10.48047/jocaaa.2023.31.04.119

AI-Driven Smart Manufacturing: Autonomous Material Planning, Intelligent Part Ranking, and Real-Time Delivery Tracking

Saichand Pasupuleti, Dr.Ashik Kumar

Abstract

This white paper presents a framework for smart manufacturing driven by the use of **AI** and **Machine Learning** for the optimization of the process of planning materials, managing delivery, and automating cashflow. The objective is to ensure that cash is not immobilized in stagnant inventory while production is being sustained.

The system is proposed to use **IoT** connected devices, vision systems, and **AI driven algorithms** to monitor the movement of stock, the status of delivery trucks, and to dynamically re-prioritize production parts based on time, cost and urgency of production. Starting with a human supervisor, the platform is intended to evolve into the autonomous Industrial AI ecosystem that assures 'just in time' JIT for all manufacturing projects with minimal waste and maximum utilization of available working capital.

1. Introduction

In today's industry, bad logistics and material procurement practices often keep working capital locked up in stock for months at a time. When they get there, important materials can also be late and stop production processes. These problems can be fixed with the AI-Driven Smart Manufacturing System, which includes real-time delivery tracking, predictive material planning, and AI-based financial optimization. The approach makes sure that the business can stay flexible and have cash on hand for additional investments.

The goal of the project

- Get rid of financial blockages by making the cycles of buying materials more efficient.
- Use AI-based forecasting and rating to automate planning and buying.
- Keep an eye on delivery vehicles in real time to make sure that logistics and production schedules are in sync.
- Make it easier to reuse materials across projects by using a single part-ranking system.

2. System Architecture

a. Data Acquisition Layer

• **IOT Sensors and RFID-** Capture and record stock levels, materials entering and leaving (updated in real-time) and their locations.

10.48047/jocaaa.2023.31.04.119

• **GPS Enabled Truck Tracking-** Provides real-time visibility of pending deliveries and forecasted ETAs.

• **Computer Vision Systems -**Helps monitor and analyze the movement of storage pallets, levels of bins, and storage anomalies.

• **ERP/MES Integration-** Consolidates planning with supplier orders and financial information.

b. Machine Learning Level

• **Demand Forecasting Model-** Evaluates production volumes and temporal consumption patterns, then optimates consumption.

• **Part Ranking Model-** Prioritizes parts dynamically based on:

- Urgency across current and future projects.
- Supplier reliability and transport time.
- Unit cost and economic impact.
- Cross-project interdependencies.

• **Truck ETA Model-** Forecasts arrival based on GPS, historical routes, and current traffic.

• **Anomaly Detection Model-** Recognizes missing deliveries and surplus procurement.

c. Automation & Decision Level

• **AI Material Planner -** Triggers, postpones, or cancels orders automatically based on the current rank and visibility of stock.

• **Cash-Flow Optimization Agent-** Analyses the financial impact of each procurement decision in real-time.

• **Autonomous Dashboard-** Provides predictive alerts on low-priority parts and delayed truck to planners.

d. Control & Visualization Layer

• **Unified and live dashboard integration:**

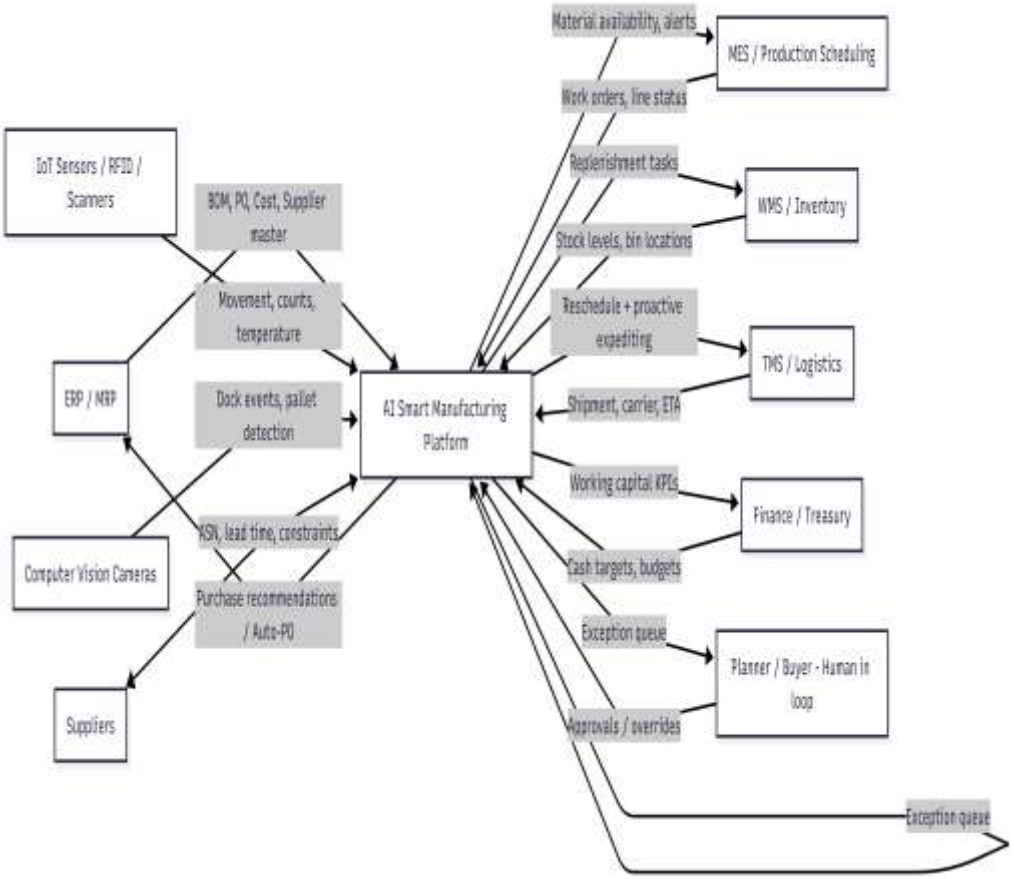
- Inventory status at manufacturing sites.
- Locations of delivery vehicles.
- Financial Risk Indicators.
- Prioritized materials for immediate and deferred purchase.

