© JUL 2026 | IRE Journals | Volume 10 Issue 1 | ISSN: 2456-8880
DOI: https://doi.org/10.64388/IREV10I1-1720066

AI-Assisted Project Monitoring in Manufacturing Systems: Enhancing Operational Performance and Risk Management

MUSHTAQ QUADER SHAROZ
ORCID: 0009-0007-9412-8652

Abstract- AI-assisted project monitoring is a governance capability, not a dashboarding technology. This distinction drives the Closed-Loop Operational Intelligence and Manufacturing Governance Architecture (CLOIMGA): a five-stage framework positioning AI monitoring as a closed governance cycle connecting sensing, prediction, prioritization, action, and learning. The paper synthesises peer-reviewed literature published between 2020 and 2025 and integrates implementation evidence from a regional FMCG organization deploying Power BI operational dashboards across a multi-site production network in the IMEA region. Before deployment, monthly reporting consumed seven hours of manual effort, audit preparation required two weeks, and approval cycles averaged 23 days; within twelve months, reporting effort fell to under one hour, audit preparation to two days, approval cycle time by roughly 40 per cent, and forecast accuracy improved by approximately 25 per cent. The implementation produced two findings not previously documented with this specificity: AI analytics can detect governance quality failures, including approval-threshold gaming invisible to conventional review; and the data architecture built at deployment becomes the foundation for progressively more capable AI governance in future cycles. A five-level operational intelligence maturity model, a four-phase adoption roadmap, and a manufacturing use-case illustration are provided. The measure of success for AI-assisted monitoring is not model sophistication but governance outcomes: better decisions, fewer disruptions, safer work, and more predictable delivery.

Keywords: AI-Assisted Monitoring, CLOIMGA, Manufacturing Governance, Operational Intelligence, Predictive Analytics, Industry 4.0, Power BI, Governance Maturity, Vision 2030

I. INTRODUCTION

Manufacturing projects are difficult to monitor well. A production line upgrade involves contractors, procurement timelines, engineering milestones, and a go-live commitment the production schedule has been built around. A predictive maintenance deployment requires data integration, sensor validation, and workforce training that can each stall independently. A plant expansion must coordinate civil works, utility connections, equipment installation, and regulatory approval in sequence. Conventional monitoring — milestone reports, earned value summaries, periodic review meetings — identifies problems after their operational consequences have already arrived.

The cost of this limitation is real. In a multi-site IMEA manufacturing organisation studied for this paper, monthly project reporting consumed around seven hours of manual consolidation per cycle. Post-implementation audit required two weeks of document recovery. Approval cycles averaged 23 days. A site engineering manager described a specific consequence: an equipment upgrade had been approved after its maintenance window had closed, requiring rescheduling with associated production disruption. These are the operational costs of inadequate monitoring governance.

AI changes the monitoring logic by detecting weak signals earlier, learning from historical patterns, and supporting corrective action before disruption becomes visible in final performance indicators (Taboada et al., 2023; Salimimoghadam et al., 2025). Müller et al. (2024) set out a research agenda for AI in project management that distinguishes between AI as an automation tool and AI as a decision-support capability — a distinction central to the governance framing developed here. But AI alone does not resolve the governance problem. A Power BI dashboard displaying project progress and approval status is an information display, not a governance instrument, unless its outputs are connected to decision authority, accountability structures, and escalation protocols. That connection is what CLOIMGA provides.

© JUL 2026 | IRE Journals | Volume 10 Issue 1 | ISSN: 2456-8880
DOI: https://doi.org/10.64388/IREV10I1-1720066

II. REVIEW METHODOLOGY

A structured literature review following PRISMA-aligned principles was conducted across Scopus, ScienceDirect, SpringerLink, IEEE Xplore, MDPI, Emerald, Taylor & Francis, and industry reports on smart manufacturing. Approximately 240 records were identified through database searching. After duplicate removal and title and abstract screening, 74 full texts were assessed for eligibility and included in the thematic synthesis. Inclusion criteria required: publication between 2020 and 2025; discussion of AI or data-driven technologies; relevance to manufacturing operations or project management; and evidence or conceptual insight on monitoring, performance, or risk. The analysis followed three coding stages: descriptive, analytical, and integrative. The most representative sources are cited directly; consistent with PRISMA-aligned narrative review practice, the synthesis draws on the wider screened corpus without citing every screened record individually.

