Digital Transformation in Warehouse Management

Introduction

Warehouses are an important part of supply chains

Any small problem can cause:

Order delays

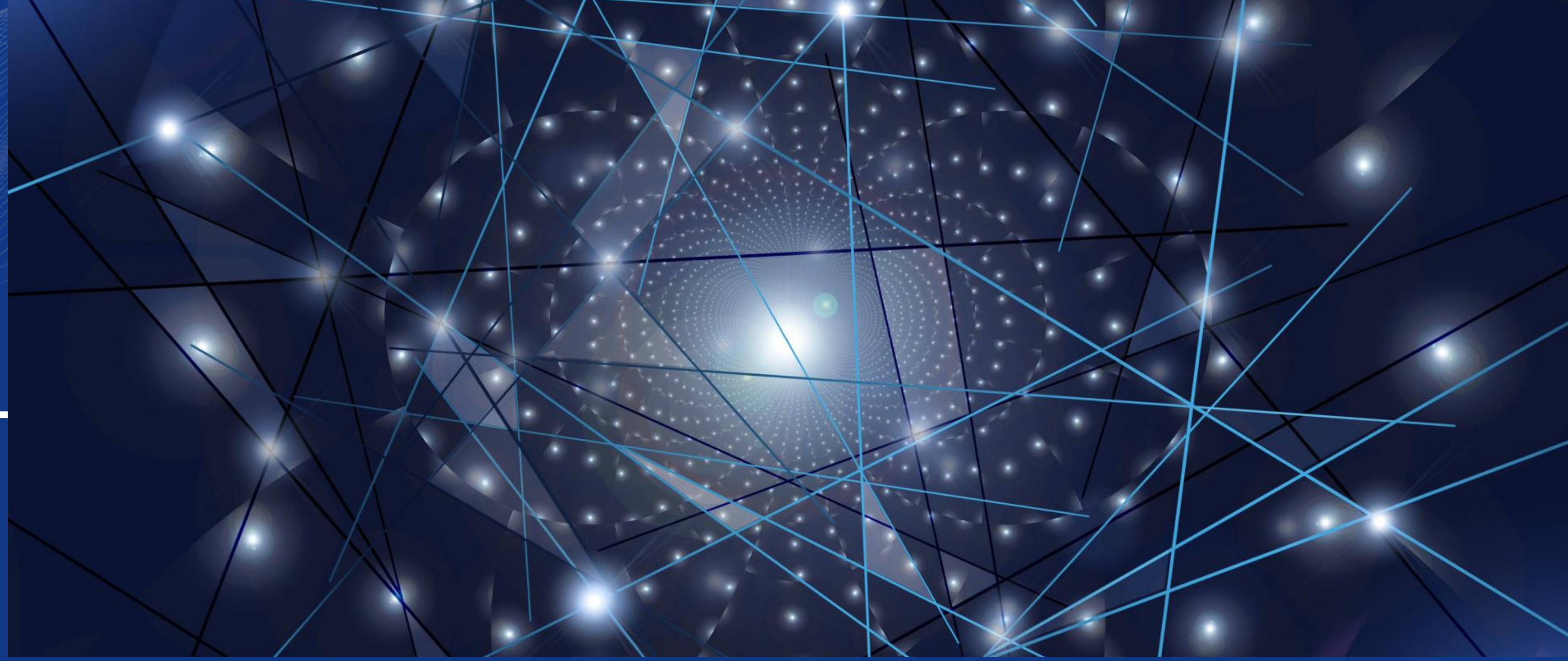
Higher costs

Digital transformation is now necessary

Research Problem

- Low inventory accuracy
- Slow order preparation
- High costs
- Dependence on manual work

Research Question & Objectives



Question: *How does combining IoT , AI & Digital Twin affect warehouse performance?*

Objectives
- Improve accuracy

Objectives
- Reduce costs

Objectives
- Speed up processes

Objectives
- Support decision-making

Theoretical Framework

Socio-technical systems theory

Technology succeeds when it works well with people

Technologies Used

Internet of Things (IoT)

collect data continually within the warehouse. It may be product flow, inventory status..

Analyses at AI (Artificial Intelligence)