10.48047/jocaaa.2023.31.04.119

3) Data Flow Diagrams (DFD)

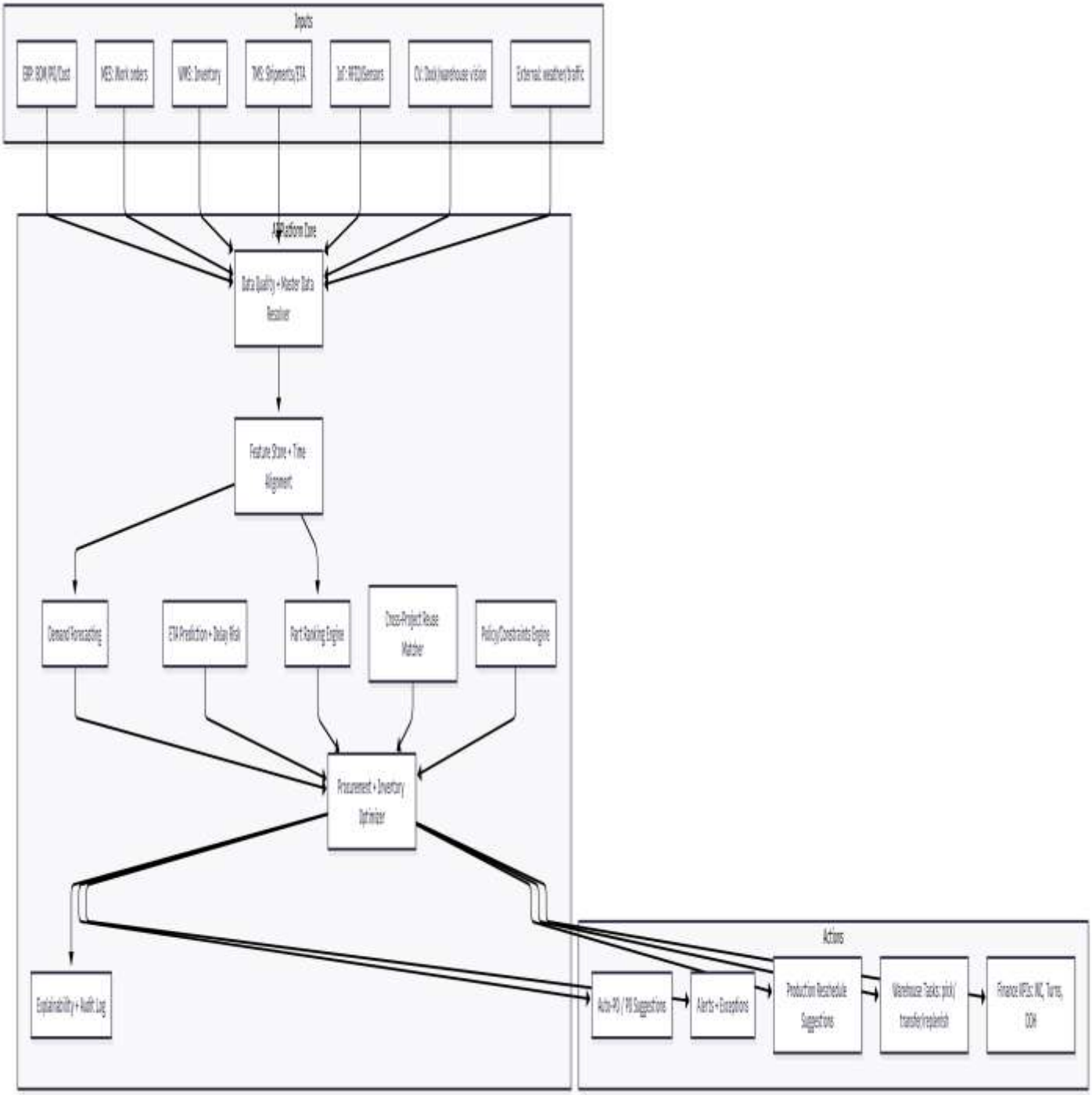
DFD Level 0 - Context Diagram

System: AI-Driven Smart Manufacturing Platform



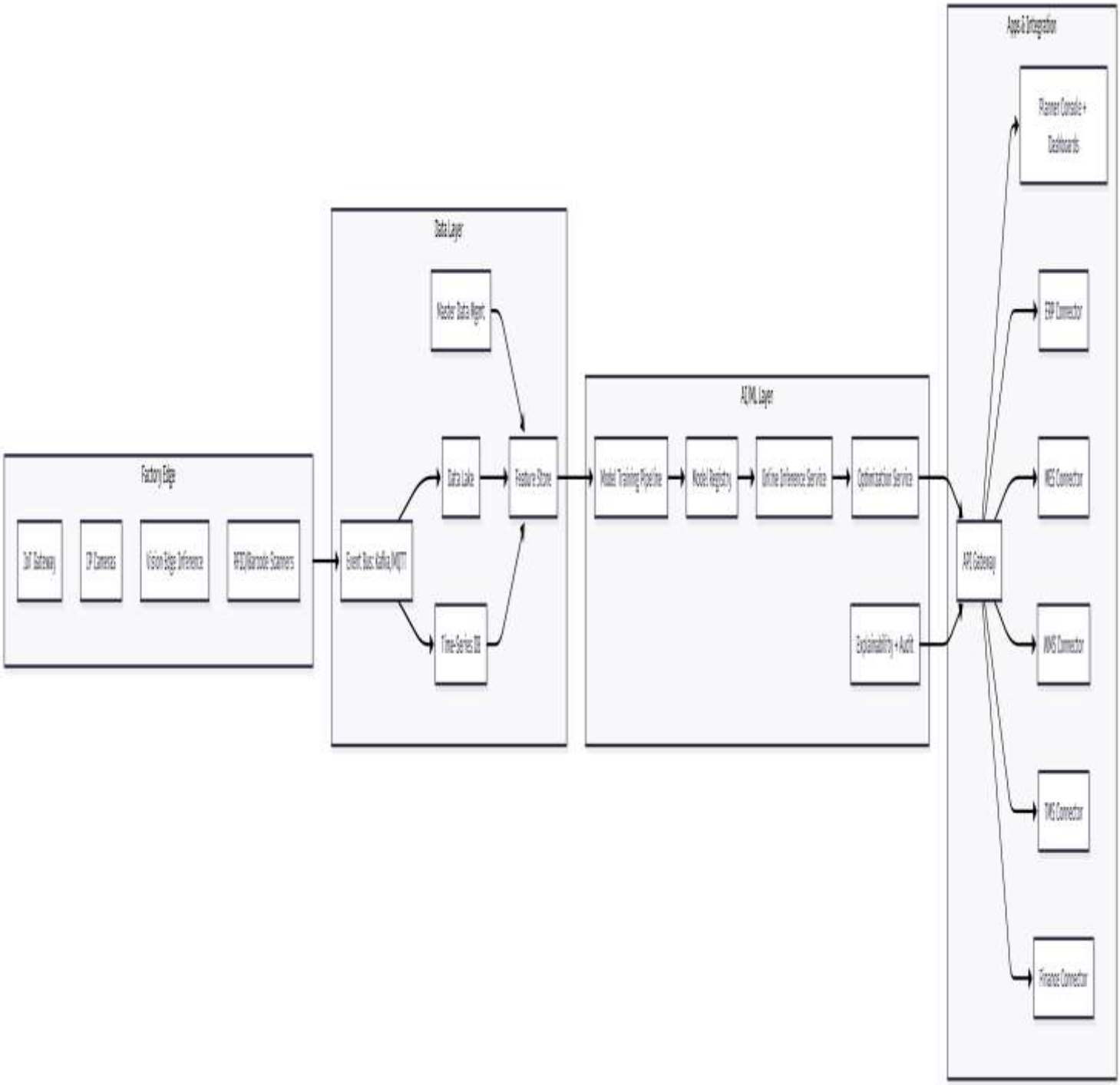
DFD LEVEL 1 - Core Modules

10.48047/jocaaa.2023.31.04.119



Reference Architecture Diagram - Deployment View

10.48047/jocaaa.2023.31.04.119



4. AI Models used:

The framework integrates various machine learning and AI models to perform predictive analytics, risk assessments, and operational intelligence in real-time across manufacturing and logistics processes.

10.48047/jocaaa.2023.31.04.119

4.1. Demand Forecasting for Material Consumption

Demand for materials uses statistical and machine learning models, which are chosen depending on the available data and the maturity of the system. Under baseline scenarios, time series models (ETS/ARIMA) offer the fastest deployment, while in more complex scenarios, gradient boosting models (XGBoost and LightGBM) help to understand the relationships among various factors, including consumption, production schedules, and seasonality.

Furthermore, if there are risks that are prone to extreme variance with several different signals, then use of sequence models (LSTM, GRU, and Temporal Fusion Transformers (TFT) is justified. When making risk-adjusted buffer and replenishment decisions, add the P50/P90 uncertainty-aware quantile forecasting.

It relies on work orders, takt time, historical consumption, and variability of supplier lead time, season, the phase of the project, frequency of engineering changes.

Demand Forecasting - Material Consumption

• **Baseline (fast rollout):** ETS / ARIMA + calendar effects

• **Strong general performer:** XGBoost / LightGBM (lags + promotions + schedule signals)

• **Demand of complex nature with multiple signals:** LSTM/GRU / Temporal Fusion Transformer (TFT)