In addition to the structured literature review, implementation evidence was collected through: (a) a formal pre-implementation governance audit involving fourteen participants across site engineering management, regional finance, procurement, and operations (sessions of 45 to 90 minutes, structured around three questions: where do approvals stall; where does information get lost; what data do you need that you cannot access); (b) twelve-month post-deployment Power BI performance monitoring; and (c) qualitative follow-up interviews with five original audit participants at six and twelve months. The author was involved in the design and deployment of the platform studied; this is acknowledged as a methodological limitation mitigated through transparent reporting of failures as well as successes. All evidence is presented in anonymised and generalised form.

III. THE CLOIMGA FRAMEWORK

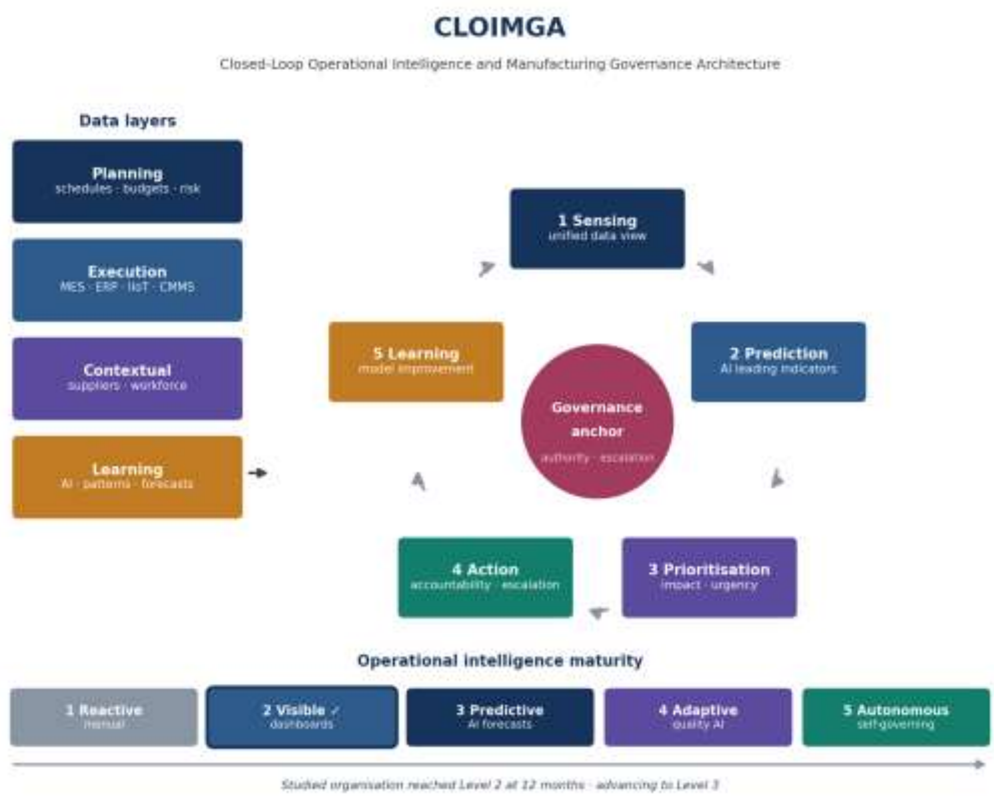

Figure 1. CLOIMGA: Closed-Loop Operational Intelligence and Manufacturing Governance Architecture. Five-stage closed governance cycle (centre), four data layers (left panel), and five-level operational intelligence maturity model (bottom). The governance anchor in the cycle centre represents the accountability structures and escalation protocols that convert AI outputs into governance action. Source: Author.

CLOIMGA integrates four data layers project planning data, operational execution data, contextual data, and learning intelligence within a five-stage governance cycle.

Stage 1 — Sensing: Data from dispersed sources is collected into a unified governance view, eliminating the manual consolidation that consumed seven hours monthly in the studied organisation.

Stage 2 — Prediction: AI models forecast delay, quality drift, equipment risk, or resource constraint as leading indicators rather than lagging measures, enabling intervention before disruption is visible in final performance metrics.