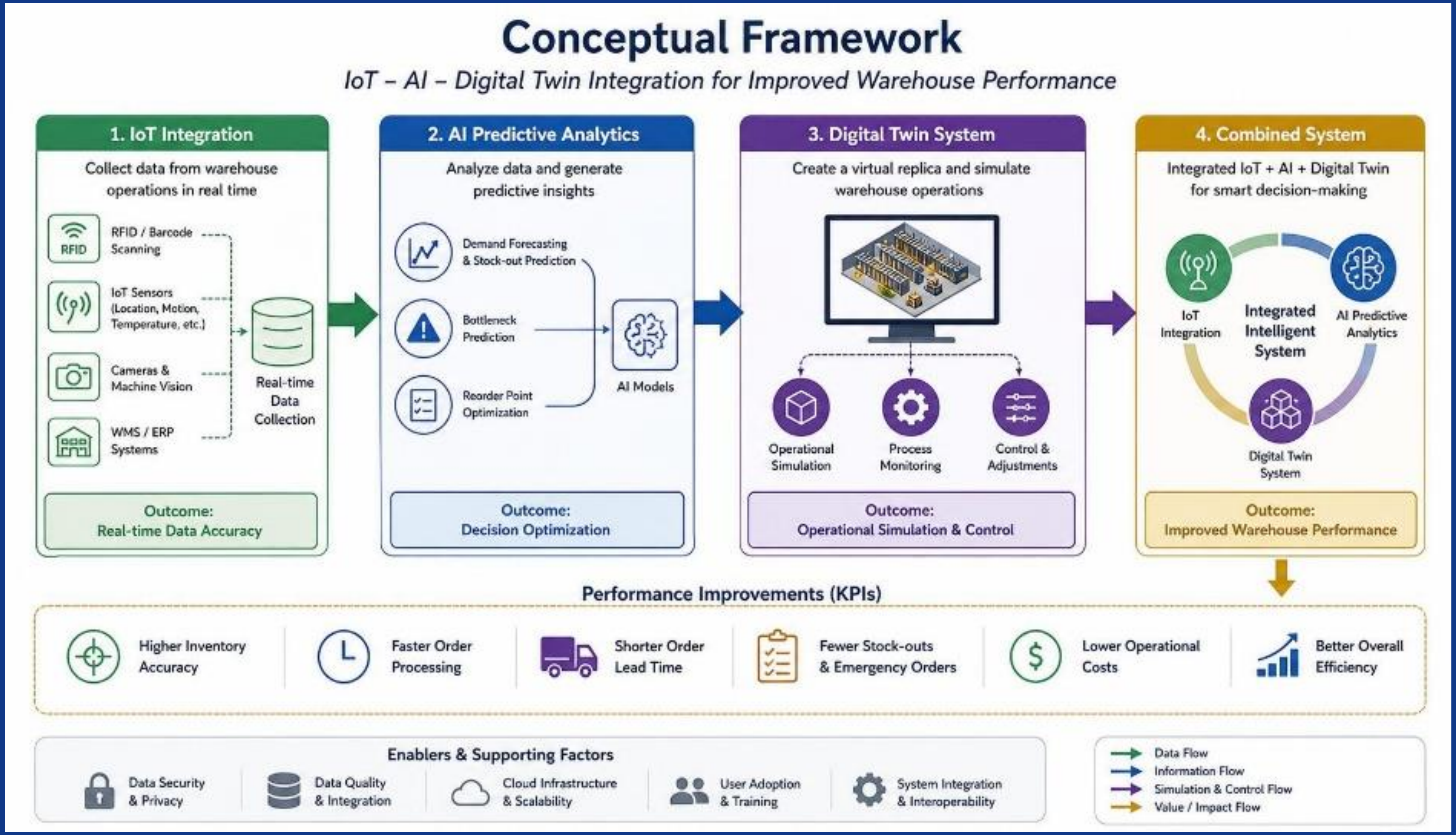
provide early predictions of issues by dissecting information.'.

Digital Twin

A replica of a warehouse is utilized for simulation and upgrade in real-time before any real changes are made..

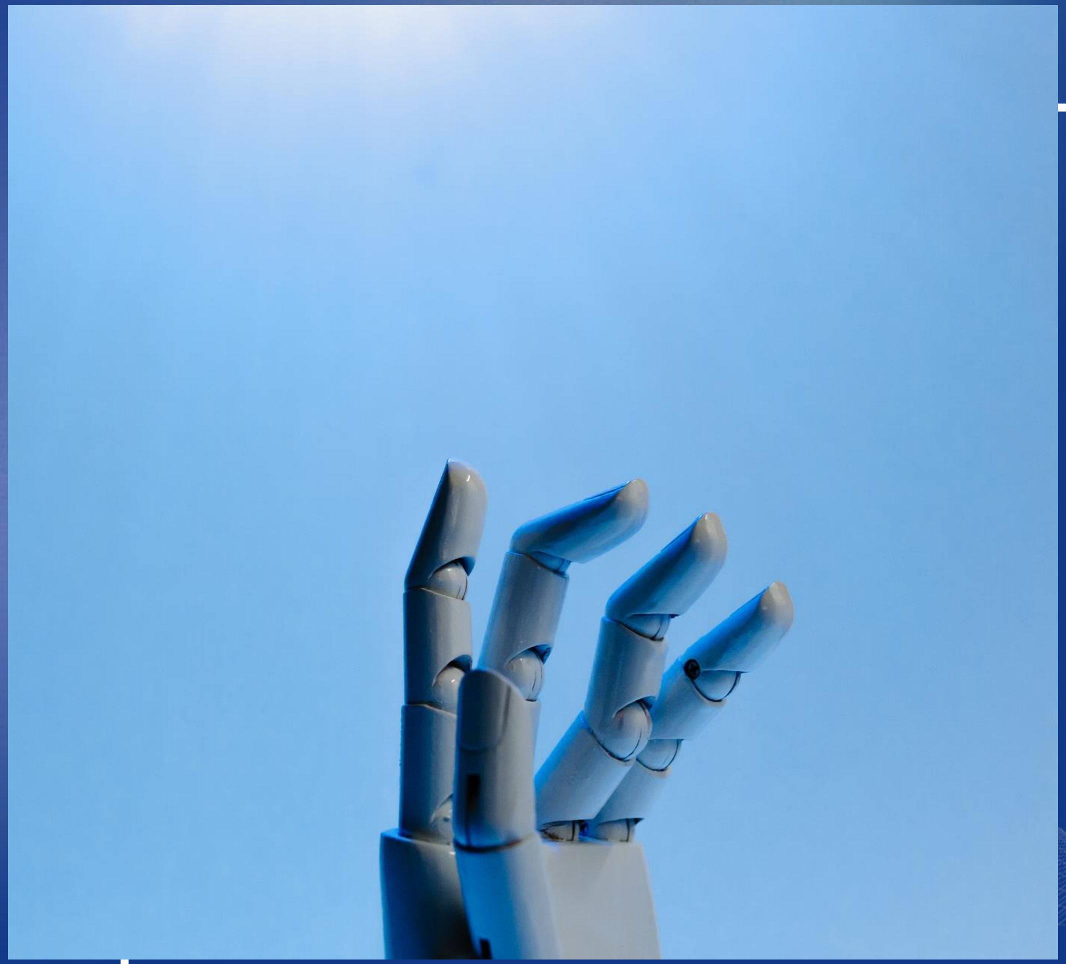
Conceptual Framework

It integrates the three pools of technology-relation-centric literature,that focusing specifically on IoT, AI, and Digital Twin technologies in the warehouse performance context being considered and widely referred to in quite a substantial amount of work.