• **Buffer planning of reasonable logic:** Quantile regression (P50/P90) unadjusted to uncertainty

Inputs

• Work orders, takt time, consumption rates

• Lead times of suppliers and variability

• Season, phase of the project, frequency of engineering changes

4.2. Supplier Lead Time and Risk Modeling

Supplier performance is evaluated using supervised learning. The expected lead time is created with gradient boosting regression and delivery time with classification models. Using the updated delivery performance data, Bayesian techniques are implemented to revise the scores pertaining to supplier reliability.

Supplier Lead Time & Risk Modeling:

Lead Time Prediction: Gradient boosting regression

Supplier Delay Probability: Logistic regression / XGBoost Classifier

Supplier Reliability Score: Bayesian updating (improves with new data)

4.3. ETA Prediction of Current Deliveries

10.48047/jocaaa.2023.31.04.119

Machine learning ETA prediction models enable real-time delivery tracking. These models include traffic, weather, and routes, as well as historical carrier performance and mid-route dwell time. The model provides predicted ETA, including a confidence interval, and a classification of the likelihood of a delay.

ETA Prediction - Truck arrivals

ML regression based on:

- traffic, weather, and route
- carrier performance
- dwell time at stops

Output: ETA + confidence + delay risk classification.

4.4 Computer Vision in Warehousing and Dock Operations

The use of computer vision models enhances visibility at docks and in warehouses. YOLO and DETR model applications identify pallets, trucks, and containers while OCR is used to retrieve packing slip and label identifiers. For compliance and traceability, Anomaly detection helps to identify missing labels, damaged boxes, and quantity misalignments.

