moving Average (ARIMA) are frequently used in time-series forecasting because they can capture linear and seasonal patterns in historical data. However, this method has limitations when demand patterns are nonlinear and fluctuate over time [4][12]. In contrast, Extreme Gradient Boosting (XGBoost) can model nonlinear relationships and interactions among variables, making it effective for analysing more complex sales data [3][13]. Nevertheless, the independent use of either method may not optimally capture all patterns within the data [5]. These limitations have encouraged the use of hybrid approaches that combine statistical and machine-learning models within a single forecasting framework. A hybrid ARIMA–XGBoost model utilises ARIMA's ability to capture linear patterns and XGBoost's ability to capture nonlinear patterns, thereby producing more stable predictions for data characterised by diverse demand patterns [12].

The forecasting results are subsequently used as a basis for inventory decision-making, particularly in determining ordering policies and maintaining stock availability. Concepts such as the reorder point (ROP), safety stock, and service level are employed to anticipate demand uncertainty and maintain a balance between product availability and the risk of stock shortages [14][15]. High demand variability may increase the risk of stockouts when it is not supported by accurate forecasting. Therefore, forecasting accuracy is a key factor in supporting more systematic and data-driven inventory management [1][5][6].

Various studies have demonstrated that hybrid approaches can improve forecasting accuracy for data with diverse patterns. However, most studies continue to focus on improving predictive performance and have not directly integrated their results into inventory-control decision-making at the Stock Keeping Unit (SKU) level [12]. In contrast, research conducted in the optical retail context has integrated forecasting with inventory management, but it has continued to rely on a single model and has not employed a hybrid approach to address variations in demand across SKUs [16]. This condition indicates an ongoing need to integrate hybrid models with more practical inventory-control policies.

This need is evident in the Grand Optic case study, where inventory management continues to be based on experience without the support of a structured forecasting system. Stock inspections are conducted weekly; however, ordering decisions are not yet based on systematic prediction results. Consequently, the inventory-control process is not fully data-driven. Furthermore, forecasting results have not been integrated with the calculation of ROP, safety stock, and service level, meaning that ordering decisions continue to depend on intuition. These conditions indicate that the decision-making process remains suboptimal because it is not supported by an integrated forecasting system.

Based on these conditions, this study applies a hybrid ARIMA–XGBoost model to forecast eyeglass frame sales at Grand Optic. The forecasting results are used as the basis for inventory decision-making at the SKU level. These results are presented through a dashboard that functions as a decision support system to facilitate more systematic and data-driven inventory planning.

1.2 Problem Formulation

Based on the background described above, the problems formulated in this study are as follows:

1. How does the hybrid ARIMA–XGBoost model perform in forecasting the weekly sales of eyeglass frame products?
2. How can the forecasting results be used in calculating inventory control policies by considering the service level and lead time?

3. How can the integration of forecasting results and inventory control policies be presented in the form of a dashboard as a decision support system?

1.3 Research Objectives

Based on the problem formulation presented above, the objectives of this study are formulated as follows:

1. To analyse the performance of the hybrid ARIMA–XGBoost model in forecasting the weekly sales of eyeglass frame products.
2. To use the forecasting results in calculating inventory control policies by considering the service level and lead time as a basis for decision-making.
3. To develop a dashboard as a decision support system that presents forecasting results and inventory control recommendations.

1.4 Research Benefits

The expected benefits of this study include the following practical and theoretical benefits:

1. Practical Benefits
    - To assist Grand Optic in obtaining weekly sales estimates that can be used as a basis for inventory planning.
    - To provide recommendations for product restocking planning by utilising demand forecasting results and calculating inventory control parameters such as the ROP and service level.
    - To reduce the potential for stock shortages and inventory accumulation through the use of a hybrid ARIMA–XGBoost model integrated with inventory control policies.
2. Theoretical Benefits
    - To contribute to the development of demand forecasting research using a hybrid ARIMA–XGBoost approach.
    - To serve as a reference for future studies that relate time-series forecasting results to inventory control.
    - To enrich the literature on the application of hybrid models in the context of inventory management in optical retail.

1.5 Research Limitations

To maintain the focus of the study and ensure the achievement of the established objectives, the research limitations are defined as follows:

1. This study focuses on eyeglass frame products at Grand Optic and uses transaction and sales data from the 2021–2025 period as the basis for analysi.
2. Forecasting is performed using weekly aggregated sales data to capture demand trends and fluctuations.
3. The modelling approach is limited to the use of a hybrid ARIMA–XGBoost model, with the prediction results combined using a weighted ensemble method.
4. Model performance is evaluated using the MAE, RMSE, and MAPE metrics to measure forecasting accuracy.
5. The weekly forecasting results are used as the basis for developing inventory control policies at Grand Optic, which are subsequently applied to product-ordering planning.
6. The inventory control calculations in this study consider the ROP parameter, estimated demand during a seven-day lead time (one period), and the target service level as the basis for product-restocking planning.
7. The study is implemented in the form of a dashboard as a decision support system to assist with product-restocking planning at the SKU level at Grand Optic.