Methodology

Comparing two situations, one before and the other after the system was implemented to assess the real impact.



Study period:

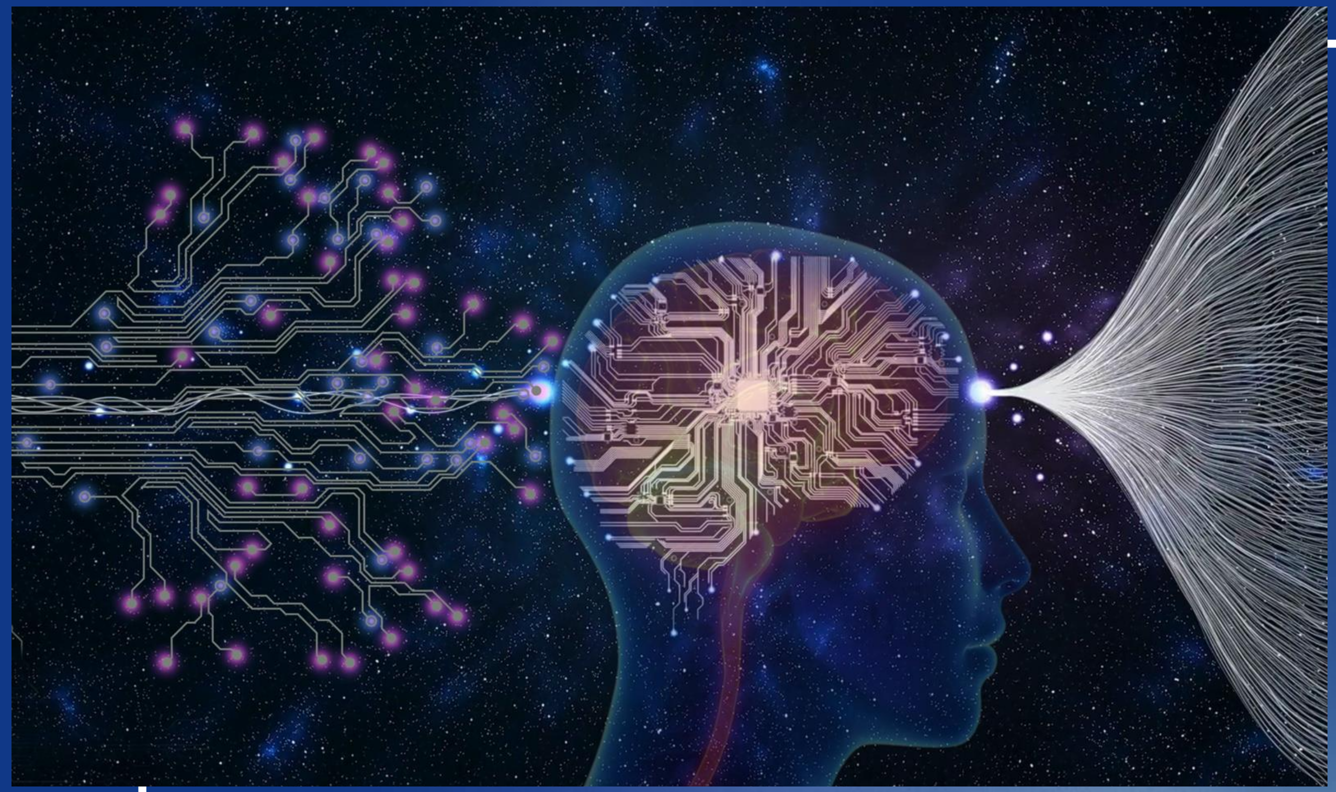
Simplifying complex topics

Creating summaries and notes

Real environment: Study done in a real warehouse in the UAE

Data Sources

WMS (Warehouse Management System): The system records daily operational data which includes order processing times and inventory movements and all system errors.



IoT Devices: The system uses RFID and sensor technology to track product movements in actual time.

Interviews & Surveys: The study gathers employee feedback about system usability and their overall contentment with the system.