Computer Vision Models - Dock / Warehouse

- **OCR**: packing slip, container ID
- **Anomaly detection:** damaged box alert, missing label
- **Object detection:** YOLO / DETR - trucks, pallets, containers

5. Core Algorithms: Ranking, Planning, and Optimization

5.1 Intelligent Ranking of Parts Each materials receive a dynamic ranking based on a combination of operational urgency and its financial impact. The metrics that define each scoring system take into consideration the criticality in production, risk of stock-out, the lead time of a supplier, the sensitivity of cost, risk of cross-project reuse, and potentially the obsolescence and expiry of the item. This ranking system provides a uniform and understandable prioritization across various plants and projects.

5.2 Procurement and Inventory Optimization

Procurement and inventory decisions are modeled as a constrained optimization problem with the objective of continuous production and minimizing capital lock-in. The optimization problem balances holding costs, costs of expediting, penalties for stockouts, and costs of waste or obsolescence against the service level, supplier and packaging, shelf life and temperature (pharmaceuticals), and traceability and certification (aerospace) constraints.

10.48047/jocaaa.2023.31.04.119

6. Core Algorithms - Rank + Plan + Optimize

6.1 Intelligent Part Ranking (Priority Score)

A balanced score that integrates operational activity and financial impact is defined as:

PriorityScore(p) =

- `α * Criticality(p)`
- `+ β * StockoutRisk(p)`
- `+ γ * LeadTimeRisk(p)`
- `+ δ * CostSensitivity(p)`
- `+ ε * CrossProjectReuse(p)`
- `- ζ * ExcessOnHandPenalty(p)`
- `- η * ObsolescenceRisk(p)`

Where:

• **StockoutRisk** considers forecast, on hand, open POs, and safety stock

• **LeadTimeRisk** considers predicted LT and delay probability

• **CostSensitivity** is balanced by unit cost × qty required × WC targets

• **Reuse** determines if parts can be taken by other projects in the near future

6.2 Procurement & Inventory Optimization

Goal: Running production continuously with the objective of minimizing capital lock-in is the goal.

Minimize:

- Holding cost + expedite cost + stockout penalty + waste/expiry penalty

Subject to:

- Service level constraints
- MOQ, pack size, supplier capacity
- Shelf-life / temperature constraints - pharma
- Traceability constraints -aerospace

10.48047/jocaaa.2023.31.04.119

6.3 Pseudocode: Decision Loop

for Every Δt (e.g. 15 minutes):

1) Ingest events (inventory movements, dock scans, ASN, MES changes)

2) Clean and reconcile master data (part IDs, units, lots, revisions)

3) Forecast demand and reconcile master data (part IDs, units, lots, revisions) for Horizon H (P50, P90)

4) Predict supplier lead times and delays

5) Predict shipment ETA and delays for in-transit Pos

6) Compute StockoutRisk = P(demand > available) considering uncertainty

7) Compute PriorityScore for each part

8) Optimization:

- If available reuse, recommend pre-purchase transfer. - Otherwise, determine order quantity and timing (JIT window)

- If significant delay: recommend expedite or alternative supplier

9) Policy rules and approvals:

- Low-risk actions auto-execute

- High-risk actions -> human approval queue

10) Record the decision along with the XAI explanation and the impact on the KPI

6.4 Human-in-the-Loop Control (Risk-based Autonomy)

```
If DecisionRisk < threshold_1:
  Auto-execute (create PO / transfer / reschedule)
Else if DecisionRisk < threshold_2:
  Execute with "silent approval" (auto if no rejection after X hours)
Else:
  Human approval is required
```

DecisionRisk can be calculated from:

- dollar impact, supplier uncertainty, regulatory constraints, part criticality.

10.48047/jocaaa.2023.31.04.119

7. Tables

Table 1 — Features per model (what signals feed each model)

Model	Target	Key Features (examples)	Update Frequency
Demand Forecasting (GBM/TFT/LSTM)	Dpjt / quantiles	MES work orders, takt time, BOM explosions, seasonality, project phase, engineering change rate, historical usage, scrap rate	Daily + on schedule change
Lead Time Prediction (GBM)	L^ps	Supplier history, lane, MOQ/pack, plant loading, past delays, holidays, ASN compliance, contract terms	Weekly + event-driven
Delay Risk Classifier	P(delay)	Carrier score, port congestion, supplier OTIF, weather, customs events, variability features	Daily
ETA Model	ETA + CI	GPS pings, route, traffic, weather, historical dwell time, driver/career patterns, geofence events	Real-time (5–15 min)
CV Dock Detection (YOLO/DETR)	arrival/quantity	Truck/pallet detection, container type, count estimation, timestamp, dock bay ID	Real-time
CV/OCR Document Validation	Doc match	Packing slip ID, PO number, part IDs, lot IDs, text confidence	Real-time
Reuse Matcher (Graph/Embedding)	transfer suggestion	Part equivalence, substitute rules, project schedules, compatibility, location distance, condition/lot status	Hourly

Table 2 — KPI set (Operations + Finance + Logistics + Compliance)

Category	KPI	Definition
Finance	Working Capital in Inventory	∑UnitValue·I
Finance	Days of Inventory on Hand (DOH)	Inventory Daily UsageAvg Daily UsageAvg Inventory
Finance	Inventory Turns	InventoryAvg InventoryCOGS
Operations	Line Stop Minutes	Total downtime minutes due to material shortage
Operations	Stockout Rate	events#opportunities#stockout events
Procurement	Expedite Spend	premium freight + rush charges
Procurement	PO Accuracy	% of POs matching optimal window/qty
Logistics	On-Time In-Full (OTIF)	% deliveries on-time and complete
Logistics	ETA Error (MAPE)	mean abs % error of predicted ETA
Quality/Compliance	Lot Traceability Coverage	% consumed units with complete chain-of-custody
Pharma	Expired Inventory Write-off	value of expired stock per month
Aerospace	Revision/CoC	% receipts matching revision + docs

