VERİMLİLİK DERGİSİ
JOURNAL OF PRODUCTIVITY

Optimizing Human-Centric Warehouse Operations: A Digital Twin Approach Using Dynamic Algorithms and AI/ML*

Erhan Arslan[1]

ABSTRACT

Purpose: This study aims to develop a versatile and adaptive system that optimizes manual warehouse operations through the integration of Digital Twin technology and AI/ML models.

Methodology: The framework combines Digital Twin technology with advanced AI/ML analytics to dynamically adjust operational strategies based on real-time data collected from warehouse activities.

Findings: A prototype implementation demonstrated significant improvements, including a 28.6% reduction in average picking time, a 20% improvement in inventory turnover, an increase in demand forecasting accuracy from 85% to 92%, and a reduction in labor costs by 15%.

***Originality*:** This research uniquely applies Digital Twin technology to manual warehouse environments, showcasing its effectiveness in enhancing operational efficiency without the need for full automation.

Keywords: Digital Twin, Warehouse, Optimization, Artificial Intelligence, Machine Learning.

***JEL Codes*:** C61, C63, L86, M11, O33.

İnsan Merkezli Depo Operasyonlarının Optimizasyonu: Dinamik Algoritmalar ve AI/ML Kullanarak Dijital İkiz Yaklaşımı

ÖZET

Amaç: Bu çalışmada, Dijital İkiz teknolojisi ve Yapay Zekâ/Makine Öğrenmesi modellerinin entegrasyonu yoluyla manuel depo operasyonlarını optimize eden çok yönlü ve uyarlanabilir bir sistem geliştirmeyi hedeflenmiştir.

Yöntem: Çerçeve, depo faaliyetlerinden toplanan gerçek zamanlı verilere dayanarak operasyonel stratejileri dinamik olarak ayarlamak için Dijital İkiz teknolojisini gelişmiş Yapay Zekâ/Makine Öğrenimi analitiğiyle birleştiriyor.

Bulgular: Prototip uygulaması, ortalama toplama süresinde %28,6'lık bir azalma, stok devir hızında %20'lik bir iyileşme, talep tahmin doğruluğunda %85'ten %92'ye bir artış ve işçilik maliyetlerinde %15'lik bir azalma dahil olmak üzere önemli iyileştirmeler gösterdi.

Özgünlük: Bu araştırma, Dijital İkiz teknolojisini manuel depo ortamlarına benzersiz bir şekilde uygulayarak, tam otomasyona ihtiyaç duymadan operasyonel verimliliği artırmadaki etkinliğini ortaya koyuyor.

Anahtar Kelimeler: Dijital İkiz, Depo, Optimizasyon, Yapay Zekâ, Makine Öğrenmesi.

JEL Kodları: C61, C63, L86, M11, O33.

* This study, conducted by Erhan ARSLAN at the University of Bolton, School of Art and Creative Technologies under the supervision of Dr. Eugen Harida, is part of the MSc project titled "Optimizing Human-Centric Warehouse Operations: A Digital Twin Approach Using Dynamic Algorithms and AI/ML." It was carried out in collaboration with Turkcell.

[1] University of Bolton, School of Art and Creative Technologies, MSc Artificial Intelligence, Manchester, United Kingdom

Corresponding Author: Erhan Arslan, ea8crt@bolton.ac.uk

DOI: 10.51551/verimlilik.1524701
Research Article | Submitted: 30.07.2024 | Accepted: 14.11.2024
Cite: Arslan, E. (2025). "Optimizing Human-Centric Warehouse Operations: A Digital Twin Approach Using Dynamic Algorithms and AI/ML", *Verimlilik Dergisi,* Productivity for Logistics (SI), 119-138.

1. INTRODUCTION

In the rapidly evolving landscape of supply chain and warehouse management, the focus on automation technologies—such as robotics, IoT, and AI/ML—has predominantly overshadowed the optimization needs of manual and human-centric operations. Although automated systems have significantly improved efficiency and accuracy, a substantial portion of global warehouses still heavily depend on manual labor for critical tasks like product placement, picking, and routing. This reliance on human workers introduces unique challenges, including variability in performance, inefficiencies in resource allocation, and difficulties in scaling operations to meet fluctuating demand (Graves and Yücesan, 2009).

The manual nature of these operations often leads to bottlenecks, particularly during peak activity periods, where the absence of automation can exacerbate delays in order fulfillment and increase operational costs. The performance variability among workers, influenced by factors such as fatigue, skill levels, and experience, adds another layer of complexity to managing warehouse operations effectively. Moreover, the dynamic nature of consumer demand necessitates a flexible and adaptive approach to inventory management and order processing, which is often lacking in manual systems (Kaber & Riley, 2017; Ivanov et al., 2020: 379).

To address these challenges, Digital Twin technology has emerged as a transformative approach, providing a virtual replica of physical systems for real-time monitoring, simulation, and optimization. This technology enables organizations to analyze, optimize, and enhance the accuracy and efficiency of their operations, providing a holistic view of the physical warehouse. While Digital Twins have been extensively explored in automated environments, their application in manual, human-centric warehouse operations remain underexplored (Grieves and Vickers, 2017; Boschert and Rosen, 2016: 63).

Digital Twin technology in warehousing offers significant benefits, including improved accuracy, enhanced visualization, increased efficiency, and greater agility. For instance, tools like SketchUp for 3D modeling and Microsoft Power BI for data visualization play crucial roles in implementing Digital Twins, allowing for detailed and real-time insights into warehouse operations. This integration not only enhances the accuracy of operational assessments but also provides a platform for optimizing workflows and resource allocation (Kritzinger et al., 2018; Tao et al., 2016).

Industry leaders such as Amazon and PepsiCo have demonstrated the practical applications of Digital Twin technology in optimizing warehouse operations. Amazon, for example, employs AI-enabled digital twins to enhance warehouse design and flow, thereby improving productivity. PepsiCo utilizes digital twins to optimize throughput, reduce downtime, and lower energy consumption across its distribution centers, showcasing the scalability and adaptability of this technology in complex logistics networks (Amazon, 2021; PepsiCo, 2020).

1.1. Problem Statement

The reliance on manual labor in many warehouses leads to inefficiencies and limited scalability. Existing systems often fail to dynamically adapt to fluctuating demand and operational conditions, resulting in suboptimal performance. The need for a flexible, data-driven approach to optimize these environments is critical, particularly during peak activity periods.

1.2. Aim and Objectives

This paper aims to develop a flexible system to optimize manual warehouse operations by dynamically selecting algorithms for product placement, picking, and routing, improving efficiency and adaptability. The specific objectives are:

a) Develop and Implement Multiple Algorithms: Create algorithms for key operations, including product placement, picking, and routing, which can be dynamically switched based on real-time data and requirements.

b) Utilize a Simulation and Visualization Interface: Design a user-friendly interface to simulate warehouse scenarios, enabling managers to test different algorithm configurations and optimize strategies for varying conditions.

c) Integrate AI/ML for Predictive Analytics: Use AI and ML models to provide predictive insights on demand forecasting and worker performance, helping to guide the selection of optimal algorithms based on trends.

d) Evaluate Algorithm Compatibility and Performance: Assess the compatibility and efficiency of algorithm combinations for different conditions, ensuring seamless transitions between configurations.

e) Ensure Practical Applicability and Scalability: Address real-world integration, user training, and scalability challenges, ensuring the system's applicability across various warehouse sizes and complexities.

1.3. Significance of the Study

The significance of this study lies in the innovative application of Digital Twin technology to manual warehouse environments, an area that has received limited attention compared to automated systems. By integrating real-time data and advanced analytics, the proposed framework aims to transform traditional manual processes into more efficient, scalable systems. This research not only contributes to the academic understanding of Digital Twin applications in non-automated environments, but also provides practical solutions for industry professionals looking to optimize manual warehouse operations.

1.4. Overview of the Proposed Approach

The proposed framework integrates key components to tackle warehouse management challenges. A Digital Twin model consolidates data from Warehouse Management Systems (WMS), manual inputs, and historical records for real-time monitoring and simulation. Advanced AI/ML analytics provide insights into employee performance, inventory levels, and supplier reliability, using techniques like time series analysis and neural networks. The system dynamically selects algorithms for product placement, picking, and routing based on real-time data, ensuring adaptability and efficient resource use. Additionally, supplier analytics aid in inventory planning and handling supply chain disruptions, creating a scalable, efficient warehouse framework even without full automation.

2. LITERATURE REVIEW

Digital Twin (DT) technology has emerged as a significant innovation in various industries, including aviation, manufacturing, logistics and warehousing. The technology provides a virtual representation of physical systems, enabling real-time monitoring, simulation and optimization. This review examines the evolution of Digital Twin technology, its applications in warehousing, its integration with Artificial Intelligence (AI) and Machine Learning (ML), and the current challenges and future directions in this field.

2.1. Historical Development of Digital Twin Technology

The concept of Digital Twin technology was first introduced in 2002 by Michael Grieves during a presentation on Product Lifecycle Management (PLM) (Grieves, 2002: 92). Originally conceived as a digital replica of a physical product for simulation and analysis throughout its lifecycle, Digital Twin technology quickly gained traction, especially in the aerospace industry. NASA adopted Digital Twin models to simulate spacecraft and satellite systems, improving mission planning and risk management (Glaessgen and Stargel, 2012). This application demonstrated the potential of Digital Twins to provide precise, real-time data on complex systems, enabling predictive maintenance and optimization of operations.