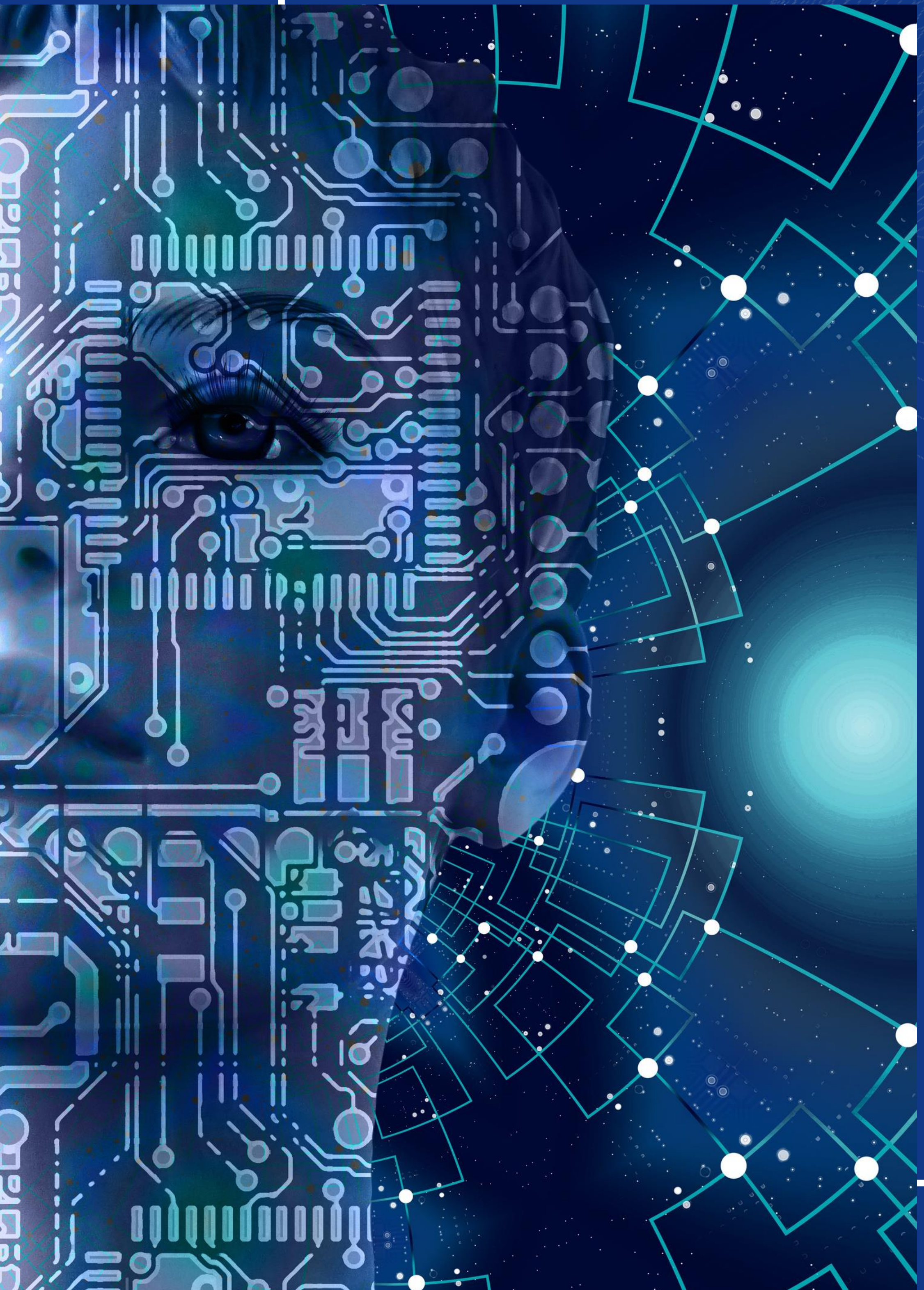
Proposed System

Save The system gathers sensor data together with Warehouse Management System data at all times.

The system transforms data into a model which shows the complete functioning of the warehouse.

The system presents results through an easy-to-use dashboard which enables users to make fast decisions.

Overall Results



The system exhibits better performance through enhanced speed and accuracy and decreased error rates.

The test results demonstrate statistical reliability because they do not show random variations.

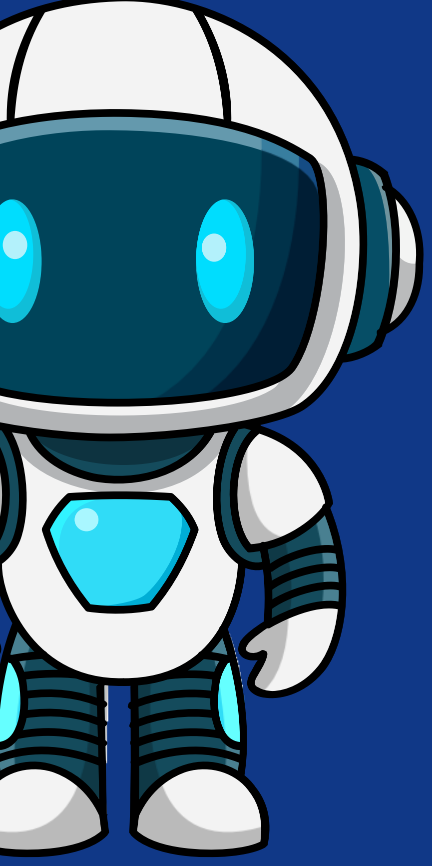
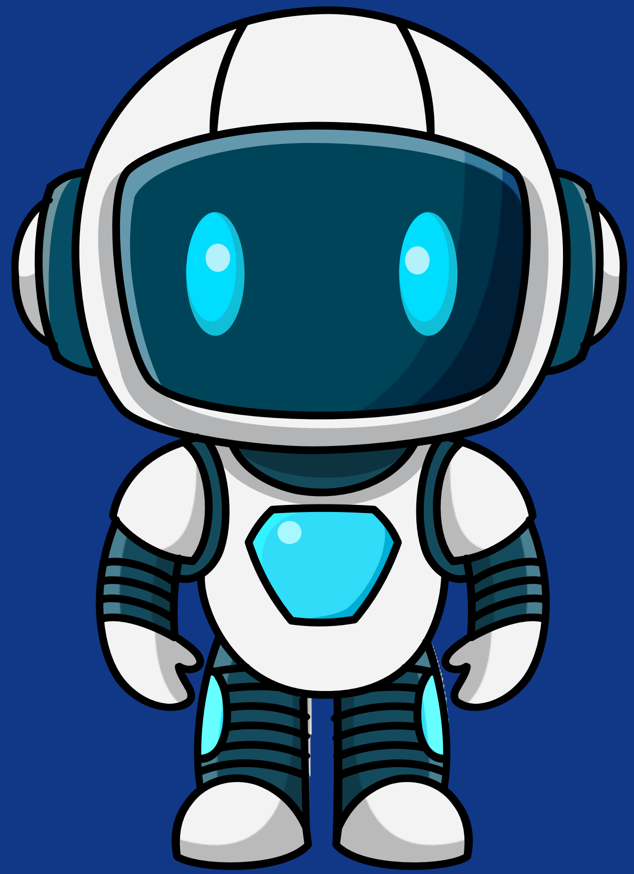