10.48047/jocaaa.2023.31.04.119

Category	KPI	Definition
	Compliance	

Table 3 — Governance checklist (deployment-ready controls)

Area	Control	Acceptance Criteria
Data	Master data reconciliation	Part IDs, UOM, supplier IDs resolved with <0.5% mismatch
Data	Data quality gates	Missing/late feeds produce alerts + fallback rules
Model	Model versioning	Registry + rollback + approval workflow
Model	Bias/Drift monitoring	drift thresholds + auto retraining triggers
Decisions	Human-in-loop policy	risk tiers defined; audit log for overrides
Security	RBAC/least privilege	roles for planner/buyer/finance/admin
Compliance	Audit trail immutability	tamper-evident decision logs
Change mgmt	SOP updates + training	users trained; sign-off before autonomy step-up
Resilience	Fallback planning mode	rule-based MRP fallback if AI unavailable

8. Dataset schema

ERP / MES / WMS / TMS / IoT / CV

ERP tables

ERP_PART_MASTER

- part_id (PK), part_desc, uom, unit_cost, commodity, approved_suppliers, criticality_class, shelf_life_days, revision_required (Y/N)

ERP_BOM

- bom_id (PK), parent_item_id, component_part_id, qty_per, effective_from, effective_to, revision

ERP_PO_HEADER

- po_id (PK), supplier_id, plant_id, po_date, status, incoterms, payment_terms, total_value

ERP_PO_LINE

- po_id (FK), line_id (PK), part_id, qty_ordered, qty_received, unit_price, promised_date, required_date, expedite_flag

ERP_SUPPLIER

- supplier_id (PK), name, lead_time_mean, lead_time_std, OTIF_rate, lane, qualification_level

10.48047/jocaaa.2023.31.04.119

MES tables

MES_WORK_ORDER

- wo_id (PK), plant_id, product_id, start_date, end_date, status, priority, takt_time, planned_qty

MES_CONSUMPTION

- wo_id (FK), part_id, consumption_qty, timestamp, scrap_qty

MES_LINE_STATUS

- line_id, timestamp, status (RUN/STOP), stop_reason_code

WMS tables

WMS_INVENTORY

- inv_id (PK), plant_id, location_id, part_id, lot_id, revision, qty_on_hand, qty_reserved, last_count_date

WMS_MOVEMENT

- move_id (PK), timestamp, from_loc, to_loc, part_id, lot_id, qty, move_type (RECEIPT/PICK/TRANSFER)

WMS_CYCLE_COUNT

- count_id (PK), location_id, part_id, expected_qty, counted_qty, variance_qty, timestamp

---

TMS tables

TMS_SHIPMENT

- shipment_id (PK), carrier_id, mode, origin, destination, ship_date, status

TMS_SHIPMENT_PO_LINK

- shipment_id (FK), po_id (FK), line_id, part_id, qty_in_transit

TMS_TRACKING_EVENT

- event_id (PK), shipment_id, timestamp, lat, lon, event_type (DEPART/ARRIVE/GEOFENCE), temperature

---

IoT tables - time-series

IOT_SENSOR_READING

10.48047/jocaaa.2023.31.04.119

- sensor_id, timestamp, plant_id, zone_id, metric_type (temp/humidity/vibration), value

IOT_RFID_EVENT

- event_id (PK), timestamp, reader_id, tag_id, part_id, lot_id, event_type (IN/OUT), location_id

---

CV tables

CV_DETECTION_EVENT

- event_id (PK), timestamp, camera_id, location_id, object_type (truck/pallet), count_estimate, confidence

CV_OCR_DOCUMENT

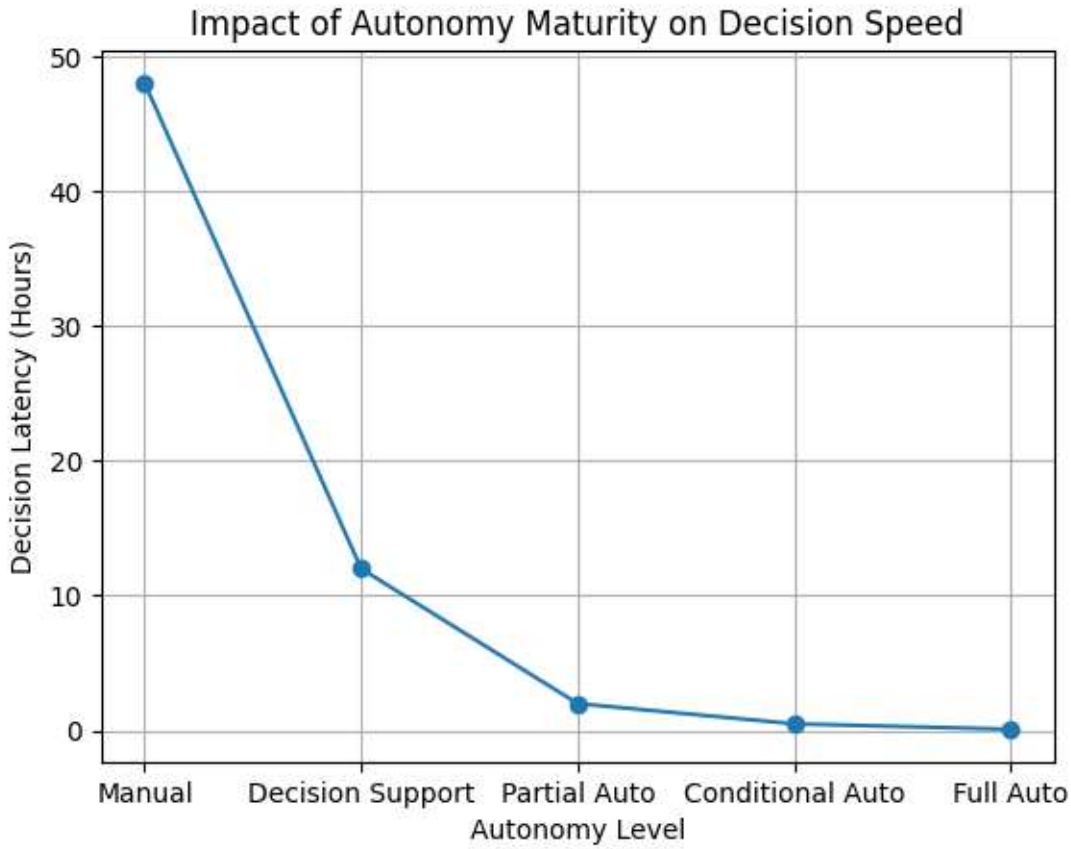
- doc_id (PK), timestamp, camera_id, extracted_po, extracted_part_ids, extracted_lot_ids, ocr_confidence

