AI READINESS ASSESSMENT

Assessment Report

Client: GlobalTech Manufacturing

Industry: Manufacturing

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Assessor: Huw Ringer

SMART ASSOCIATES

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1. Executive Summary

GlobalTech Manufacturing exhibits Developing-level analytics maturity (2.3 average) with significant variation across dimensions. The organisation has solid foundational infrastructure with Snowflake and Power BI, and some advanced capabilities like a production ML model for demand forecasting. However, critical gaps exist in data quality monitoring, governance frameworks, and organisational capacity. The company suffers from fragmented data definitions, undocumented ETL processes, and heavy vendor dependency. While Finance and Marketing have strong BI adoption, predictive capabilities remain limited despite clear ROI opportunities like predictive maintenance that could prevent $1M in annual losses. The organisation shows readiness for structured improvement with executive awareness of gaps and a pragmatic CFO willing to fund ROI-positive initiatives.

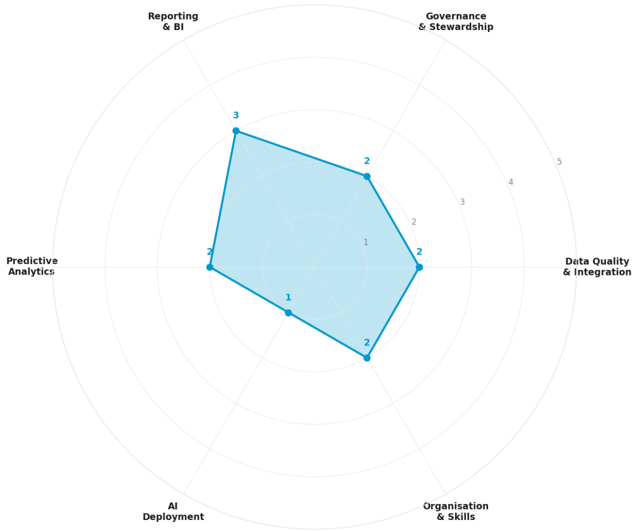
2. Methodology

The Smart Associates AI Readiness Assessment evaluates an organisation's analytics maturity across six critical dimensions. Each dimension is scored on a scale of 1-5:

Score	Level	Description
1	Initial	Ad-hoc, reactive, no formal processes
2	Developing	Some processes emerging, inconsistent application
3	Defined	Documented processes, consistent within teams
4	Managed	Measured, controlled, organisation-wide standards
5	Optimised	Continuous improvement, industry-leading practices

The overall maturity score is calculated using a weighted formula that accounts for both the average score and the weakest dimension, reflecting the reality that analytics capability is often constrained by its weakest link.

3. Overall Maturity Assessment



Overall Maturity Level

1.7

Developing

Building blocks emerging; focus on consistency and governance

Organisation & Skills

2/5

AI Deployment

1/5

Predictive Analytics

2/5

Reporting & BI

3/5

Data Quality & Integration

2/5

Governance & Stewardship

2/5

4. Dimension Findings

4.1 Organisation & Skills — Score: 2/5

Rationale

Small but technically competent core team, however significantly understaffed compared to industry benchmarks. High vendor dependency (30% outsourced), recruitment challenges, and no formal career paths for data professionals. Data literacy program shows promise but limited reach.

Evidence

- 2 data scientists and 3 data engineers vs. industry benchmark of double that size
- 90 people completed data literacy training out of 400 target
- Two data engineering roles open for 6 months
- 30% of data capability currently outsourced
- No formal career development path for data professionals
- Lost ML engineer to competitor due to lack of progression

Risks Identified

- Knowledge drain from key personnel turnover
- Vendor dependency creating cost and knowledge risks
- Inability to execute roadmap due to resource constraints
- Competitive disadvantage in talent acquisition

Recommendations

- Create formal career ladders for data roles with clear progression
- Expand data literacy program with sustained engagement mechanisms
- Develop internal capabilities to reduce vendor dependency
- Implement knowledge management system to reduce key person risk
- Establish data community of practice for knowledge sharing
- Partner with universities for graduate recruitment pipeline

4.2 AI Deployment — Score: 1/5

Rationale

No formal AI strategy, minimal infrastructure utilization (unused GPU instances), and no AI governance framework. Limited experimentation with basic chatbot and computer vision concepts but no production AI deployments beyond traditional ML.

Evidence

- No formal AI strategy document
- Azure OpenAI chatbot built but has low usage
- Computer vision for quality inspection discussed but not started
- GPU instances available through Databricks but never used
- No vector databases or LLM fine-tuning capability
- Unstructured data in SharePoint is essentially unsearchable
- No responsible AI policy or bias testing protocols

Risks Identified

- Regulatory non-compliance with emerging AI regulations (EU AI Act)
- Competitive disadvantage from lack of AI capabilities
- Security vulnerabilities from ungoverned AI experimentation
- Missed opportunities in quality inspection and document processing

Recommendations

- Develop comprehensive AI strategy and roadmap
- Implement vector database for unstructured data processing
- Create responsible AI governance framework
- Establish AI experimentation sandbox with proper controls
- Implement the AWARE framework (https://workai.com/aware) for governing AI agents and generative AI deployments securely, covering Actor Intent, Work Context, Autonomous Guardrails, Real-time Risk Scoring, and Ecosystem Observability
- Pilot computer vision for manufacturing quality inspection

4.3 Predictive Analytics — Score: 2/5

Rationale

One production ML model (demand forecasting at 78% accuracy) demonstrates capability, but infrastructure is minimal with notebook-based development, no MLOps pipeline, and significant knowledge risk. Feature engineering is duplicated across data scientists.