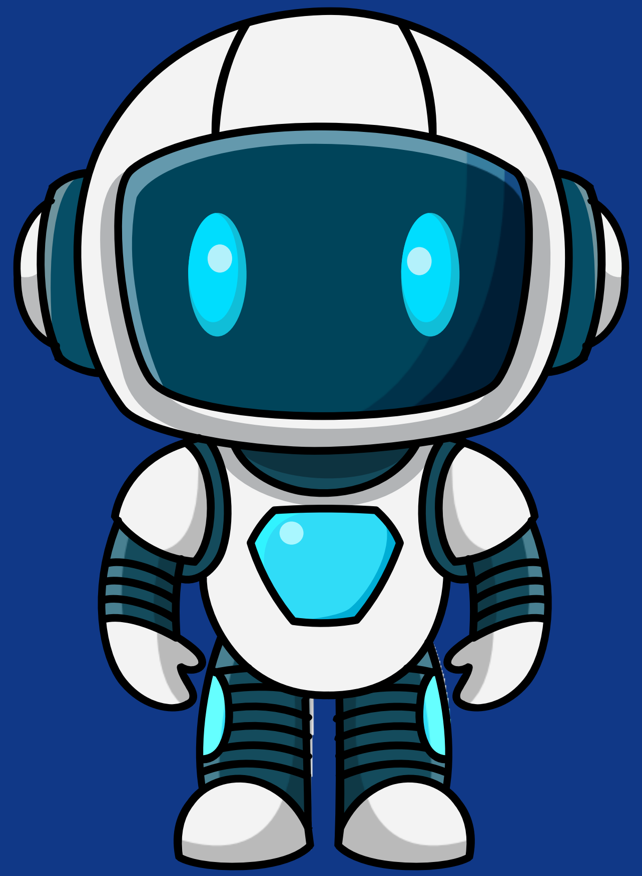
Table 4.1 presents the main warehouse KPIs which show their performance before the intervention and after the intervention. The results demonstrate that all operational indicators which researchers measured showed statistically significant improvements.

KPI	Pre-intervention Mean (SD)	Post-intervention Mean (SD)	Relative Change (%)	Test Statistic	p-value	Effect Size (Cohen's d)
Inventory accuracy (%)	88.4 (4.9)	96.7 (1.8)	+9.5%	paired t = 32.1	< .001	1.87
Picking time per order line (minutes)	7.8 (2.3)	5.2 (1.4)	−33.3%	paired t = 28.6	< .001	1.36
Order lead time (hours)	24.3 (6.1)	18.1 (4.7)	−25.5%	paired t = 17.9	< .001	1.03
Emergency purchase orders (monthly)	12 (3.8)	4 (1.6)	−66.7%	Wilcoxon Z = −4.21	< .001	—
Operational cost per hour (USD)	120.4 (18.9)	98.2 (12.7)	−18.4%	paired t = 9.8	< .001	0.79

The study developed classification models to identify inventory discrepancies using time-based test data. The two most effective models demonstrate their performance through Table 4.2.



Model	Accuracy	Precision	Recall	F1-score	ROC-AUC
Random Forest (tuned)	0.89	0.82	0.78	0.80	0.91
XGBoost (optimized)	0.91	0.85	0.80	0.82	0.93