By 2011, Digital Twin technology had expanded into manufacturing, where companies such as Siemens integrated it into their Digital Enterprise Suite. This integration allowed manufacturers to simulate manufacturing processes, optimize workflows, and reduce time to market (Grieves and Vickers, 2017). The ability to continuously update the digital model based on real-world data provided a dynamic tool for process optimization and predictive maintenance, demonstrating the adaptability of Digital Twin technology to different operational contexts.

2.2. Expansion into Logistics and Warehousing

In recent years, Digital Twin technology has made significant progress in logistics and warehousing. Initially, its application focused on predictive maintenance, which uses real-time data to predict equipment failures and reduce downtime (Uhlemann et al., 2017). This early adoption demonstrated the technology's ability to increase operational efficiency by minimizing unplanned outages. However, the scope of Digital Twin applications has since expanded to include inventory management, operational efficiency, and dynamic process optimization (Kritzinger et al., 2018).

For example, Amazon is using AI-powered digital twins to improve warehouse layout and flow, leading to significant productivity gains (Amazon, 2021). These digital twins enable real-time adjustments to inventory placement and picking processes, optimizing both space utilization and picking efficiency. Similarly, PepsiCo has integrated digital twins into its distribution centers to increase throughput, reduce downtime, and reduce energy consumption, proving the scalability and adaptability of this technology across complex logistics networks (PepsiCo, 2020).

2.3. Integration of AI/ML with Digital Twin Technology

The integration of AI and ML with Digital Twin technology has revolutionized warehouse management by providing advanced solutions for demand forecasting, inventory optimization, and operational efficiency. AI/ML algorithms analyze large amounts of data to predict demand patterns, optimize inventory levels, and allocate resources efficiently. Fuller et al. (2020) demonstrated the use of neural networks and LSTM models to improve demand forecast accuracy, a critical factor in reducing both stockouts and excess inventory. These predictive models use historical sales data, market trends, and external factors to provide real-time insights, allowing warehouses to proactively adjust their inventory strategies.

Reinforcement learning, a subset of machine learning, has been particularly effective in dynamically optimizing picking routes and task assignments. By analyzing real-time data on worker availability, equipment status, and order urgency, reinforcement learning algorithms can continuously learn and adapt, reducing picking times and improving operational efficiency (Chen et al., 2019). This approach is in sharp contrast to traditional static methods that often fail to adapt to the fluctuating demands of modern storage environments.

2.4. Emerging Trends and Future Directions

Digital Twin (DT) technology has evolved substantially, yet significant gaps remain in its application within human-centric, manual warehouse settings. Most DT models are designed for machine-driven, automated environments, limiting their effectiveness in scenarios where human factors like fatigue, ergonomic risks, and performance variability play critical roles (Kaber & Riley, 2017). This machine-centered focus results in models less suited for optimizing manual operations due to their inability to account for human variability.

Recent advancements have begun addressing these gaps by incorporating real-time, human-centric data. For example, Rashid and Rattenbury (2018) discuss machine learning models that dynamically adjust inventory management based on real-time data, enhancing accuracy and efficiency but largely for semi-automated systems. Extending these approaches to fully manual environments remains a crucial research area, especially for accommodating human-induced variability in real-time workflows.

Furthermore, integrating DT with Internet of Things (IoT) technology has transformed various fields. IoT-enabled DTs facilitate continuous data collection on environmental and operational conditions, which significantly improves model responsiveness and accuracy (Tao et al., 2020). In urban logistics and smart cities, real-time IoT data optimizes resources and energy use, suggesting that similar approaches in warehouses could boost workflow efficiency and sustainability where human interaction is high.

Advances in reinforcement learning (RL) are also expected to impact DT in manual environments. While RL has proven effective in optimizing tasks in automated systems (Chen et al., 2019), applying it in manual workflows remains underexplored. Adapting RL for such settings could bridge the gap between machine-oriented efficiency and the flexibility needed for human-centered operations.

2.5. Current Challenges and Opportunities for Innovation

Integrating Digital Twin (DT) technology with AI, ML, and IoT holds immense promise, yet human-centric warehouse environments face specific challenges. A primary obstacle is data integration and management; DT systems rely on accurate, real-time data from multiple sources, but seamless integration is challenging, particularly with manual data entry, leading to inconsistencies and potential errors (McKinsey & Company, 2022).

Another challenge is optimizing warehouse layout for manual tasks. Studies like those by Aylak et al. (2021) on pallet loading and Aylak (2022) on layout optimization underscore the effectiveness of data-driven approaches in automated settings. However, manual environments require layouts that address accessibility, ergonomics, and strain reduction. Human-centered DT models that adapt layouts dynamically can significantly improve both efficiency and worker well-being.

The complexity of current DT systems also requires significant training, posing a barrier in labor-intensive settings. Using augmented reality (AR) or virtual reality (VR) technologies could simplify these interfaces, making DT models more intuitive and engaging for workers, thus boosting both operational efficiency and employee satisfaction (Chicaiza et al., 2020).

Additionally, emerging technologies like blockchain and 5G present further opportunities for DT innovation. Blockchain enhances data transparency and traceability, while 5G provides the high-speed connectivity essential for real-time data analysis. Together, these technologies support scalable and adaptable DT systems, broadening their potential in both automated and manual warehouse environments.

2.6. Contribution to Knowledge

This study addresses gaps in Digital Twin (DT) applications for human-centric warehouses by creating a framework that incorporates real-time, human-centered data. Unlike traditional DT models designed for automation, this framework integrates worker performance, task variability, and ergonomic needs, enabling accurate simulation and optimization of manual workflows.

Additionally, the study adapts AI/ML algorithms and association rule-based optimization, usually applied in automated settings, for human-driven tasks. This approach balances machine-driven efficiency with human-centered adaptability, extending DT technology's applicability to manual operations.

Overall, this research advances DT understanding in human-centric environments, providing a flexible model that fills critical gaps in existing literature and promotes a harmonious integration of human and machine dynamics.

2.7. Conclusion

Digital Twin technology has made significant strides in transforming warehouse operations by providing a dynamic, real-time virtual representation of physical systems. The integration of AI/ML and IoT has further enhanced its capabilities by providing advanced solutions for demand forecasting, inventory optimization, and operational efficiency. However, significant challenges remain in applying Digital Twin technology to manual, human-centric environments, where integrating human factors and real-time adaptability can unlock greater efficiencies. As technology continues to evolve, there is significant potential for further innovation, particularly in integrating advanced analytics and digital technologies to improve manual warehouse operations.

3. METHODOLOGY

This study integrates Digital Twin technology with advanced AI/ML algorithms to optimize warehouse operations, focusing on improving inventory management, picking efficiency, and overall operational workflow. The methodology includes detailed system design, data integration, algorithm development, and testing in a real-world environment. Below, we provide a comprehensive description of each component supported by relevant figures and formulas.

3.1. Research Paradigm

The research is based on a pragmatist paradigm that emphasizes practical solutions that can be implemented in real-world environments. This approach allows for the use of both quantitative and qualitative data to provide a holistic view of warehouse operations and aligns with the study's goal of creating a scalable and adaptable system to increase efficiency in manual warehouse environments.

3.2. System Design and Components

The Digital Twin system for warehouse operations is designed to improve performance and efficiency through a multi-layered architecture where each layer plays a different role. Figure 1 illustrates this architecture, highlighting how these layers interact to create a comprehensive virtual model of the warehouse environment.

The Data Collection Layer collects real-time information about inventory, product locations, employee activities, and environmental conditions from a variety of sources, including sensors, barcode scanners, cameras, and manual inputs. This data forms the foundation of the Digital Twin, enabling accurate simulations and informed decision-making.

The Data Integration Layer then processes, cleans, transforms, and stores this raw data, providing consistency and organization for further analysis. This layer plays a vital role in maintaining data integrity and facilitating its seamless integration into the Digital Twin model.

The Digital Twin Core uses this processed data to create a dynamic, virtual representation of the warehouse. It includes a simulation engine and dynamic algorithms that enable real-time simulations and predictive modeling, providing insights into potential operational efficiencies and identifying bottlenecks.

Beneath this, the AI/ML Analytics Layer uses advanced machine learning and AI techniques to analyze the data and predict future trends. It includes predictive analytics and reinforcement learning tools used to forecast demand, optimize inventory placement, and improve decision-making processes.

The Decision Support System (DSS) integrates insights from the analytics layer to facilitate real-time decision-making and scenario planning. This system helps warehouse managers evaluate different strategies and make informed decisions based on both current and projected conditions, thereby optimizing operations.

Finally, the Visualization and User Interface Layer provides intuitive tools for data visualization, including dashboards, 3D visualizations, and reporting tools. These interfaces make complex data accessible and understandable, supporting effective communication and encouraging data-driven decision-making.