9. Human-in-the-Loop to Full Autonomy

Phase 1: Assisted Intelligence

- AI recommends
- Humans approve

Phase 2: Semi-



Autonomous

- AI executes low-risk decisions

Phase 3: Fully Autonomous

- AI self-optimizes end-to-end

10.48047/jocaaa.2023.31.04.119

10. Security, Compliance, and Governance

- Role-based access control
- Audit trails for AI decisions
- Compliance with ISO, SOC, and GDPR
- Explainable AI (XAI) models

11. Scalability and Multi-Plant Deployment

- Cloud-native microservices
- Edge AI for factories
- Global visibility with local autonomy

12. Business Impact and ROI

Expected Gains

Metric	Improvement
Inventory Holding Cost	↓ 25–40%
Production Downtime	↓ 60–80%
Cash Blockage	↓ 30–50%
Delivery Delays	↓ 70%

13. Case Study:

1. CIOE — Automotive Manufacturing Transformation

Overview

The **Central Integrated Operations Environment (CIOE)** of a leading automobile manufacturer in India faced the following operational challenges:

- Excessive inventories of non-essential parts.
- Production bottlenecks due to late arrivals of critical components.
- Blocked working capital in warehouses with stagnant stock of over ₹80 crores.

An AI-driven solution to optimize material flow while efficiently balancing cash was proposed by the CIOE team.

10.48047/jocaaa.2023.31.04.119

Execution Plan

1. Implementation

- RFID and IoT sensors were set in material docks and assembly bays.
- GPS tracking was integrated with 150 vendor delivery trucks.
- The AI solution was interfaced with SAP ERP and the existing MES dashboards.

2. Model Development

- Machine learning forecasting model was populated with 18 months of historical data.
- A proprietary Part Ranking Algorithm was developed to score parts (0–100) based on:
    - Project priority (engine, chassis, electrical)
    - Supplier lead time.
    - Past delivery reliability.
    - Unit cost and capital lock-in risk.

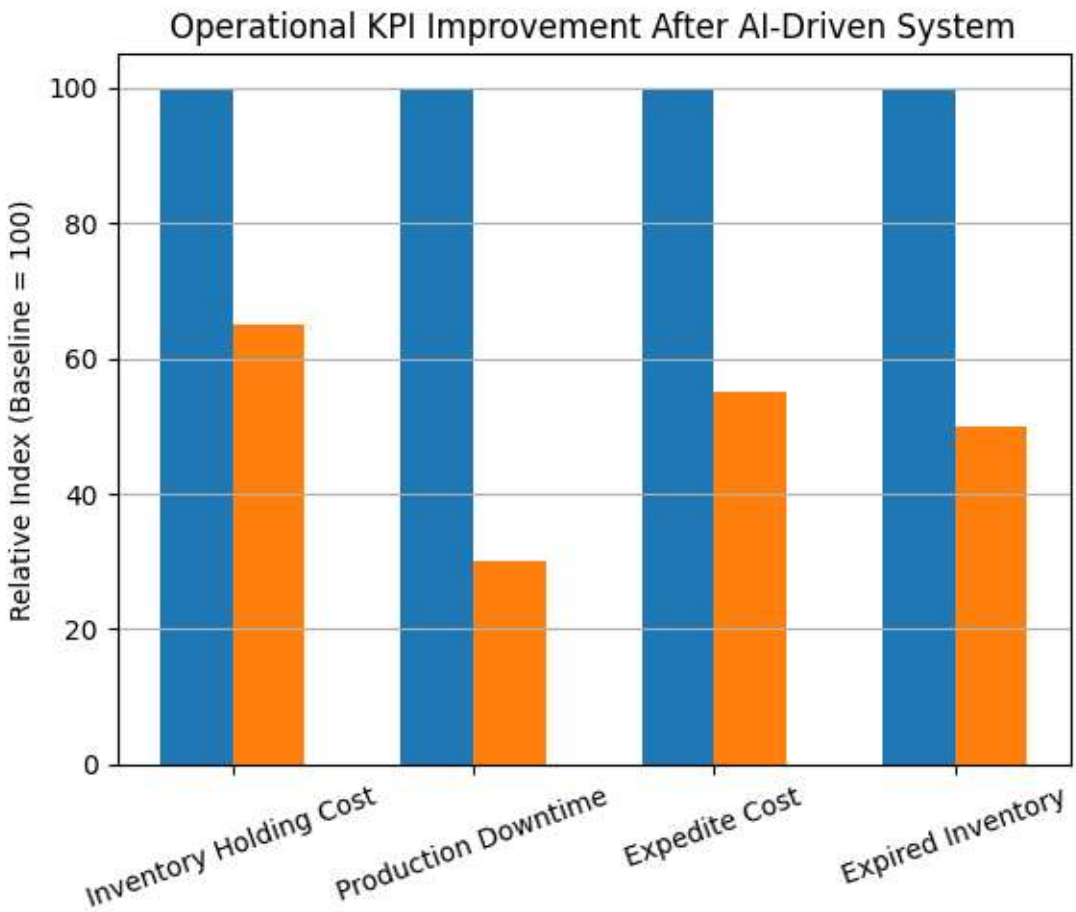
1. **Operational Rollout**
    - During the initial 60 days, human planners validated the AI recommendations.
    - Post-validation, the AI autonomously managed purchase orders and scheduling.