Evidence

- Demand forecasting model in production with 78% accuracy
- Customer churn model built but not deployed
- No MLOps pipeline, model registry, or automated retraining
- Models run as scheduled Python scripts on EC2
- No feature store, features computed ad hoc in notebooks
- Both data scientists independently created mismatched recency features

Risks Identified

- Knowledge loss if data scientists leave
- Model drift without automated retraining
- Inefficient feature development with duplication
- Inability to scale ML operations

Recommendations

- Implement MLOps pipeline with model registry and automated retraining
- Establish feature store to reduce duplication and improve consistency
- Create model documentation and handover procedures
- Deploy customer churn model to production
- Implement model monitoring and drift detection
- Establish ML model governance framework with approval processes

4.4 Reporting & BI — Score: 3/5

Rationale

Strong Power BI adoption with 180 active users and 350 reports. Self-service capabilities exist with good adoption in Finance and Marketing. However, KPI inconsistencies persist and diagnostic analytics remain largely manual and ad hoc.

Evidence

- 180 active Power BI users with 350 published reports
- Strong self-service adoption in Finance and Marketing
- Executive dashboard KPIs standardized
- Gross margin calculated three different ways in departmental reports
- 2-4 week turnaround for new complex requirements
- Mostly descriptive reporting with some manual diagnostic analysis

Risks Identified

- Decision-making conflicts from inconsistent KPI calculations
- Missed business insights from lack of automated anomaly detection
- Growing backlog of 45 requests with limited analyst capacity

Recommendations

- Standardize KPI definitions and calculations across all reports
- Implement automated anomaly detection and alerting
- Expand self-service training to Operations and HR
- Create report certification process to ensure consistency
- Establish diagnostic analytics playbooks for common use cases

4.5 Data Quality & Integration — Score: 2/5

Rationale

While the Snowflake migration provides modern infrastructure, significant legacy issues persist with 60 undocumented ETL jobs, no automated quality monitoring, and 47% customer record duplication. Ad hoc quality checks only occur when problems surface.

Evidence

- 60 out of 200 ETL jobs in Informatica are undocumented
- Customer addresses hadn't been updated for 3 years in source system
- No automated quality gates or profiling
- 47% customer record duplication (340k records, ~180k unique)
- Ad hoc quality checks only when something goes wrong

Risks Identified

- Regulatory compliance issues due to poor data quality
- Business decisions based on inaccurate data
- Audit failures due to inability to trace data lineage
- Increasing technical debt from undocumented processes

Recommendations

- Implement automated data quality monitoring using Great Expectations (https://greatexpectations.io), an open-source framework for data validation and profiling
- Establish data quality SLAs with automated alerting
- Create a master data management program starting with customer entity resolution
- Document and rationalize the 60 undocumented ETL processes
- Implement data lineage tracking using DataHub (https://datahubproject.io), an open-source metadata platform for end-to-end lineage and governance

4.6 Governance & Stewardship — Score: 2/5

Rationale

A Data Governance Council exists but lacks executive sponsorship and consistent participation. The business glossary covers only 40% of terms and isn't maintained. Eight different customer definitions across departments indicate weak data stewardship.

Evidence

- Data Governance Council established 6 months ago with monthly meetings
- Inconsistent attendance and CEO sees governance as overhead
- Business glossary in Confluence covers 40% of critical terms
- 8 different definitions of 'customer' across business units
- Revenue defined 3 months ago but teams already using different definitions
- No formal data classification policy

Risks Identified

- Regulatory non-compliance with GDPR due to weak PII handling
- Audit failures from inability to reconstruct data lineage
- Inconsistent business metrics undermining decision-making
- Data breaches from inappropriate access controls

Recommendations

- Secure executive sponsorship for governance with clear accountability
- Implement data stewardship roles with defined responsibilities
- Expand and maintain business glossary using collaborative tools
- Establish data classification framework with automated tagging
- Create standardized definitions for critical business entities
- Implement regular access reviews and role-based security model

5. Quick Wins

The following quick wins can be achieved within 90 days:

#	Initiative	Effort	Impact	Owner	Timeline
1	**Document Critical ETL Processes** Document the 60 undocumented Informatica ETL jobs starting with the most critical 20 based on downstream impact analysis	Medium	High	Data Engineering Team	45 days
2	**Standardize Customer Definition** Workshop with department heads to create single customer definition and implement in executive dashboards	Low	Medium	Data Governance Council	30 days
3	**Deploy Customer Churn Model** Move existing customer churn model from notebook to production using current infrastructure	Medium	Medium	Data Science Team	60 days
4	**Implement Basic Data Quality Monitoring** Set up Great Expectations for automated quality checks on critical datasets with email alerting	Medium	High	Data Engineering Team	45 days
5	**Executive AI Strategy Workshop** Conduct half-day workshop with leadership to define AI strategy priorities and governance principles	Low	Medium	CDO with CTO support	21 days

6. Strategic Roadmap

Short-term

Initiative	Effort	Impact	Duration	Dependencies
Master Data Management Implementation Implement comprehensive MDM solution starting with customer master data, including entity resolution, golden records, and data stewardship workflows	High	High	6 months	Executive sponsorship, Data stewardship roles defined
MLOps Platform Development Build comprehensive MLOps platform using MLflow or similar tools, including model registry, automated testing, deployment pipelines, and monitoring	High	High	4 months	Additional data engineering resources
Data Lineage and Catalog Implementation Deploy DataHub for comprehensive data lineage tracking, metadata management, and data discovery across the organization	Medium	High	3 months	Data engineering resources

Medium-term

Initiative	Effort	Impact	Duration	Dependencies
Predictive Maintenance Implementation Develop and deploy predictive maintenance models for manufacturing equipment using existing IoT sensor data, targeting $700k annual savings	High	High	8 months	MLOps platform, Additional data science resources
Advanced Analytics Center of Excellence Establish formal CoE with standardized processes, training programs, and innovation initiatives to scale analytics capabilities	Medium	High	6 months	Organizational restructuring approval
AI-Powered Document Processing Implement vector database and LLM-based processing for engineering documents and	High	Medium	6 months	AI strategy approval, Vector database infrastructure

quality reports, including semantic search and automated insights extraction				
AWARE Framework AI Governance Implementation Deploy the AWARE framework for comprehensive AI agent and generative AI governance, including Actor Intent validation, Work Context analysis, Autonomous Guardrails, Real-time Risk Scoring, and Ecosystem Observability	Medium	High	4 months	AI strategy, Security team collaboration

Long-term

Initiative	Effort	Impact	Duration	Dependencies
Computer Vision Quality Inspection Develop and deploy computer vision models for automated quality inspection on production lines, reducing manual inspection time and improving defect detection accuracy	High	High	10 months	MLOps platform, AI governance framework, Manufacturing equipment integration
Real-time Analytics Platform Expand Kafka-based streaming architecture to enable real-time analytics and decision-making across manufacturing and supply chain operations	High	Medium	8 months	Data engineering team expansion, Infrastructure upgrade
Advanced Pricing Analytics Develop dynamic pricing models using ML to optimize pricing strategies based on market conditions, competitor analysis, and customer behavior	Medium	High	6 months	MLOps platform, External market data integration

7. Appendix: Scoring Rubric

Data Quality & Integration

Score	Criteria
1	No data quality processes; silos everywhere; manual data movement
2	Some quality checks; limited integration; known issues not addressed
3	Quality metrics defined; major systems integrated; some automation
4	Quality monitored continuously; single source of truth for key domains
5	Proactive quality management; real-time integration; self-healing pipelines

Governance & Stewardship

Score	Criteria
1	No data ownership; definitions vary by user; no policies
2	Informal ownership; some documentation; policies exist but not enforced
3	Formal ownership model; business glossary; access controls in place
4	Active stewardship; lineage tracked; policies enforced; regular audits
5	Data as asset mindset; automated policy enforcement; regulatory excellence

Reporting & BI

Score	Criteria
1	Spreadsheet-based; manual reporting; no single version of truth
2	Basic dashboards; limited self-service; definitions inconsistent
3	Modern BI platform; self-service for power users; consistent KPIs
4	Embedded analytics; organisation-wide adoption; performance optimised
5	Real-time insights; predictive elements in dashboards; data democratisation

Predictive Analytics

Score	Criteria

1	No ML in production; all analysis is backward-looking
2	Pilot ML projects; limited production deployment; manual processes
3	Multiple models in production; feature engineering practices; basic MLOps
4	Robust ML pipeline; automated retraining; model monitoring; feature store
5	ML at scale; AutoML capabilities; continuous experimentation; ML governance

AI Deployment

Score	Criteria
1	No AI initiatives; no capability or infrastructure
2	Exploring AI; some experimentation; no governance framework
3	Defined AI strategy; pilot projects; basic governance; some success stories
4	Production AI systems; robust governance; human oversight; measured ROI
5	AI embedded in operations; responsible AI practices; competitive advantage

Organisation & Skills

Score	Criteria
1	No dedicated data team; limited skills; complete vendor dependence
2	Small data team; basic skills; heavy vendor reliance; talent gaps
3	Established data function; developing skills; balanced vendor partnerships
4	Strong data culture; deep expertise; strategic vendor relationships
5	Data-driven organisation; continuous learning; talent magnet; innovation hub