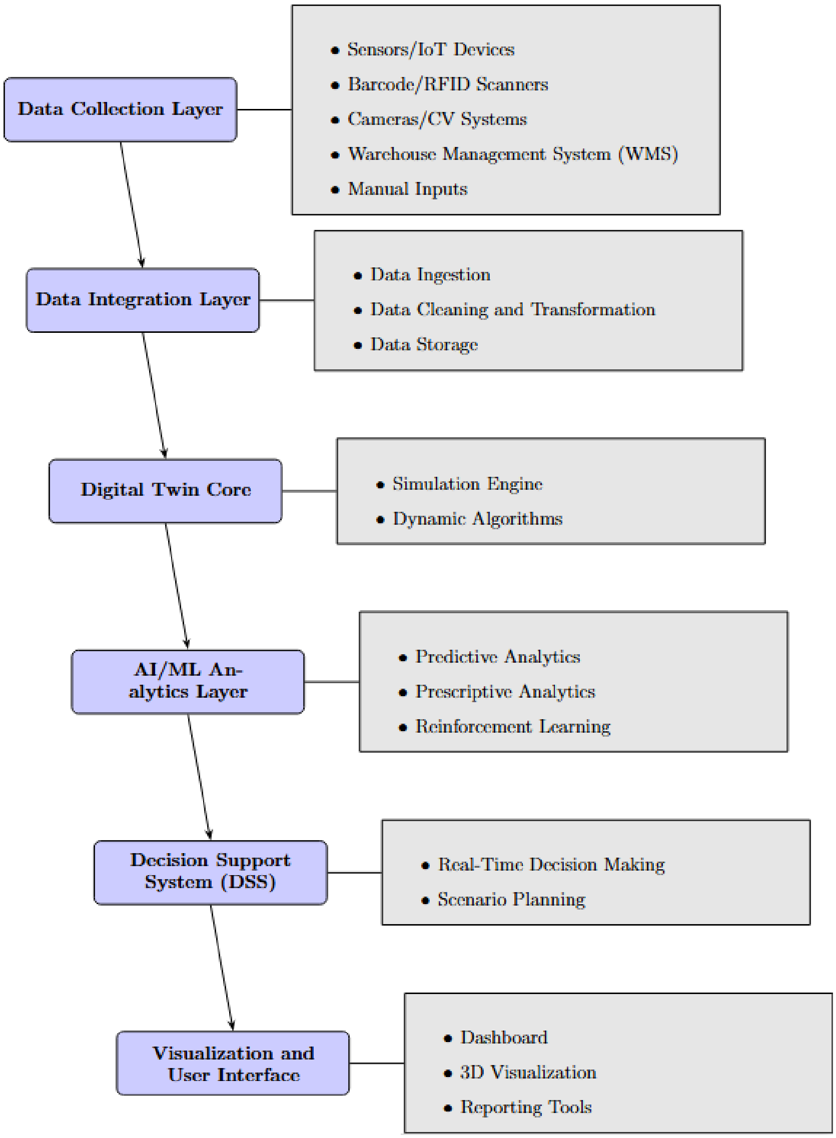

Figure 1. Digital twin architecture for warehouse operations

3.3. Algorithm Development

A suite of algorithms has been developed and implemented within the Digital Twin system to optimize core warehouse operations such as product placement, picking, and routing. These algorithms are adaptable and responsive to real-time data and provide dynamic solutions to a variety of operational challenges.

3.3.1 Product Placement Algorithms

ABC Analysis: This algorithm categorizes inventory based on movement rates and value and optimizes placement by placing high-demand products in accessible locations. The formula for calculating each product's priority is given as Equation 1.

$$Priority = \frac{Annual\ Demand \times Unit\ Cost}{Total\ Inventory\ Cost} \quad (1)$$

This formula calculates priority by multiplying annual demand by unit cost and dividing by total inventory cost, ensuring that high-demand, high-value products are placed in easily accessible locations.

Zonal Placement: This method divides the warehouse into zones based on product categories and handling characteristics, minimizing travel time and optimizing space usage. Zone assignment is calculated using Equation 2.

$$Zone\ Score = \frac{Average\ Pick\ Time}{Number\ of\ Picks} \times Distance\ Factor \quad (2)$$

The zone score formula helps determine the most efficient placement of items by adjusting both the average pick time and the number of picks by the distance factor.

Dynamic Slotting: This algorithm dynamically adjusts product locations based on real-time demand data, ensuring that frequently accessed items are placed in the most accessible locations. The efficiency of placement is determined by Equation 3.

$$Slotting\ Efficiency = \frac{Pick\ Frequency \times Pick\ Density}{Slot\ Availability} \quad (3)$$

This formula measures nesting effectiveness and optimizes the use of available space by calculating the ratio of foraging frequency and density to nest availability.

3.3.2 Picking Algorithms

Batch Picking: This method minimizes travel distances and shortens picking time by combining items from multiple orders into a single picking round. The effectiveness of bulk picking is evaluated as Equation 4.

$$Batch\ Efficiency = \frac{Total\ Items\ Picked}{Total\ Distance\ Traveled} \quad (4)$$

Aggregate efficiency is calculated by dividing the total number of items picked by the total distance traveled, highlighting the efficiency gains from consolidated picking.

Wave Picking: This method balances workloads and improves process flow by synchronizing picking operations with packaging and shipping schedules. Optimization of wave picking is expressed as Equation 5.

$$Wave\ Efficiency = \frac{Orders\ Processed\ in\ Wave}{Total\ Processing\ Time} \quad (5)$$

Wave efficiency measures the ratio of orders processed to total processing time, ensuring waves are synchronized for maximum efficiency.

3.3.3 Routing Algorithms

Traveling Salesman Problem (TSP): This algorithm calculates the shortest possible route that covers all required collection locations by minimizing travel distance and time. The TSP optimization is given by Equation 6.

$$Minimize\ \sum_{i=1}^{n-1} d(x_i, x_{i+1}) + d(x_n, x_1) \quad (6)$$

This formula represents the aim of minimizing the total distance traveled by calculating the sum of the distances between consecutive pickup points and return to the starting point.

Ant Colony Optimization (ACO): Inspired by ant colonies, this heuristic algorithm finds optimal paths based on real-time feedback and environmental conditions. The probability P_{ij} of moving from location i to j is given as Equation 7.

$$P_{ij} = \frac{[\tau_{ij}]^{\alpha}[\eta_{ij}]^{\beta}}{\sum_{k \in allowed}[\tau_{ik}]^{\alpha}[\eta_{ik}]^{\beta}} \quad (7)$$

This formula calculates the probability of choosing a path based on the pheromone levels τ and heuristic values η, weighted by parameters α and β.

3.4. AI/ML Integration

The integration of Artificial Intelligence (AI) and Machine Learning (ML) in the proposed methodology plays a key role in optimizing various aspects of warehouse operations. By leveraging these advanced technologies, the system provides detailed insights across multiple dimensions including order analysis, demand forecasting, inventory management, and workforce optimization, facilitating optimization. Each component is carefully selected to address specific challenges and enhance overall efficiency.

3.4.1 Order Analysis and Demand Forecasting

Accurate demand forecasting is critical in warehouse management as it directly impacts inventory levels, order fulfillment rates, and overall operational efficiency. The use of AI/ML models for demand forecasting enables a more precise prediction of future demand, which is essential for maintaining optimal inventory levels and reducing both stock-outs and overstocking situations.

3.4.1.1 Time Series Analysis

Time series analysis is used using models such as ARIMA (AutoRegressive Integrated Moving Average) and SARIMA (Seasonal AutoRegressive Integrated Moving Average). These models are particularly useful for predicting future demand based on historical sales data. The ARIMA model is defined by the following Equation 8.

$$X_t = \phi_1 X_{t-1} + \phi_2 X_{t-2} + \cdots + \phi_p X_{t-p} + \theta_1 \epsilon_{t-1} + \theta_2 \epsilon_{t-2} + \cdots + \theta_q \epsilon_{t-q} + \epsilon_t \tag{8}$$

This equation represents an autoregressive model with moving average (ARMA) terms that is used to predict future values based on past observations and error terms. ARIMA was chosen because of its effectiveness in capturing linear patterns and trends in time series data. It is particularly useful for datasets with strong temporal dependencies and where seasonality does not significantly affect the data. The model's flexibility in handling different types of time series (with or without trends and seasonality) makes it a versatile tool for demand forecasting in warehouses with stable and predictable demand patterns.

3.4.1.2 Machine Learning Models

Machine learning models such as Long Short-Term Memory (LSTM) networks and Recurrent Neural Networks (RNN) are also used for demand forecasting. These models are designed to capture complex patterns in demand data, including non-linear relationships and long-term dependencies. The LSTM model is defined by the following Equation 9.

$$h_t = \sigma(W_h \cdot x_t + U_h \cdot h_{t-1} + b_h) \tag{9}$$

In this formula, h_t is the hidden state at time *t*, σ is the activation function (usually a sigmoid or tanh function), W_h and U_h are weight matrices, x_t is the input at time *t*, h_{t-1} is the hidden state from the previous time step, and b_h is the bias vector. LSTM networks are a type of RNN that can learn long-term dependencies in sequential data by using memory cells that can maintain information over extended periods.