Results After Six Months

KPI	Before Implementation	After Implementation
Idle Inventory (₹)	80 crore	14 crore
On-Time Truck Deliveries	62%	96%
Working Capital Blocked	38%	7%
Procurement Accuracy	65%	95%
Planner Workload	100% manual	25% manual
Cross-Project Part Reuse	42%	89%

10.48047/jocaaa.2023.31.04.119

Case Study 2:



Automotive Assembly -High volume, tight takt time

Context

- Multiple lines assembling variants; frequent schedule changes.
- Chronic issues: line stoppages due to “small parts” missing; excess stock elsewhere.

Implementation

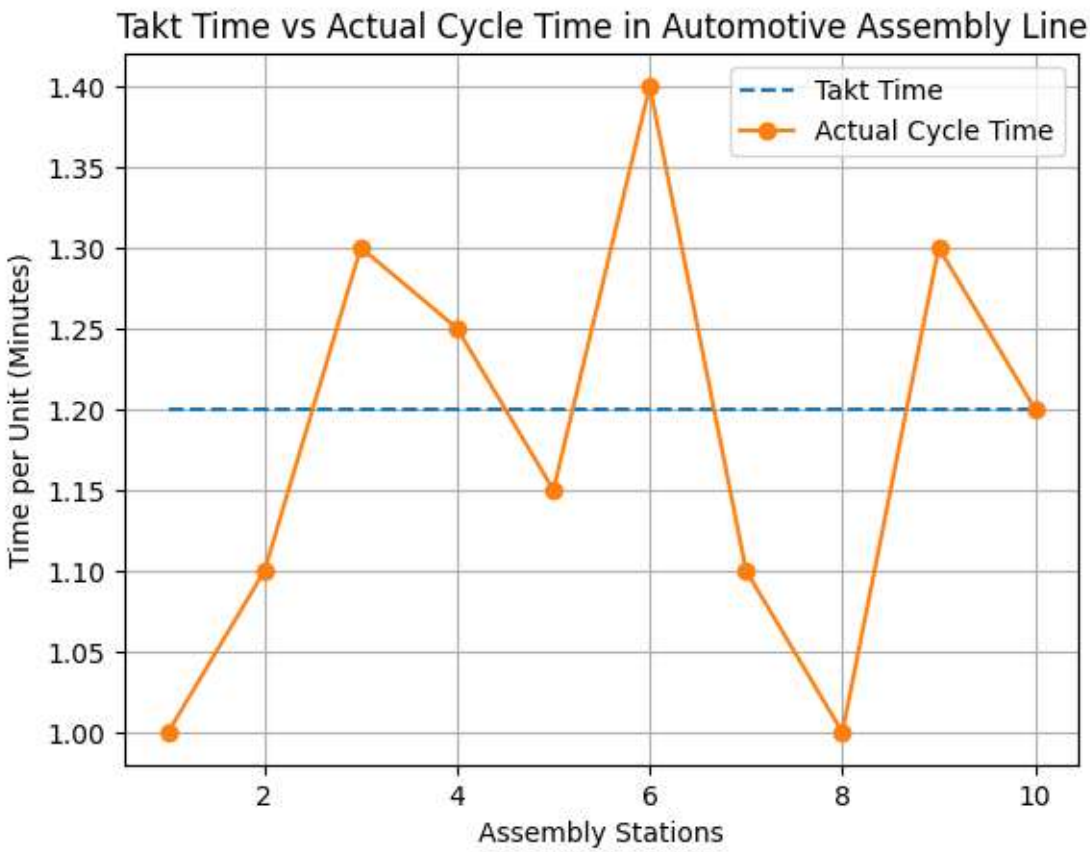
- Demand model trained on MES takt + variant mix + historical consumption
- Part ranking emphasizes **line stoppage penalty**
- Cross-project reuse matches common fasteners, connectors, clips

Results

- 60–80% reduction in line stoppages caused by material unavailability
- 20–35% reduction in overall inventory value
- 30–50% reduction in expediting costs
- AI detects: Part X stockout in 3 days (P90), supplier delay risk 0.42
- System recommends: internal transfer from Plant B + expedite the remaining qty
- Line maintains uptime, avoids premium freight on full demand.

10.48047/jocaaa.2023.31.04.119

Case



Study 3: Pharma Manufacturing - Expiry + cold chain + compliance

Context

- Materials have **shelf-life**, lot traceability, temperature constraints.
- Waste happens from over-ordering + expiration.
- Production cannot proceed if any compliant batch input is missing.