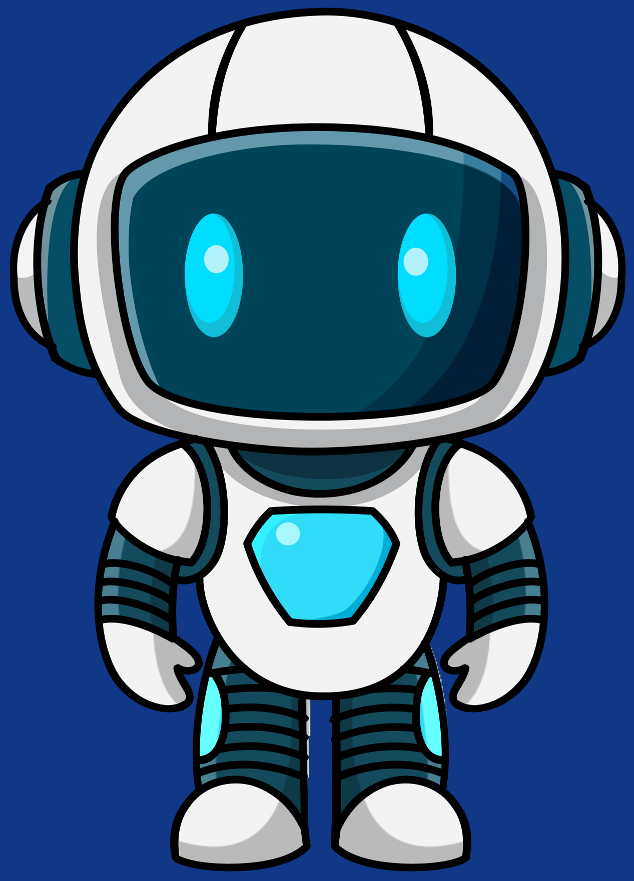
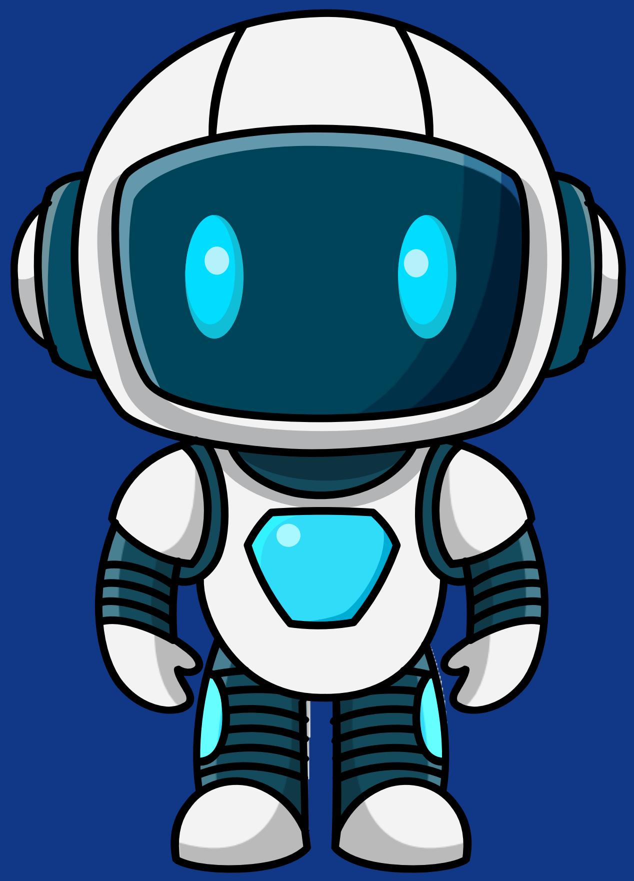


Table 4.3

	Predicted: No discrepancy	Predicted: Discrepancy
Actual: No discrepancy	3,810	128
Actual: Discrepancy	162	372

The XGBoost model achieved high accuracy in classifying data through its confusion matrix analysis because it produced only a small number of incorrect results. The model functions as an early-warning system because the results show its operational effectiveness.

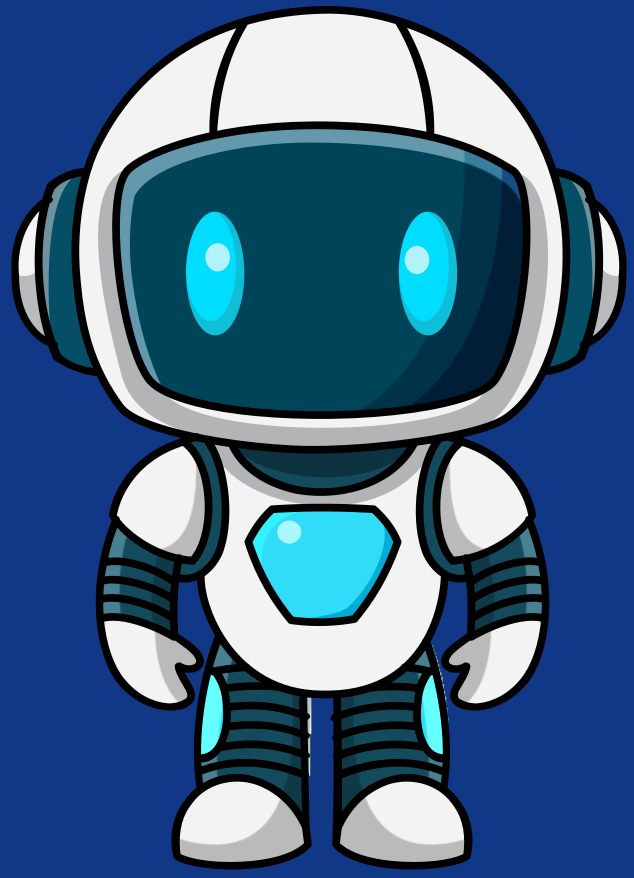


Regression Model Performance for Picking-Time Prediction

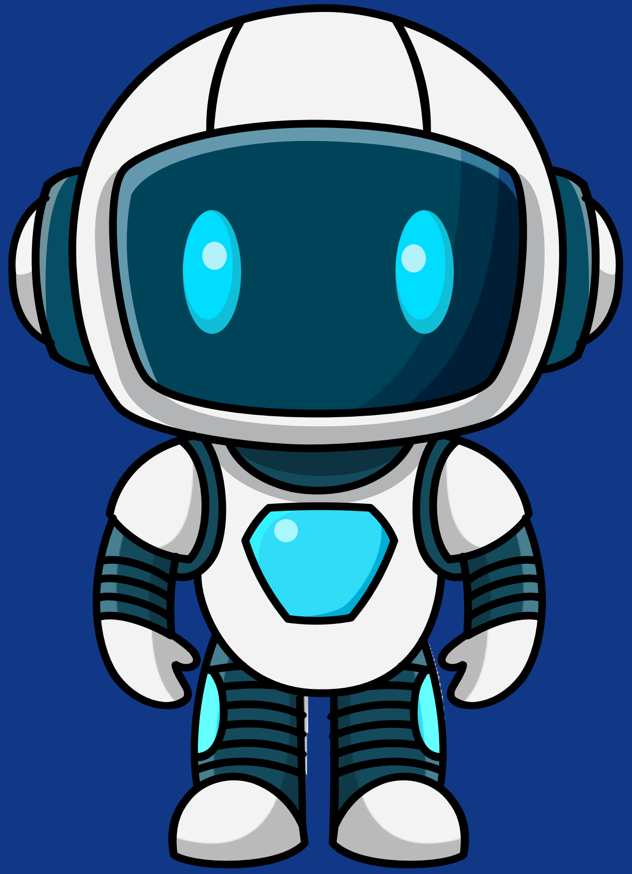
Model	RMSE (minutes)	MAE (minutes)	R^2
Gradient Boosting Regression	1.25	0.98	0.72
LSTM (time-series)	1.12	0.92	0.76