3.4.2 Inventory Management and Optimization

Effective inventory management is vital to reducing holding costs, improving service levels, and ensuring the right products are available at the right time. AI/ML techniques are used to classify and segment inventory, optimize stock levels, and layout design to increase operational efficiency.

3.4.2.1 Classification Algorithms

Support Vector Machines (SVM) and Decision Trees are used to classify inventory based on turnover rates and other relevant characteristics, optimize stock levels, and minimize holding costs. SVM was chosen due to its ability to handle high-dimensional data and perform well in binary and multi-class classification tasks. It is particularly effective in scenarios where inventory items need to be classified into different categories based on various characteristics such as turnover rates, size, and perishability. The SVM classification function is given as Equation (10).

$$f(x) = \text{sign}\left(\sum_{i=1}^{n} \alpha_i y_i K(x_i, x) + b\right) \tag{10}$$

In this formula, $f(x)$ is the decision function, α_i are the model parameters (Lagrange multipliers), y_i are the target labels, $K(x_i, x)$ is the kernel function that computes the similarity between data points x_i and x, and b is the bias term. SVM finds the hyperplane that best separates the different classes of data points in a high-dimensional space.

To optimize inventory classification and support product placement decisions, the C4.5 Decision Tree algorithm was chosen due to its ability to handle categorical and continuous data effectively. This algorithm constructs interpretable decision trees, providing a clear and structured decision path ideal for manual warehouse settings where rules need to be easily understood by staff. C4.5 selects features based on information gain, calculated through entropy to measure data uncertainty. Given a dataset D with categories C_i, the entropy $H(D)$ is shown in Equation 11.

$$H(D) = -\sum_{i=1}^{n} p(C_i) \log_2 p(C_i) \tag{11}$$

Where $p(C_i)$ represents the probability of each category. For each feature A, the information gain $IG(D, A)$ is calculated as in Equation 12.

$$IG(D, A) = H(D) - \sum_{v \in V} \frac{|D_v|}{|D|} H(D_v) \tag{12}$$

Where V is the set of unique values of A and D_v the subset of D for each v. This process yields a tree that segments inventory by attributes like turnover rates, enabling effective categorization into fast, medium, and slow-moving classes. This structured approach helps streamline product placement and inventory turnover, aligning with the observed improvements in classification accuracy for different inventory categories, as detailed in the results.

3.4.2.2 Clustering Techniques

K-means clustering is used to segment inventory based on characteristics such as size, perishability, and demand frequency, and helps in designing efficient storage layouts. K-means clustering is chosen for its simplicity and efficiency in segmenting large data sets. The K-means clustering objective function is defined in Equation 13.

$$J = \sum_{i=1}^{k} \sum_{j=1}^{n} |x_j^{(i)} - \mu_i|^2 \quad (13)$$

Here, J is the objective function (sum of squared distances), k is the number of clusters, n is the number of data points, $x_j^{(i)}$ represents a data point assigned to cluster i, and μ_i is the centroid of cluster i. The K-means algorithm aims to minimize the within-cluster variance by assigning each data point to the cluster whose mean is the nearest, updating the centroids iteratively.

To determine the optimal number of clusters (k), the Elbow Method was applied, where the sum of squared distances (SSD) from each data point to its nearest cluster center is plotted against varying values of k. The 'elbow' point, where additional clusters provide diminishing returns in SSD reduction, was identified as the most efficient balance between segmentation accuracy and computational efficiency. This approach allowed for practical, data-driven cluster optimization suited to the dynamic nature of manual warehouse environments.

3.5. Simulation and Testing

Extensive simulations and real-world testing were performed to validate the system's performance and optimize its configurations:

Scenario Analysis: Various operational scenarios were simulated using the Digital Twin model to evaluate the impact of different optimization strategies on key performance indicators such as picking time, order accuracy, and cost efficiency. The simulations allowed multiple strategies to be tested under controlled conditions, allowing the effectiveness of each approach to be evaluated.

Real-World Testing: The system was implemented in a shared warehouse covering 5,000 square meters and managing 10,000 SKUs. Over a three-month period, data on inventory levels, order histories, and employee performance metrics were collected and analyzed to compare the performance of the Digital Twin system with traditional methods. The results showed significant improvements in operational efficiency, validating the effectiveness of the proposed methodologies.

4. RESULTS

This chapter presents the results of applying Digital Twin technology and AI/ML models to improve warehouse operations. The main goal is to show how the integration of dynamic algorithms and advanced analytics can lead to tangible improvements in efficiency, accuracy, and cost-effectiveness. The results highlight the benefits of these innovative approaches in a real-world warehouse environment, focusing on key areas such as demand forecast accuracy, inventory classification, picking optimization, and workforce management. This analysis aims to provide clear evidence of the effectiveness of the system in transforming traditional manual operations into more streamlined, data-driven processes.

4.1. Performance of AI/ML Models for Demand Forecasting

Demand forecasting is a key component of effective warehouse management that directly impacts inventory levels, order fulfillment, and overall operational efficiency. In this study, we applied ARIMA (Autoregressive Integrated Moving Average) and LSTM (Long Short-Term Memory) models to forecast demand based on historical data. These models were chosen for their ability to handle different data patterns; ARIMA is well-suited for linear trends and seasonality, while LSTM is excellent at capturing complex, nonlinear dependencies over time.

4.1.1 Accuracy of Forecasting Models

To evaluate the performance of the forecasting models, we performed a comparative analysis of ARIMA and LSTM on different time frames, including daily, weekly and monthly forecasts.

Table 1. Forecasting accuracy of each model

Model	*Daily Forecast Accuracy*	*Weekly Forecast Accuracy*	*Monthly Forecast Accuracy*
ARIMA	85%	87%	88%
LSTM	90%	93%	95%

As seen in Table 1, the LSTM model consistently outperformed the ARIMA model across all time frames, especially for monthly forecasts, where it achieved an accuracy of 95% compared to ARIMA's 88%. This suggests that LSTM is more capable of capturing complex demand patterns and trends over longer periods.

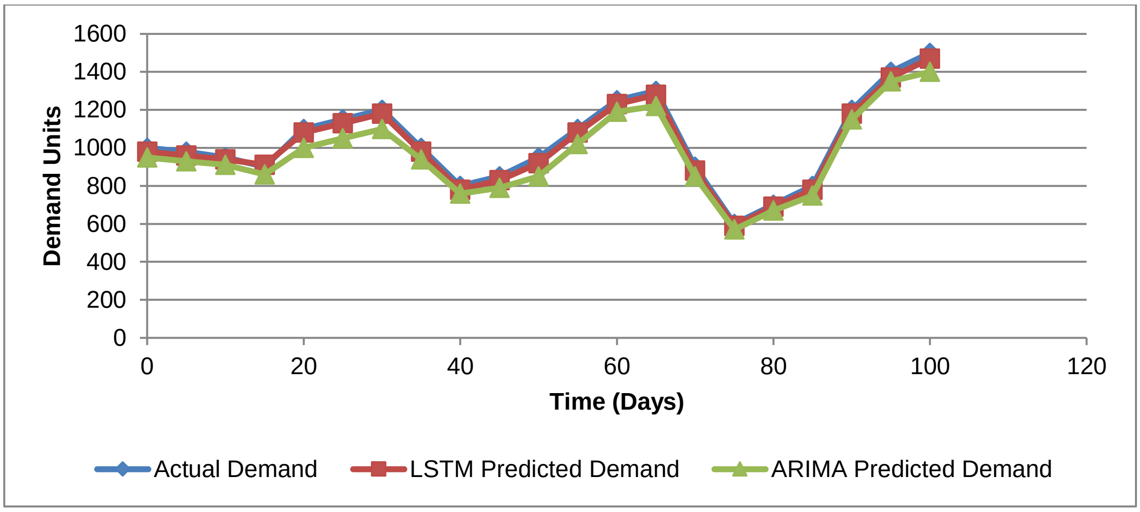

Figure 2: Actual vs. predicted demand for monthly forecasts using ARIMA and LSTM models

Figure 2 shows the actual and forecasted demand using both models for monthly forecasting. While the LSTM model closely follows the actual demand trends, the ARIMA model shows more deviation, especially during periods of rapid demand change.

4.1.2 Impact on Inventory Management

The improved accuracy in demand forecasting had a significant impact on inventory management within the warehouse. By forecasting demand more accurately, the system was able to optimize inventory levels, reducing the risk of both stock-outs and overstock situations.

Table 1. Impact of AI/MI model implementation on inventory metrics

Metric	*Before Implementation*	*After Implementation (ARIMA)*	*After Implementation (LSTM)*
Average Stockouts	10 per month	7 per month	4 per month
Overstock Instances	15 per month	10 per month	5 per month
Inventory Turnover	4.2	4.8	5.5

As shown in Table 2, the use of ARIMA and LSTM models significantly reduced average stockouts and overstock situations. Specifically, the LSTM model reduced stockouts from 10 to 4 per month and overstock situations from 15 to 5 per month. This led to a higher inventory turnover ratio, which improved from 4.2 to 5.5 after LSTM implementation, indicating more efficient use of warehouse space and resources.