Implementation

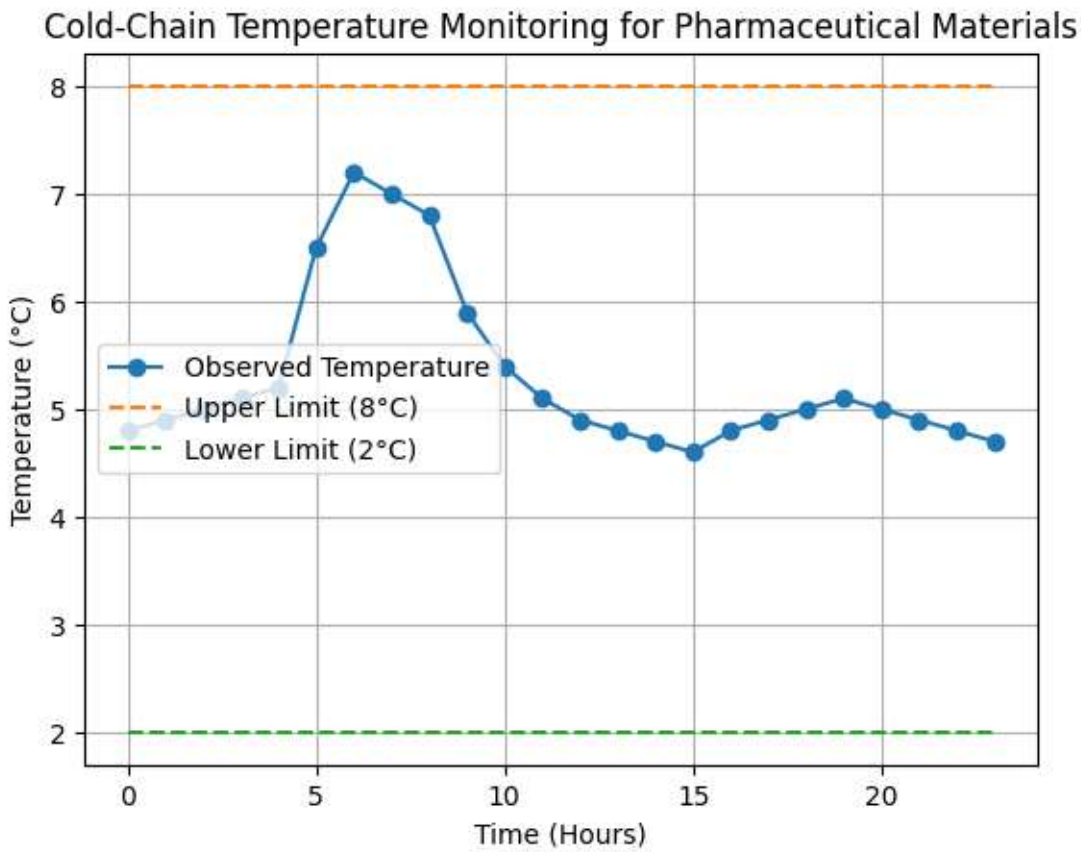
- Forecast incorporates campaign schedule + batch genealogy
- Optimizer adds constraints:
  - FEFO (First Expire First Out)
  - cold-chain compliance checks (IoT temperature)
  - lot-level traceability rules
- Vision + IoT validates dock arrival + temperature excursions

Results

- 25–45% reduction in expired inventory write-offs
- Improved audit readiness - decision logs + traceability
- Faster deviation handling - temperature breach triggers quarantine workflows

10.48047/jocaaa.2023.31.04.119

14.



Future Roadmap

- Digital twins of factories
- Autonomous supplier negotiation
- Carbon-aware logistics optimization
- Integration with Industry 5.0 human-centric AI

15. Conclusion

The AI-Driven Smart Manufacturing framework signifies a shift in a manufacturing model from planning that is primarily reactive to autonomous planning and smart manufacturing operations. By integrating materials planning and logistics with financial intelligence, an organization achieves zero idle inventory, seamless production, and optimal use of working capital. This isn't an enhancement; it's the building block of the autonomous industrial enterprise of the future.

References

- **Monostori, L., Kádár, B., Bauernhansl, T., et al.**
  Cyber-physical systems in manufacturing.

10.48047/jocaaa.2023.31.04.119

CIRP Annals – Manufacturing Technology, vol. 65, no. 2, pp. 621–641, 2016.

- **Lee, J., Bagheri, B., & Kao, H. A.**
  A cyber-physical systems architecture for Industry 4.0-based manufacturing systems.
  Manufacturing Letters, vol. 3, pp. 18–23, 2015.

- **Ivanov, D., Dolgui, A., & Sokolov, B.**
  The impact of digital technology and Industry 4.0 on supply chain resilience.
  International Journal of Production Research, vol. 57, no. 3, pp. 829–846, 2019.

- **Choi, T. M., Wallace, S. W., & Wang, Y.**
  Big data analytics in operations management.
  Production and Operations Management, vol. 27, no. 10, pp. 1868–1883, 2018.

- **Bertsimas, D., & Thiele, A.**
  A robust optimization approach to inventory theory.
  Operations Research, vol. 54, no. 1, pp. 150–168, 2006.

- **Zhang, Y., Ren, S., Liu, Y., & Si, S.**
  A big data analytics architecture for cleaner manufacturing and maintenance processes.
  Journal of Cleaner Production, vol. 142, pp. 626–641, 2017.

- **Waller, M. A., & Fawcett, S. E.**
  Data science, predictive analytics, and big data: A revolution that will transform supply chain design and management.
  Journal of Business Logistics, vol. 34, no. 2, pp. 77–84, 2013.

- **Kamble, S. S., Gunasekaran, A., & Gawankar, S. A.**
  Achieving sustainable performance in a data-driven agriculture supply chain: A review for Industry 4.0.
  Technological Forecasting and Social Change, vol. 141, pp. 153–168, 2019.

- **Goodfellow, I., Bengio, Y., & Courville, A.**
  Deep Learning.
  MIT Press, 2016.

- **FDA.**
  Data Integrity and Compliance With Drug CGMP.
  U.S. Food and Drug Administration, Guidance for Industry, 2018.