Stage 3 — Prioritisation: Risks are ranked by probability, impact, urgency, and controllability — connecting analytical output to decision relevance rather than producing undifferentiated alert volumes that cause managers to disengage.

Stage 4 — Action: Project teams implement mitigation within defined accountability structures and escalation protocols. Without this anchor, prediction and prioritisation produce insight without action.

Stage 5 — Learning: Model outputs and human decisions are reviewed to improve future predictions, converting monitoring into a continuous governance improvement cycle. This stage is what distinguishes CLOIMGA from a conventional analytics platform.

The critical architectural principle is that each stage must be anchored in governance, not just analytics. The loop only generates value when all five stages are connected to the organization's decision authority structures — which is why a technically identical platform can function as a governance instrument in one organization and as an information display in another.

A scope distinction is important for interpreting the evidence in this paper. The implementation evidence validates the data, workflow, and governance foundations of CLOIMGA — the sensing stage, the governance anchor, and the reporting and escalation mechanisms. The predictive, adaptive, and autonomous capabilities described in the higher maturity levels remain proposed development stages requiring future empirical validation. The machine-vision example in Section 7.2 is presented as an implementation illustration of monitoring governance rather than a validated AI-performance study; model metrics such as accuracy, precision, recall, and false-positive rate were outside the scope of the governance audit and are not claimed here.

IV. AI TECHNOLOGIES SUPPORTING MANUFACTURING PROJECT MONITORING

Recent systematic reviews of AI in manufacturing confirm that machine learning, computer vision, and predictive analytics dominate current industrial applications, while governance and human-oversight dimensions remain comparatively underdeveloped (Ahmmed et al., 2024). Machine learning remains the most widely deployed AI foundation for manufacturing monitoring. Supervised learning classifies deviations and forecasts risk using labelled historical data; unsupervised learning detects anomalies without predefined labels; reinforcement learning supports dynamic scheduling and resource allocation (Bandhana & Vokrížnek, 2025; Farahani et al., 2026). Predictive maintenance models use sensor data, maintenance history, and failure patterns to estimate remaining useful life, enabling schedule coordination before disruption (Ani, 2024; Bitam et al., 2025). Computer vision supports progress verification, quality inspection, and safety observation (Madathil et al., 2025). Natural language processing extracts risk signals from meeting minutes, operator notes, supplier emails, and maintenance logs.

Low-code analytics platforms occupy a practical position the AI literature undervalues. Martinez (2023) found governance applications consistently lagging operational applications in maturity. The implementation evidence here shows a different outcome when low-code tools are deployed with governance design intent: Power BI, available under an existing Microsoft 365 licence, functioned as an AI-assisted governance instrument because it was deliberately designed to surface leading governance indicators — approval cycle trends, overdue project flags, threshold gaming patterns — rather than display historical data. The three-view dashboard architecture (calibrated by user role) was validated after three complete redesigns: user testing showed that a single dense configurable dashboard caused managers to disengage within a few weeks of deployment. Shi (2025) documents the same democratisation pattern across sectors, in which low-code platforms shift analytics development from specialist teams toward the domain experts who understand the decisions the analytics must support.

Explainability is essential in manufacturing governance contexts. AI monitoring decisions affect safety, cost, employment, and regulatory compliance. Without explanation, AI creates resistance, overconfidence, or accountability confusion (Madathil et al., 2025; Windmann et al., 2024). The CLOIMGA framework requires that predictions include a governance-interpretable rationale — not just a probability score — before they can trigger escalation protocols. This human-in-the-loop principle aligns with the human-centric orientation of Industry 5.0, in which AI augments rather than replaces human judgement in operational decisions (Nahavandi, 2022).

V. OPERATIONAL INTELLIGENCE MATURITY MODEL

Table 1 introduces a five-level operational intelligence maturity model aligned with CLOIMGA. The model enables organizations to assess their current monitoring governance state and identify specific capability gaps for the next development phase. It is structured around four dimensions: monitoring approach, data and analytics capability, human-AI interaction, and governance integration.

© JUL 2026 | IRE Journals | Volume 10 Issue 1 | ISSN: 2456-8880
DOI: https://doi.org/10.64388/IREV10I1-1720066

Table 1. CLOIMGA operational intelligence maturity model. ✓indicates achieved state at twelve months post-deployment. Source: Author.