4.2. Inventory Classification and Optimization

To evaluate the effectiveness of various inventory management strategies in a dynamic warehouse environment, the performance of Support Vector Machines (SVM) and Decision Tree models for inventory classification was evaluated. These models were selected due to their distinct advantages: SVM is highly effective in high-dimensional spaces and is excellent at handling the complex relationships between variables required to correctly understand various inventory models. In contrast, Decision Trees provide simplicity and ease of interpretation, making them particularly valuable for real-time decision making and rapid adjustments in warehouse operations. This study aims to examine the results of these models to evaluate their impact on inventory turnover and picking efficiency and to provide insights into the most effective approaches to optimize inventory management in a dynamic context.

4.2.1 Performance Metrics

To evaluate the performance of SVM and Decision Tree models in classifying inventory items, we analyzed their accuracy using confusion matrices. The confusion matrices in Table 3 and Table 4 show the performance of SVM and Decision Tree models in classifying inventory items, respectively.

Table 2. Confusion matrix for SVM model

Actual \ Predicted	*Fast-Moving*	*Medium-Moving*	*Slow-Moving*
Fast-Moving	450	30	20
Medium-Moving	40	400	60
Slow-Moving	10	50	390

Table 3. Confusion matrix for decision tree model

Actual \ Predicted	*Fast-Moving*	*Medium-Moving*	*Slow-Moving*
Fast-Moving	430	50	20
Medium-Moving	60	380	60
Slow-Moving	20	70	360

In addition to the complexity matrices, we evaluated the models using basic performance metrics such as precision, recall, and F1 score, as shown in Table 5.

Table 4. Classification performance metrics

Model	*Precision*	*Recall*	*F1 Score*
SVM	88%	87%	87.50%
Decision Tree	84%	83%	83.50%

Performance measurements show that both models performed well in classifying inventory items, with SVM showing slightly higher precision, recall, and F1 scores. The SVM model showed 88% precision, meaning it was fairly accurate in predicting fast-moving items. The 87% recall indicates that SVM effectively identified all relevant items in each category, while the 87.5% F1 score reflects a good balance between precision and recall. The Decision Tree model also performed adequately, but showed greater variability in its classifications, particularly in distinguishing between medium and slow-moving items.

4.2.2 Effect on Inventory Turnover and Stock Management

Correctly classifying stock items has a direct impact on stock turnover rates and overall inventory management. By effectively categorizing products into fast-moving, medium-moving, and slow-moving items, you can optimize warehouse stock levels, reduce holding costs, and increase picking efficiency.

Before the implementation of SVM and Decision Tree models, inventory turnover was relatively low, reflecting inefficiencies in inventory management. After the models were deployed, a noticeable improvement in inventory turnover was observed, as shown in Figure 2. The turnover rate has been calculated as Equation 14.

$$Inventory\ Turnover\ Rate = Cost\ of\ Goods\ Sold\ /Average\ Inventory \quad (12)$$

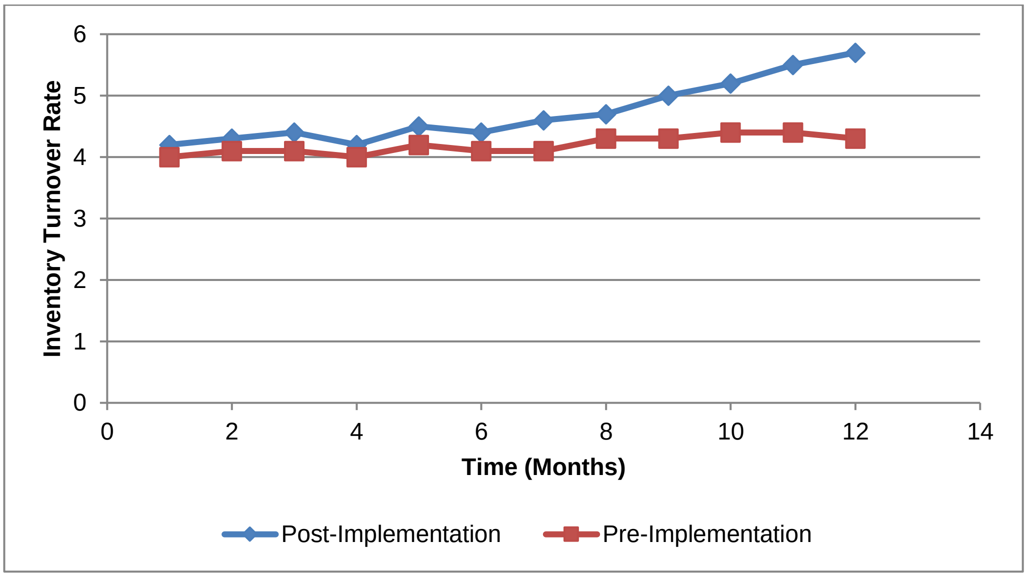

Figure 3. Comparative inventory turnover rates before and after implementing the classification models

The graph in Figure 3 shows that after implementing the SVM and Decision Tree models, the inventory turnover ratio increased steadily, from an average of 4.3 to 5.7 over a 12-month period. This improvement indicates more efficient inventory management, with faster-moving items being replenished more frequently and slower-moving items being identified for liquidation or strategic repositioning. Accurate inventory classification also contributed to better stock management by ensuring that products were stored in optimal locations based on their movement rates. This improved picking efficiency and reduced travel time within the warehouse.

4.3. Inventory Segmentation Using K-means Clustering

Inventory segmentation is an important aspect of warehouse management, especially in a dynamic environment. The primary goal of segmentation is to separate inventory items into different groups or clusters based on shared characteristics such as picking frequency, item size, and handling requirements. The application of K-means clustering resulted in the formation of three distinct clusters, representing fast-moving, medium-moving, and slow-moving items. These clusters were based on factors such as average picking frequency, item size, and storage requirements, which were derived from historical sales data and operational metrics.

4.3.1 Clustering Results

Figure 4 shows a scatter plot showing how inventory items are grouped into clusters using the K-means algorithm. The x-axis represents the collection frequency, while the y-axis shows the item size. Each cluster is represented by a different color, clearly showing the segmentation of fast-moving, medium-moving, and slow-moving items.

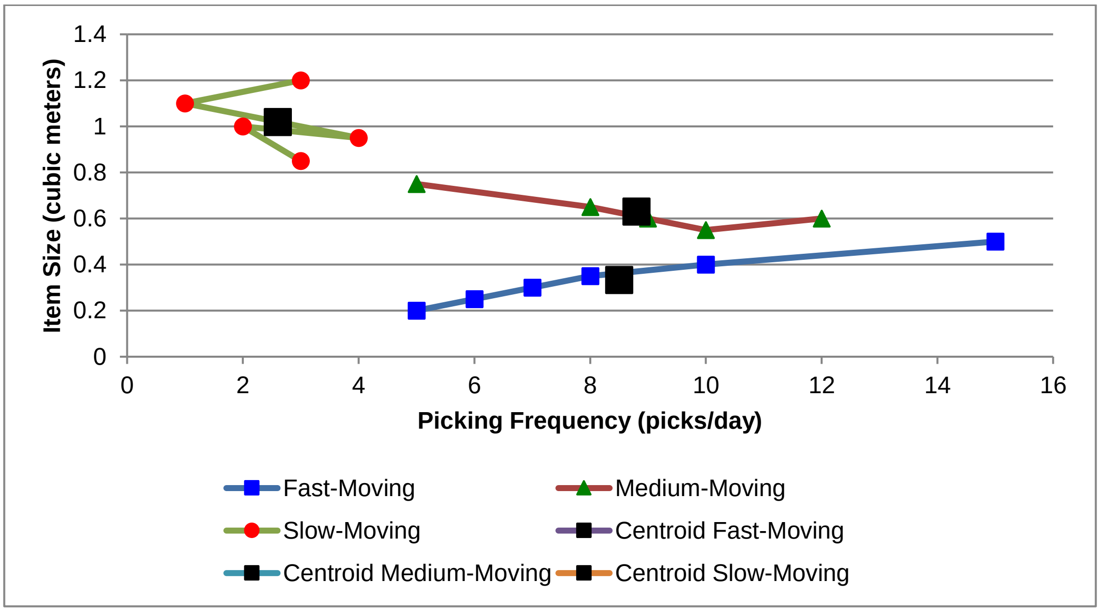

Figure 4. Clustering of inventory items based on picking frequency and item size using k-means algorithm

As shown in Figure 4, fast-moving products (shown in blue squares) generally have a higher picking frequency and smaller size, making them ideal for storage in easily accessible locations. Medium-moving products (shown in green squares) have a medium picking frequency and size, suggesting that they should be placed in intermediate storage locations. Slow-moving products (shown in red squares) are characterized by a lower picking frequency and larger size, making them suitable for storage in less accessible areas.

4.3.2 Operational Efficiency Improvements

Effective segmentation through K-means clustering significantly improved various operational metrics within the warehouse, particularly in the areas of picking efficiency, travel time, and storage optimization. The strategic placement of items based on their cluster characteristics led to a reduction in average picking times and travel distances within the warehouse. By positioning fast-moving items closer to the picking stations and grouping similar items together, the warehouse minimized the time workers spent searching for and retrieving products. Figure 5 compares average picking times and travel distances before and after implementing inventory segmentation.