The LSTM model achieved better results than the Gradient Boosting Regression model by showing both the smallest error measurements and the greatest explained variance. The system demonstrates its ability to make accurate predictions about sequential warehouse time data.

Rank	Feature	Practical Interpretation
1	7-day pick rate	Recent activity of the SKU
2	Location density	Aisle or location congestion level
3	SKU turnover	Rate of item consumption or rotation
4	Cycle-count variance	Stability of periodic inventory checks
5	Batch size	Impact of batching on efficiency
6	Distance to packing	Walking or transfer distance effect
7	Picker experience	Human operator skill influence
8	Temperature/humidity	Environmental handling constraints
9	Time of day	Shift or peak-period effects
10	Fragility flag	Special handling requirement



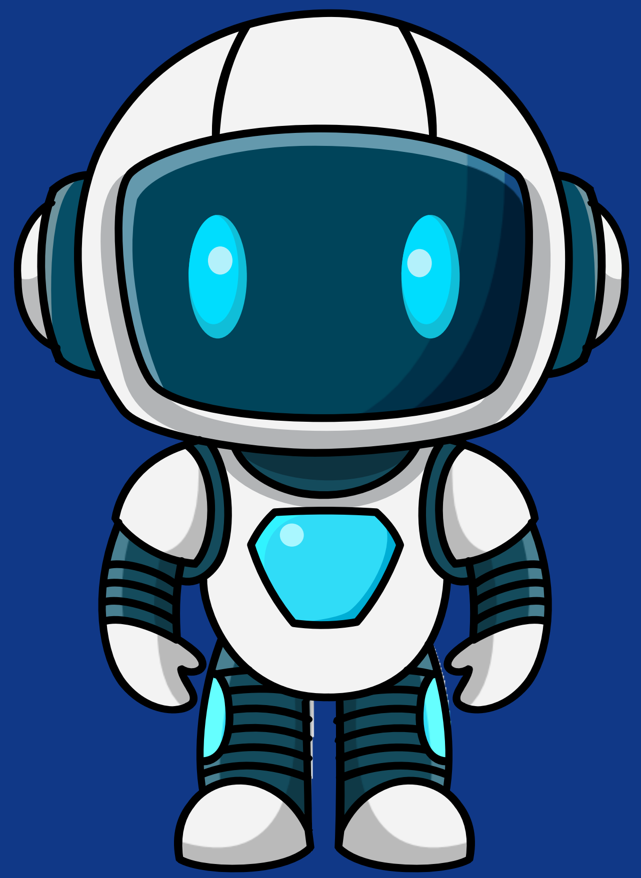
The SHAP results demonstrate that operational congestion and recent item activity together with spatial distance served as the primary factors that determined performance differences. The research results demonstrated that the operational streaming conditions of the facility served as the primary element which controlled the performance of the predictive models.

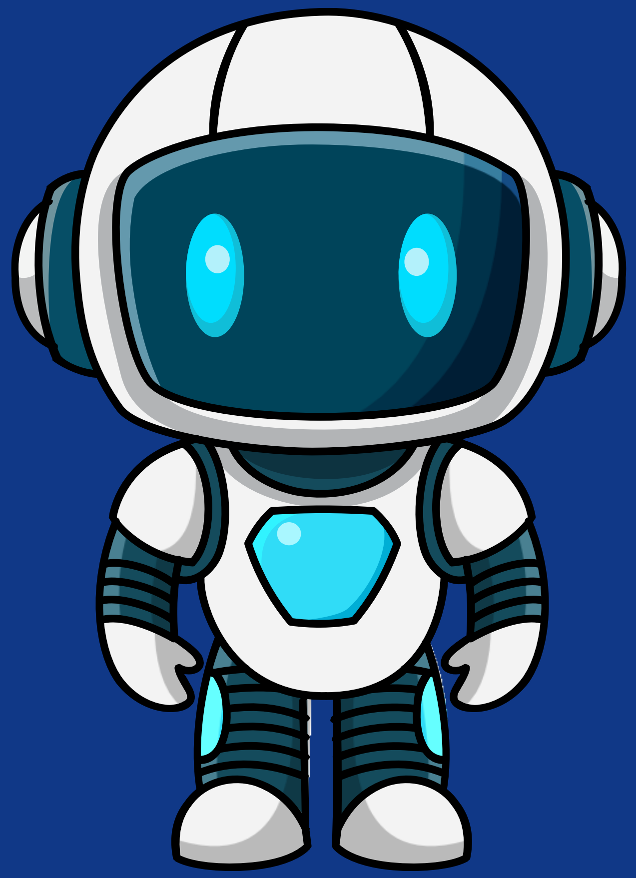


Measure	Mean	SD
Perceived usefulness	4.20	0.62
Perceived ease of use	3.78	0.74
Behavioral intention (future use)	4.02	0.58
Trust in the system	3.65	0.81

The one-sample t-tests showed that both perceived usefulness and behavioral intention exceeded the midpoint value of 3.0.