Level	Label	Monitoring approach	Data and analytics	Human–AI interaction	Governance integration
1	Reactive	Manual milestone reporting; issues identified after operational impact	Spreadsheets; no real-time data; retrospective only	Human-only decisions; no AI input	Monitoring disconnected from governance
2 ✓	Visible	Live dashboards aggregate project status; exceptions flagged	Centralised repository; near real-time KPIs	AI surfaces information; humans decide without model input	Dashboard linked to governance workflow; escalation possible
3	Predictive	AI forecasts schedule risk, quality drift, and resource constraints before impact	ML models on historical project data; failure prediction	AI recommendations with human review; explainability required	Predictions trigger escalation workflows
4	Adaptive	Governance quality monitoring: threshold gaming, submission pattern analytics	Self-improving models; sustainability scoring integrated	Human oversight of strategic decisions; AI handles routine detection	Governance audits partly automated; corrective action integrated
5	Autonomous	Routine approvals resolved by AI; humans govern strategic and safety decisions	Carbon accounting and AI governance fully integrated	AI governs routine; humans retain authority over exceptions and ethics	Full loop: monitoring, prediction, action, and learning automated and auditable

VI. OPERATIONAL PERFORMANCE ENHANCEMENT

AI-assisted monitoring improves manufacturing project performance through six governance contributions. Real-time visibility consolidates data into a common operational picture, reducing the gap between event occurrence and managerial awareness. In the studied organisation, the regional portfolio dashboard answered the most common question at every finance review — committed versus available budget across the portfolio — without requiring a week of manual preparation.

Schedule reliability improves when AI forecasts slippage using historical task durations, resource availability, machine status, and procurement lead times. An overdue project flag in the studied organisation made visible for the first time a pattern of approved-and-funded projects not being executed on schedule — invisible in conventional periodic reporting because no cross-project timeline view existed. Quality and rework reduction follows from AI connecting quality deviations to specific equipment, materials, operators, or suppliers rather than recording them as unexplained incidents (Hasan, 2025). Resource productivity improves when AI identifies

© JUL 2026 | IRE Journals | Volume 10 Issue 1 | ISSN: 2456-8880
DOI: https://doi.org/10.64388/IREV10I1-1720066

mismatches between planned resources and actual constraints before they affect the critical path; Miele et al. (2024) demonstrate measurable resource-efficiency gains from AI algorithms applied to manufacturing operations.

Operational resilience is perhaps the most underappreciated governance contribution. The threshold gaming detection in the studied organisation illustrates a point with wide applicability: AI analytics can identify governance system failures, not only operational performance deviations. This expands the value proposition beyond performance measurement into institutional integrity monitoring. Organisational learning — the sixth contribution — is the most strategically significant over time. The data accumulated in a centralised repository constitutes the training material needed for increasingly capable AI governance in future cycles. Organisations that build clean, structured repositories at Level 2 are creating the foundation for Level 3 and Level 4 capabilities they cannot build retrospectively.

Table 2. AI-assisted monitoring: governance contributions and governance risks. Source: Author synthesis of 2020–2025 literature supplemented by implementation evidence.

AI application	Governance contribution	Manufacturing project value	Key governance risks
Predictive maintenance	Failure prediction; remaining-life estimation	Prevents downtime-driven schedule slippage	Sensor quality; false alarms; escalation gaps
Quality monitoring	Computer vision; anomaly detection	Reduces rework, scrap, and release delays	Bias; data imbalance; explainability gaps
Schedule control	Forecasting; optimisation models	Improves milestone reliability and resource allocation	Weak baselines; model drift over time
Governance quality	Threshold gaming detection; submission pattern analytics	Identifies institutional integrity failures invisible to conventional review	Requires clear analytics access and escalation protocols
Digital twins	Plan versus actual state simulation	Tests recovery scenarios before implementation on shop floor	Model fidelity; integration cost; ongoing maintenance
Operational dashboards	Real-time KPI aggregation; exception alerts calibrated by role	Governance visibility connected to decision authority	Data quality; user adoption; alert fatigue

VII. IMPLEMENTATION EVIDENCE

7.1 Platform Architecture

The platform comprised five connected components. A standardised digital submission form with mandatory fields replaced spreadsheets and email attachments, with an automatically generated CAPEX reference number providing cross-system traceability that had not previously existed. The workflow governance layer automated approval routing with a five-working-day escalation rule, converting a latent governance control into a live operational one. A SharePoint central repository with role-based access and version control reduced audit preparation from two weeks to two days. Power BI provided three role-differentiated dashboard views — site engineers, regional managers, and executive sponsors — validated through user testing that showed a single dense dashboard caused managers to disengage.