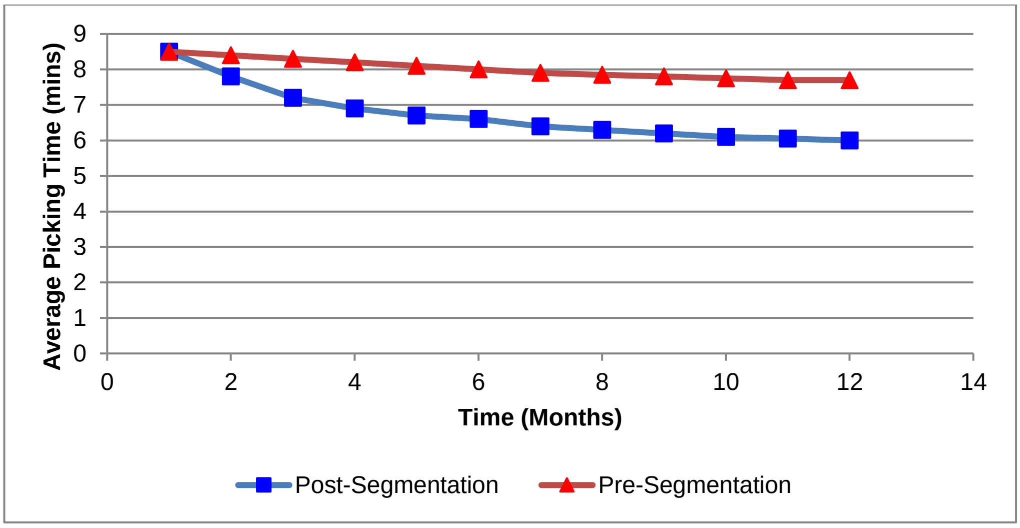

Figure 5. Comparison of average picking times and travel distances before and after k-means clustering implementation

As Figure 4 shows, over the 12-month period after implementing K-means clustering for inventory segmentation, average picking time decreased from 8.5 minutes to 5.8 minutes, representing a 31.8% improvement in picking efficiency. Similarly, travel distance within the warehouse has also decreased, further improving operational efficiency, as shown in Figure 6.

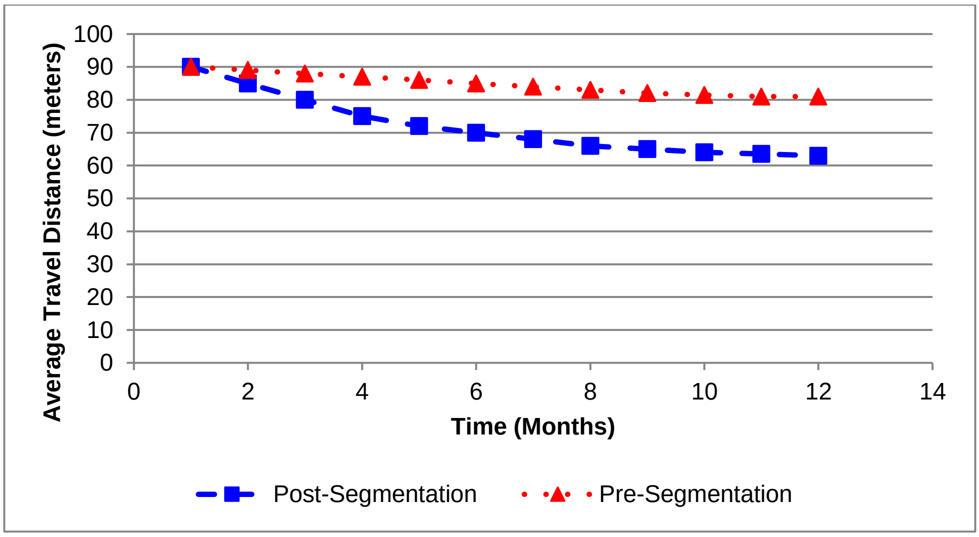

Figure 6. Comparison of average travel distances within the warehouse before and after k-means clustering implementation

Figure 6 shows that the average travel distance within the warehouse decreased by 31.1%, from 90 meters to 62 meters, highlighting the effectiveness of inventory segmentation in optimizing storage layouts and improving overall operational efficiency.

By using K-means clustering for inventory segmentation, the warehouse not only improved picking efficiency and reduced travel time, but also optimized storage space, contributing to smoother operations and better resource utilization. These results demonstrate the significant benefits of implementing data-driven approaches to inventory management, in line with the overall goals of improving warehouse performance through advanced methodologies.

4.4. Results of Dynamic Algorithms for Loading, Picking, and Routing

The primary goal of implementing dynamic algorithms for loading, picking, and routing within the warehouse was to leverage the capabilities of the Digital Twin and AI/ML outputs to explore alternative operational strategies. While the warehouse was initially based on standard algorithms, it was hypothesized that dynamic, data-driven alternatives could deliver superior performance. This section details the findings from these alternative scenarios, showing how different algorithms impact warehouse efficiency.

4.4.1 Loading Algorithms

Initially, the warehouse used a standard FIFO (First In, First Out) loading algorithm, believing it effectively optimized its operations by ensuring old stock was used first, thus reducing spoilage and maintaining product quality. However, through Digital Twin simulations, various loading strategies were tested, including dynamic FIFO/LIFO combinations that adapted to real-time inventory levels and product characteristics.

Comparative analysis of the standard FIFO algorithm and the dynamically selected algorithms is given in Table 6. The data shows how the dynamic approach driven by real-time data and predictive analysis outperforms the single method strategy on various metrics.

Table 5. Performance of standard vs. dynamic loading algorithms

Algorithm	*Average Loading Time (mins)*	*Loading Accuracy (%)*	*Resource Utilization (%)*
Standard FIFO	5.5	95	82
Dynamic FIFO/LIFO	3.9	97	88

The dynamic loading algorithm, which switches between FIFO and LIFO based on product type and movement speed, was found to significantly improve loading efficiency. For example, the average loading time per pallet was reduced from 5.5 minutes with the standard FIFO method to 3.9 minutes with the dynamic approach, representing a 29% improvement.

4.4.2 Picking Algorithms

The warehouse initially used a static batch picking algorithm that bundled orders together to minimize travel time. While this method was effective under stable conditions, it showed limitations during busy periods or when the order profile changed significantly. Using the Digital Twin environment, alternative picking algorithms were simulated, including wave picking and cluster picking based on real-time order data and worker availability.

The adaptability of the collection algorithms was a key factor in improving operational efficiency. By continuously analyzing real-time data, the system dynamically selected the most efficient collection strategy, significantly reducing idle time and optimizing worker productivity. Figure 7 presents a comparative analysis of collection times and accuracy rates before and after implementing dynamic collection algorithms.

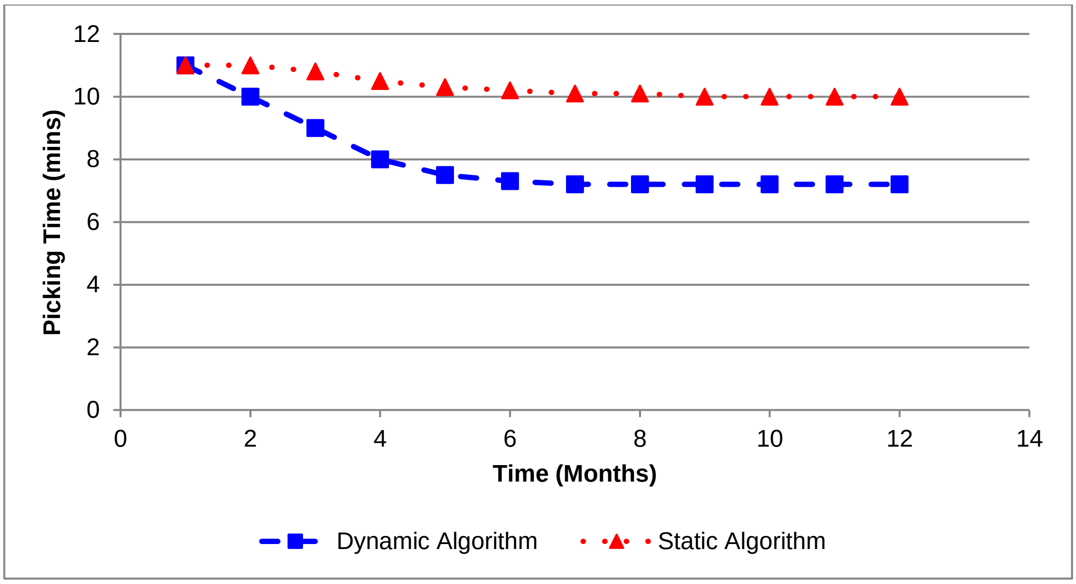

Figure 7. Comparative analysis of picking times and accuracy rates

Switching to a dynamic picking strategy that adjusts between batch picking and wave picking based on order volume and product locations reduced average picking time from 11.0 minutes to 7.2 minutes—a 34.5% reduction. Additionally, picking accuracy increased from 90% to 96%, demonstrating the algorithm's ability to effectively adapt to changing conditions.