Item	Before Intervention	After Intervention	Remarks
Successful intrusion incidents	0	0	No successful breaches recorded
Misconfiguration events	0	1	Fixed within 24 hours; minor operational impact
Personal data breaches	0	0	Data anonymization applied from project start



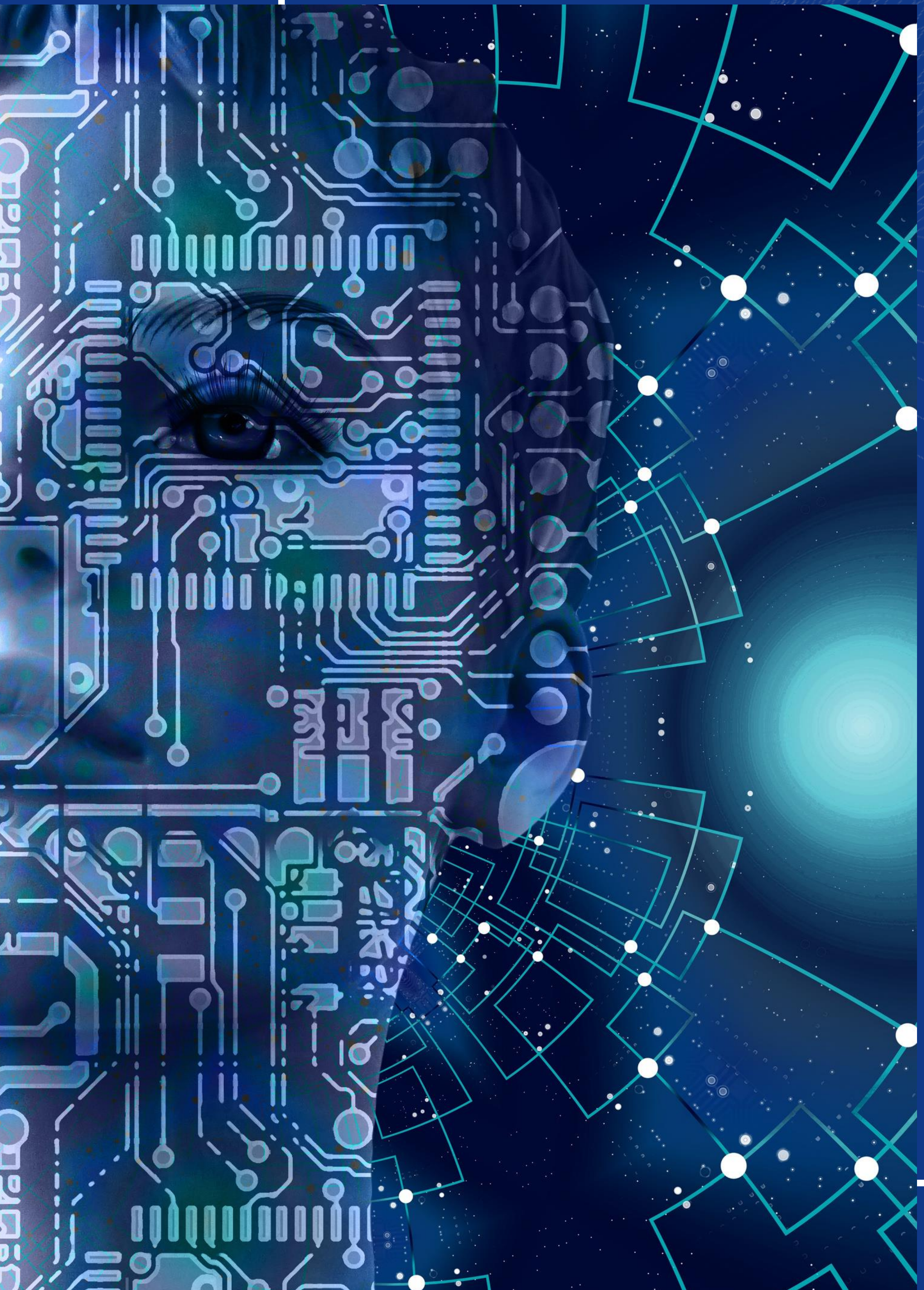


Item	Value (USD)
Initial installation (hardware + servers + integration)	28,000
Annual maintenance and licenses	6,200 per year
Estimated monthly operational savings	3,250 per month
Payback period (base scenario)	8.6 months

Key Improvements

- Inventory accuracy reached 96.7%
- Picking time reduced by 33%
- Order processing time reduced by 25%
- Emergency orders reduced by 66%
- Costs reduced by 18%

AI Results



The XGBoost model reached an accuracy level of 91 percent.

The system predicts upcoming problems before they occur.

The system enables managers to improve their decision-making process.

User Feedback

The system achieves high user satisfaction.
time

The system provides user-friendly access yet contains some flaws.

Some users require additional training to complete their tasks.

Financial Feasibility

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Cost

$28,000

Savings per month

$3,250

Payback time

8.6 months, that is less than a year

AI Results

The XGBoost model reached an accuracy level of 91 percent.

The system predicts upcoming problems before they occur.

The system enables managers to improve their decision-making process.

Recommendations

- Connect WMS with IoT for real-time data
- Use AI daily for analysis and prediction
- Train employees to use the system well
- Improve cybersecurity to protect data and systems

Conclusion

The research demonstrates that IoT and AI together with Digital Twin technology enhance the operational efficiency of warehouses through their three benefits which are improved speed and better accuracy and decreased expenses.

THANK YOU