© JUL 2026 | IRE Journals | Volume 10 Issue 1 | ISSN: 2456-8880
DOI: https://doi.org/10.64388/IREV10I1-1720066

7.2 Use-Case: Machine Vision Quality Detection System

A machine vision quality detection system installation across multiple production lines illustrates CLOIMGA monitoring governance in practice (presented as an implementation illustration rather than a validated AI-performance study). The project involved enabling real-time defect detection and SKU segregation. AI-assisted monitoring through the project-level dashboard tracked installation progress against baseline, identified resource constraints from contractor workforce utilisation patterns, and escalated a schedule deviation before milestone slippage occurred.

At 80 per cent overall project completion, the dashboard flagged that the commissioning milestone had not been confirmed. Investigation identified a dependency on parts arrival that the original project schedule had not explicitly tracked as a critical path item. The project team adjusted contractor scheduling before the delay affected the production go-live commitment. This is the CLOIMGA governance principle operating in practice: monitoring connected to decision authority creates governance value by identifying dependency failures before they become operational consequences.

7.3 Forecast Accuracy and Learning

Forecast accuracy improved by approximately 25 per cent over twelve months, measured as mean absolute percentage deviation between quarterly CAPEX spend forecasts and actual outturns. The improvement reflects both the governance effect of standardised submission data — which made forecasting inputs more consistent — and the learning effect of analytics identifying historical patterns in project pipeline behaviour. The figure is held with appropriate caution given organisational changes in the measurement period.

The more significant finding is architectural: the project data accumulated in the SharePoint repository — project types, estimated versus actual costs, approval timelines, execution durations, site characteristics, escalation events — constitutes exactly the training material a Level 3 predictive governance model requires. This is not a secondary benefit of implementation; it is the mechanism through which Level 2 deployment creates Level 3 capability. Organisations that treat deployment as a dashboarding exercise rather than a data architecture decision will face data quality constraints at Level 3 that cannot be resolved retrospectively.

Document analysis of the organisation's conventional governance artefacts — an investment guideline and a workflow procedure examined in anonymised form — confirms that established CAPEX processes already generate the structured governance records on which AI-assisted monitoring depends. Table 3 maps representative governance records to their potential analytical and predictive uses, illustrating that the data foundation for CLOIMGA's higher maturity levels is a by-product of disciplined conventional governance rather than a separate data-collection exercise.

Table 3. Mapping conventional governance records to analytical and predictive uses. Source: Author synthesis of anonymised document analysis.

Governance record	Potential analytical or predictive use
Submission and approval timestamps	Cycle-time analysis and bottleneck prediction
Returned or revised applications	Documentation-quality risk indicators
Project classification and value	Comparable-project segmentation for forecasting
Risk and sensitivity factors	Early-warning indicators for schedule and cost
Milestone plans versus actual dates	Delay prediction and critical-path monitoring
Budget and forecast revisions	Cost-overrun risk detection
Post-completion outcomes	Model feedback and benefit-realisation learning

VIII. RISK MANAGEMENT

AI-assisted monitoring converts risk management from a periodic administrative process into a

© JUL 2026 | IRE Journals | Volume 10 Issue 1 | ISSN: 2456-8880
DOI: https://doi.org/10.64388/IREV10I1-1720066

continuous governance activity. Traditional risk registers become static artefacts updated in review meetings and disconnected from live operations. AI monitoring connects risk categories to real-time evidence: schedule risk to task progress and supplier performance; cost risk to procurement variance and rework frequency; quality risk to process drift and defect detection; safety risk to incident data and abnormal operating conditions.

The threshold gaming episode in the studied organisation illustrates a less-discussed risk management contribution: AI monitoring can detect governance system failures. Power BI analytics identified clustering of request values below threshold breakpoints — not detectable through periodic review. Once identified and flagged, it stopped and prompted a threshold matrix revision. AI analytics applied to submission patterns can identify institutional integrity failures — not just operational performance deviations — a governance risk management capability the literature has not previously documented with this specificity.