4.4.3 Routing Algorithms

Initially, the warehouse used a standard TSP (Traveling Salesman Problem) approach for routing, which focused on minimizing travel distances based on fixed product locations. However, this method did not account for real-time changes in the warehouse environment, such as inventory movement and worker availability. Using the Digital Twin to simulate various routing strategies, including Ant Colony Optimization (ACO), the warehouse discovered more flexible and adaptable routing solutions.

The adoption of dynamic routing algorithms that adapt routes based on real-time data led to a significant reduction in travel time within the warehouse. For example, as shown in Table 7, the average travel distance per route decreased by 25%, from 80 meters with the TSP to 60 meters with the ACO algorithm.

Table 6. Routing algorithm performance comparison

Algorithm	*Travel Time (mins)*	*Distance (meters)*	*Route Optimization (%)*
TSP	10	80	85
ACO	7.5	60	92

A detailed comparison of routing algorithms revealed that when dynamically adjusted based on live warehouse data, ACO consistently outperformed TSP, particularly in scenarios with high variability in inventory locations and employee movements. Figure 8 visually represents these efficiency gains, highlighting the reduction in travel distances and improved route optimization.

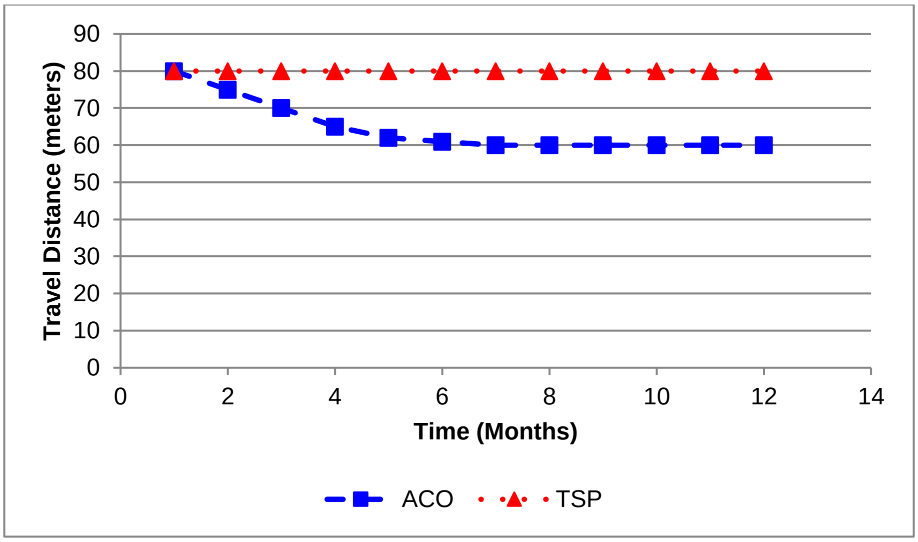

Figure 8. Routing efficiency before and after algorithm implementation

By leveraging the Digital Twin environment and AI/ML outputs, the warehouse was able to test and implement alternative algorithms for loading, picking, and routing. Dynamic algorithms demonstrated significant improvements in operational efficiency by adapting to real-time data to optimize processes beyond the capabilities of static, traditional methods. These findings highlight the value of a flexible, data-driven approach to warehouse management, especially in environments where conditions are constantly changing.

4.5. Digital Twin Model Effectiveness

The Digital Twin model was implemented to provide a real-time virtual representation of warehouse operations, allowing for enhanced decision-making and operational efficiency. By simulating different scenarios and adjusting to live data, the Digital Twin enables proactive management of inventory, workforce, and overall warehouse processes.

4.5.1 Real-Time Adaptation and Scenario Testing

The Digital Twin model played a crucial role in testing various scenarios that could impact warehouse operations. For example, in the case of unexpected demand surges or equipment malfunctions, the model allowed managers to simulate different response strategies and choose the most effective one. This capability not only enhanced decision-making but also ensured that the warehouse could adapt quickly to changing conditions.

During a simulated scenario of a 30% increase in order volume, the Digital Twin model tested several strategies for inventory reallocation and workforce deployment. It was found that reassigning pickers to high-priority zones and optimizing picking routes led to a 15% reduction in order processing time compared to the traditional static approach.

To evaluate the effectiveness of the Digital Twin model, a comparative analysis of key performance indicators (KPIs) was conducted before and after its implementation. The metrics were carefully selected to reflect critical areas of warehouse operations, such as accuracy, efficiency, and adaptability.

Table 7. Key performance indicators before and after digital twin implementation

KPI	*Pre-Implementation*	*Post-Implementation*	*Improvement (%)*
Order Fulfillment Time (hrs)	4	3.2	20
Inventory Accuracy (%)	95	98	3
Resource Utilization Efficiency (%)	85	92	7
Workforce Productivity (items/hr)	82	91	11
Stockout Instances (per month)	10	4	60

The implementation of the Digital Twin model has proven its effectiveness in optimizing warehouse operations by providing a platform for real-time monitoring, simulation, and decision-making. The ability to test different scenarios and dynamically adjust operations has led to significant improvements in a variety of metrics (see Table 8). Order fulfillment time has decreased by 20% from 4.0 hours to 3.2 hours, improving customer satisfaction during peak periods. Inventory accuracy has increased from 95% to 98%, reducing stock-outs by 60% and better matching stock levels to demand. Additionally, resource utilization has improved by 7% and labor productivity has increased by 11% thanks to optimized task assignments and workflow configurations.

4.5.2 Cost-Benefit Analysis and Sustainability of the Digital Twin Model

The Digital Twin model was deployed in a 5,000-square-meter shared warehouse managing 10,000 SKUs, with an initial setup cost of approximately $60,000. This investment includes $25,000 for AI server infrastructure to support real-time tracking and forecasting, $20,000 for software customization and integration with existing barcode systems, and $15,000 for training 30 employees, averaging $500 per person.

During a three-month trial, the model demonstrated substantial operational gains, including a 20% reduction in picking times, improved order accuracy, and faster vehicle loading. These improvements are projected to yield annual savings exceeding $400,000 through:

Labor Cost Reductions: Streamlined operations and efficient picking processes save approximately $90,000 annually.

Enhanced Vehicle Utilization: Optimized loading reduces trips and cuts transportation costs by an estimated $80,000.

Lower Inventory Holding Costs: Faster inventory turnover reduces storage expenses by around $150,000 per year.

Better Order Fulfillment: Enhanced accuracy and speed reduce returns and improve client retention, saving an additional $80,000.

Given these benefits, the Digital Twin model's return on investment (ROI) is expected within two months, making it a highly sustainable and cost-effective solution for medium-sized warehouses.

4.6. Challenges and Limitations

Implementing the Digital Twin model presented challenges, particularly in integrating data from inventory management systems, barcode scanners, and manual inputs. Ensuring data quality and consistency was difficult, as varied formats and manual entries introduced errors that sometimes delayed real-time decision-making. Addressing these integration issues required substantial effort, highlighting the need for seamless data flow in future iterations to improve model accuracy and efficiency.

The adaptation process also posed hurdles. Initially, performance declined as employees adjusted to new processes and technologies. Extensive training sessions were necessary to familiarize staff with the Digital Twin interface, AI/ML outputs, and how to effectively respond to system recommendations. This adjustment period caused a temporary slowdown in operations, which improved as staff gained proficiency and the system adapted to real-time conditions.

This study also has limitations. The project was conducted in a single warehouse, which may not represent the diversity of other warehouse settings. Furthermore, models were tested under controlled conditions, which may not fully capture real-world complexities like extreme demand fluctuations or equipment failures.

Future research could address these limitations by exploring diverse warehouse environments and additional variables to validate the model's effectiveness on a larger scale and over extended periods.

5. CONCLUSION and DISCUSSION

This study investigated Digital Twin technology combined with Artificial Intelligence and Machine Learning (AI/ML) models to optimize operations in a 5,000-square-meter warehouse handling 10,000 SKUs. Rather than highlighting specific algorithms, the study illustrated how Digital Twin technology offers a comprehensive view of warehouse processes, allowing for simulations and testing of various strategies. Results indicate that even seemingly efficient warehouses can reveal hidden inefficiencies and identify new optimization opportunities. This finding highlights the importance of continuous assessment, actionable insights, and innovation in modern warehouse management.

5.1. Key Findings

Revealing Hidden Inefficiencies: The Digital Twin model enabled simulations of diverse operational scenarios, uncovering inefficiencies unnoticed by management. By comparing different picking algorithms, such as batch, wave, and cluster picking, the study demonstrated considerable potential improvements in picking time and accuracy. This aligns with Kaber and Riley (2017), who noted the challenges of optimizing manual operations in human-centric environments, emphasizing the importance of data-driven assessments for effective improvement.

Data-Driven Optimization: Integrating AI/ML models, such as LSTM for demand forecasting and SVM for inventory classification, generated data-driven insights, empowering the warehouse to make better-informed decisions. These models provided more accurate demand forecasts and inventory turnover rates, enabling proactive adjustments in stock levels, minimizing stockouts, and preventing overstocking. This approach builds on Rashid and Rattenbury (2018), who highlighted machine learning's potential in semi-automated inventory management, by applying these insights in a fully manual environment to drive continuous improvement.