Cybersecurity requires parallel attention. The studied organisation used Microsoft 365 security architecture and role-based SharePoint access controls as the security foundation, and deliberately chose a periodic SAP extract over a live API to reduce the live-system connection surface. This pragmatic compromise — acceptable for most governance purposes, imperfect for real-time balance tracking — illustrates appropriate incremental implementation logic: deploy governance value quickly within available security architecture, then extend connectivity as readiness develops.

IX. IMPLEMENTATION BARRIERS AND ADOPTION

Data quality is the most persistent barrier, manifesting in the studied organisation not as missing data but as strategically entered data: values at the low end of estimated ranges to access faster approval paths. Analytics made the pattern visible; governance protocols addressed it. Without digital analytics, this form of data quality failure is essentially undetectable through conventional review.

Adoption resistance is underestimated in implementation planning. Two sites persisted with email submission for six months. The resolution was not technical: engineering managers set the expectation that email submissions would be returned unsigned. Within four weeks, adoption normalised. Technology enables adoption; management drives it. Legacy system integration remains a structural constraint: the SAP connection in the studied organisation operates through a periodic extract rather than a live API, an acknowledged limitation for high-velocity spending periods that represents an acceptable starting point rather than a permanent architecture.

Table 4. CLOIMGA adoption roadmap: four phases grounded in implementation evidence. Source: Author.

Phase	Implementation focus	Evidence required	Governance priority
1. Diagnostic	Baseline KPIs: approval cycle, reporting hours, audit burden, completeness	Governance audit; process mapping	Quantify governance cost to justify investment
2. Pilot (Level 2)	Standardised forms, digital routing, role-differentiated dashboards for one site	Cycle time, completeness, adoption rate	Management commitment to close legacy submission channels

© JUL 2026 | IRE Journals | Volume 10 Issue 1 | ISSN: 2456-8880
DOI: https://doi.org/10.64388/IREV10I1-1720066

Phase	Implementation focus	Evidence required	Governance priority
3. Scale (Level 3)	Regional rollout; AI forecasting on accumulated data; threshold governance	Portfolio cycle time, forecast accuracy, audit preparation time	Governance quality monitoring: submission pattern analytics
4. Institutionalise (Level 4+)	Sustainability scoring integration; AI governance on project history	Forecast improvement trend; governance maturity benchmark	Data architecture for future AI capability; carbon accounting integration

X. DISCUSSION

AI-assisted monitoring creates governance value only when embedded in accountability structures. Industry surveys confirm that the gap between smart manufacturing investment and realised operational benefit remains wide, with governance and workforce factors among the most common barriers (Deloitte, 2025). The studied organisation had modern digital infrastructure and still produced 23-day approval cycles because governance architecture connecting that infrastructure to decision authority was absent. The CLOIMGA maturity model makes this progression concrete: most organisations sit at Level 1 or early Level 2, not because they lack technology but because they have not applied governance design to the systems they already have. Moving from Level 1 to Level 2 requires a governance audit, standardised forms, digital routing, and differentiated dashboards — not new infrastructure or AI capability. Moving to Level 3 requires accumulated clean data and the organisational willingness to act on AI forecasts.

For Saudi Vision 2030, CLOIMGA supports smart factory transformation through governance that is grounded, scalable, and evidence-based. The workforce development finding — Saudi engineers building governance design capabilities through low-code architecture participation — points to a dimension of AI implementation deserving deliberate design in national industrial programmes: not just deploying AI capability, but developing the human governance capability to design, monitor, and improve it over time.

XI. FUTURE RESEARCH DIRECTIONS

The most immediately valuable future contribution would be a multi-organisation comparative study across GCC FMCG manufacturers, generating governance maturity benchmarks currently absent from the literature. Single-organisation evidence establishes feasibility; it cannot establish what is generalisable. A study covering five to ten organisations varying in size, technology maturity, and governance structure could identify which CLOIMGA framework components produce consistent improvements and generate the first governance maturity benchmarks for this industry-region combination.