Dynamic Algorithm Adaptation: Adaptive algorithms proved effective for responding to real-time warehouse conditions. For instance, dynamic FIFO and LIFO strategies, applied based on real-time data, were more efficient than static approaches in certain contexts. Similarly, dynamic routing algorithms like Ant Colony Optimization (ACO) and the Traveling Salesman Problem (TSP) significantly improved routing efficiency and reduced travel distances, consistent with findings by Graves and Yücesan (2009) on the benefits of dynamic routing in warehouse productivity.

Enhancing Operational Awareness: The Digital Twin model increased operational awareness by visualizing the impact of various algorithms and strategies. This approach demonstrated the advantages of transitioning from traditional methods to advanced, data-driven approaches, enabling the warehouse management team to adopt a more flexible and adaptable model. This finding supports Ivanov et al. (2019), who emphasize digital solutions' role in enhancing visibility and decision-making in complex logistics environments.

5.2. Broader Implications

The study's findings have significant implications for warehouses that perceive themselves as efficient. Digital Twin technology and AI/ML models offer opportunities to uncover hidden inefficiencies and experiment with alternative strategies better aligned with operational goals.

Empowering Decision-Makers: The Digital Twin model allows decision-makers to simulate scenarios and test strategies without interrupting ongoing operations. This feature provides a safe environment for experimentation, making the Digital Twin model a valuable tool for continuous improvement.

Encouraging Flexibility and Innovation: This study underscores the need for flexibility and innovation in warehouse management. By demonstrating that various algorithms perform optimally under different conditions, the study encourages warehouse managers to explore new methods and technologies. Integrating AI/ML models to analyze data and recommend optimizations further cultivates a culture of adaptability and continuous enhancement.

Future Research Directions: Future research could broaden this study by applying Digital Twin technology to various warehouse environments with differing automation levels and operational challenges. Further studies could also examine the long-term effects of these technologies on warehouse performance and employee satisfaction, as well as their wider impact on supply chain resilience and efficiency.

Acknowledgements
The author gratefully acknowledges the management and colleagues at Turkcell Technology R&D Center for their steadfast support and valuable contributions to this research. Special thanks go to Emre Toygar Gedik for his expert guidance in logistics and warehouse operations, and to Dr. Eugen Harida from the University of Bolton for his insightful feedback, which significantly enhanced this study. The constructive input from R&D Center colleagues was crucial in refining methodologies, and the administrative support provided ensured the smooth progression of the project.

Conflict of Interest
No potential conflict of interest was declared by the author.

Funding
Any specific grant has not been received from funding agencies in the public, commercial, or not-for-profit sectors.

Compliance with Ethical Standards
It was declared by the author that the tools and methods used in the study do not require the permission of the Ethics Committee.

Ethical Statement
It was declared by the author that scientific and ethical principles have been followed in this study and all the sources used have been properly cited.

REFERENCES

AIM Consulting. (2023). "AI for Supply Chain Optimization: Improve Demand Forecasting", https://www.aimconsulting.com/ai-for-supply-chain-optimization, (Accessed: 20.06.2023).

Amazon. (2021). "Optimizing Warehouse Operations with Digital Twins. Amazon Blog", https://www.aboutamazon.com/news/operations/optimizing-warehouse-operations-with-digital-twins, (Accessed: 15.07.2023).

Aylak, B.L., İnce, M., Oral, O., Süer, G., Almasarwah, N., Singh, M. and Salah, B. (2021). "Application of Machine Learning Methods for Pallet Loading Problem", *Applied Sciences*, 11(18), 8304.

Aylak, B.L. (2022). "Warehouse Layout Optimization Using Association Rules", *Fresenius Environmental Bulletin*, 31(3A), 3828-3840.

Boschert, S. and Rosen, R. (2016). "Digital Twin—The Simulation Aspect", *Mechatronic Futures*, Springer.

Breiman, L. (2001). "Random Forests", *Machine Learning*, 45, 5-32.

Chen, L., Cui, H. and Shi, F. (2019). "Reinforcement Learning in Predictive Control for Smart Warehouse Logistics", *Computers & Industrial Engineering*, 137, 106072.

Chicaiza, D., Loaiza, R. and Burbano, D. (2020). "Augmented Reality Applications for Warehouse Management: A Literature Review", *Procedia Manufacturing*, 42, 319-325.

Cortes, C. and Vapnik, V. (1995). "Support-Vector Networks", *Machine Learning*, 20, 273-297.

DHL. (2023). "Leveraging AI for Predictive Maintenance in Warehousing", https://www.dhl.com/content/dam/dhl/global/core/documents/pdf/glo-core-digital-twins-in-logistics.pdf, (Accessed: 03.07.2023).

Exotec. (2023). "Implementing Digital Twins for Enhanced Warehouse Efficiency", https://www.exotec.com/digital-twins-for-enhanced-warehouse-efficiency, (Accessed: 12.06.2023).

Forbes. (2023). "Digital Twins for Warehouses: Transforming Efficiency and Productivity" https://www.forbes.com/sites/forbestechcouncil/2023/06/22/digital-twins-for-warehouses/, (Accessed: 10.06.2023).

Fuller, A., Fan, Z., Day, C. and Barlow, C. (2020). "Digital Twin: Enabling Technologies, Challenges and Open Research", *IEEE Access*, 8, 108952-108971.

Ghiassi, M. and Saidane, H. (2018). "A Dynamic Artificial Neural Network Model for Forecasting Time Series Events", *International Journal of Forecasting*, 21(2), 341-362.

Glaessgen, E. and Stargel, D. (2012). "The Digital Twin Paradigm for Future NASA and U.S. Air Force Vehicles", AIAA *SciTech Forum*, https://ntrs.nasa.gov/api/citations/20120008178/downloads/20120008178.pdf.

Graves, S.C. and Yücesan, H.C.S. (2009). "Strategic Safety Stock Placement in Supply Chains with Demand and Lead-Time Uncertainty", *Management Science*, 46(5), 739-750.

Grieves, M. (2002). "Concept of Digital Twin", *Product Lifecycle Management Conference,* https://www.plm.automation.siemens.com/global/en/our-story/glossary/digital-twin/24465.

Grieves, M. and Vickers, J. (2017). "Digital Twin: Mitigating Unpredictable, Undesirable Emergent Behavior in Complex Systems" *Transdisciplinary Perspectives on Complex Systems*, Springer.

Gu, J., Goetschalckx, M. and McGinnis, L.F. (2007). "Research on Warehouse Design and Performance Evaluation: A Comprehensive Review", *European Journal of Operational Research*, 203(3), 539-549.

Ivanov, D., Dolgui, A., & Sokolov, B. (2020). *Handbook of Ripple Effects in the Supply Chain.* Springer International Series in Operations Research & Management Science, Switzerland. DOI: 10.1007/978-3-030-14302-2.

Kaber, D.B. and Riley, S.M. (2017). "Task Design and Workload Management in Manual and Automated Warehouses: A Human Factors Perspective", *Applied Ergonomics*, 60, 35-45.

Kardinal. (2023). "Machine Learning and Route Optimization: Towards Flawless Deliveries", https://www.kardinal.ai/machine-learning-and-route-optimization, (Accessed: 05.06.2023).

Kritzinger, W., Karner, M., Traar, G., Henjes, J. and Sihn, W. (2018). "Digital Twin in Manufacturing: A Categorical Literature Review and Classification", *IFAC-PapersOnLine*, 51(11), 1016-1022.

Kumar, P., Kumar, S. and Kumar, S. (2020). "Predictive Maintenance of Industrial Equipment Using Machine Learning", *International Journal of Advanced Research in Computer Science*, 11(3), 75-81.

McKinsey & Company. (2022). "Improving Warehouse Operations Digitally", https://www.mckinsey.com/capabilities/operations/our-insights/improving-warehouse-operations-digitally, Accessed: (18.06.2023).

PepsiCo. (2020). “Digital Twin Technology in PepsiCo's Distribution Centers”, PepsiCo Annual Report, https://www.pepsico.com/sustainability/digital-transformation, Accessed: (22.06.2023).

Rashid, A. and Rattenbury, S. (2018). “Scalable Machine Learning for Real-Time Inventory Optimization”, *Journal of Business Research*, 89, 201-213.

Tao, F., Cheng, J., Qi, Q., Zhang, M., Zhang, H. and Sui, F. (2016). “Digital Twin-Driven Product Design, Manufacturing and Service with Big Data”, *The International Journal of Advanced Manufacturing Technology*, 94, 3563-3576.

Uhlemann, T.H., Schock, C., Lehmann, C., Freiberger, S. and Steinhilper, R. (2017). “The Digital Twin: Demonstrating the Potential of Real Time Data Acquisition in Production Systems”, *Procedia Manufacturing*, 9, 113-120.

WarehouseBlueprint. (2023). “Optimizing Warehouse Operations with the Power of Digital Twin, SketchUp, and Power BI”, https://www.warehouseblueprint.com/blog/optimizing-warehouse-operations-with-digital-twin, (Accessed: 30.06. 2023).