Research is also needed on the Level 2 to Level 3 transition: specifically, what volume and quality of historical project data is required before AI forecasting models become reliable enough to inform governance decisions, and how organisations validate those models before acting on their outputs. Future work should also examine AI governance maturity within Saudi Vision 2030 smart manufacturing programmes and the long-term relationship between governance digitalization quality and investment decision quality over a five-year asset life.

XII. CONCLUSION

The measure of success for AI-assisted project monitoring is not model sophistication. It is the quality of decisions made, the disruptions prevented, and the predictability delivered to manufacturing operations. CLOIMGA formalises this standard by positioning AI monitoring as a five-stage closed governance loop, supported by a five-level maturity model enabling organisations to assess their current state and plan their progression from reactive monitoring to autonomous governance.

Implementation evidence confirms both the value and the conditions: a 40 per cent approval cycle reduction, 85 per cent reporting reduction, 86 per cent audit preparation reduction, and 25 per cent forecast improvement, delivered through existing licensing with line management commitment as the decisive adoption variable. Two findings extend beyond the studied organisation and constitute the paper's most transferable contribution: AI analytics can detect governance quality failures — including institutional integrity failures like threshold gaming — that are invisible to conventional review; and the data architecture decisions made at deployment determine the AI governance capabilities available in future cycles. Organisations that build clean, structured governance data repositories at Level 2 are creating the foundation for Levels 3, 4, and 5. Those that treat deployment as a dashboarding exercise rather than a governance architecture decision will face data quality constraints that cannot be resolved retrospectively.

REFERENCES

[1] Ahmmed, M. S., Uddin, M. N., & Islam, M. R. (2024). A systematic review of Industry 4.0 and artificial intelligence in manufacturing. Machines, 12(10), 681.

[2] Ani, O. (2024). Machine learning in advanced manufacturing: Predictive maintenance, quality control and process optimisation. Research Journal of Engineering Sciences, 13(2), 1–12.

[3] Bandhana, A., & Vokrížnek, J. (2025). AI-driven manufacturing: Surveying for Industry 4.0 and beyond. Operations Research Forum, 6, 145.

[4] Bitam, T., Mellouk, A., & Zeadally, S. (2025). Artificial intelligence of things for next-generation predictive maintenance. Sensors, 25(24), 7636.

[5] Deloitte. (2025). 2025 Smart Manufacturing and Operations Survey. Deloitte Insights.

[6] Farahani, M. A., Khan, M. I., & Wuest, T. (2026). Hybrid agentic AI and multi-agent systems in smart manufacturing. Journal of Manufacturing Systems, 86, 612–623.

[7] Hasan, M. M. (2025). AI-driven quality control in manufacturing and construction: A critical review. Engineering Research Express, 7(1), 015002.

[8] Madathil, A. P., Luo, X., Liu, Q., Walker, C., Madathil, R., & Jin, Y. (2025). A review of explainable artificial intelligence in smart manufacturing. International Journal of Production Research, 63(23), 8654–8697.

[9] Martinez, E. (2023). Benefits and limitations of using low-code development to support digitalization in industry. Automation in Construction, 154, 104965.

[10] Miele, L., Dallasega, P., & Rauch, E. (2024). Artificial intelligence algorithms for resource efficiency in manufacturing. Procedia CIRP, 120, 650–655.

[11] Müller, R., Drouin, N., and Sankaran, S. (2024). Artificial intelligence and project management. Project Leadership and Society, 5, 100120.

[12] Nahavandi, S. (2022). Industry 5.0: A human-centric solution. Sustainability, 14(17), 10540.

[13] Salimimoghadam, S., AbouRizk, S., & Mohamed, Y. (2025). The rise of artificial intelligence in project management. Buildings, 15(7), 1130.

[14] Shi, Z., Dong, L., & Gan, C. (2025). Democratizing digital transformation: A multisector study of low-code adoption patterns, limitations, and emerging paradigms. Applied Sciences, 15(12), 6481.

[15] Taboada, I., Daneshpajouh, A., Toledo, N., & de Vass, T. (2023). Artificial intelligence enabled project management: A systematic literature review. Applied Sciences, 13(8), 5014.

[16] Windmann, A., Wittenberg, P., Schieseck, M., & Niggemann, O. (2024). Artificial intelligence in Industry 4.0: A review of integration challenges. at — Automatisierungstechnik, 72(8), 615–632.