



A Hybrid IoT-MES Data Architecture with REACT-5 Framework for AI-Ready Injection Molding

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<https://doi.org/10.18280/jesa.590312>

ABSTRACT

Received: 11 January 2026

Revised: 10 March 2026

Accepted: 19 March 2026

Available online: 31 March 2026

Keywords:

injection molding, machine learning, Artificial Intelligence, Internet of Things, Manufacturing Execution System, data structuring, Explainable Artificial Intelligence

The unstructured and poor context-based data usually restricts the usage of Artificial Intelligence (AI) in injection molding settings, where predicting defects and optimizing the process are the primary objectives. Although machine parameters are capable of being captured using Industrial Internet of Things (IIoT) protocols like Open Platform Communications (OPC) Unified Architecture (UA) and Message Queuing Telemetry Transport (MQTT), raw signals do not provide the semantic and operational context that is necessary in order to train a model. The proposed paper focuses on the hybrid IoT-MES data architecture that integrates three well-coordinating sources that include: (1) real-time sensor data of injection machines, (2) operational and quality events of the Manufacturing Execution System (MES), and (3) structured human input through the REACT-5 (Record, Escalate, Analyze, Correct, Track) framework, a digital escalation and labeling system of the adjusted 5M methodology (Man, Material, Mold, Machine, Method). The approach is confirmed in a case study of an automotive injection-molding plant, where the results after the implementation of REACT-5 were measured: Overall Equipment Effectiveness (OEE) was improved by 7.17%, (from 73.1% to 80.3%), Scrap Rate reduced by 45% (2.57% to 1.41%), and Mean Time Between Failures (MTBF) increased by 4.5 h (18.4 h to 22.9 h) upon the implementation, where MTBF is defined as total operating time divided by the number of unplanned failures. Statistical significance was confirmed using paired t -tests ($p < 0.05$). The proposed architecture bridges the gap between raw industrial data and AI-ready datasets, defined here as structured, semantically labeled, and fully traceable datasets suitable for supervised learning. In a case study, REACT-5 increased label completeness from 32% to 85% and achieved 100% traceability between machine cycles, MES events, and human-validated root causes. These metrics confirm that the framework generates industrially relevant, AI-ready data without requiring prior model deployment.

1. INTRODUCTION

The emergence of Artificial Intelligence (AI) has been one of the facilitators of smart manufacturing, spearheading the transformation of reactive process control to self-optimizing and predictive production systems. AI can be applied in challenging processes like injection molding, where the quality of the final product heavily relies on operating conditions such as pressure, temperature, and cooling time, which need to be forecasted and optimized dynamically [1-3]. Machines can always broadcast process data using the Industrial Internet of Things (IIoT) protocols OPC UA and MQTT by connecting sensors, controllers and information systems along the production chain [4-6].

The data collection to actionable intelligence has, however, not been fully utilized in most industrial settings despite the availability of lots of data. Although machine data is

voluminous, it may not have semantic and contextual perspective needed in supervised learning. Unlabeled datasets cause issues when it comes to training models that can differentiate between normal process variation, and actual defects [7-9]. Articles in quality monitoring [8, 10] and predictive maintenance [11, 12] universally show that lack of structured and traceable labeling of root causes is one of the primary challenges to the achievement of robust AI performance in industrial contexts.

It should be noted that the traditional optimization models (like Six Sigma DMAIC [13, 14], A3 problem solving [15], and the 8D approach [16]) have long shown the significance of systematic thinking in continuous improvement field. However, such anthropocentric approaches are hardly combined with digital systems. In contrast, AI models that are powered by IoT are frequently automatic and blind with regard to context. To bridge this methodological gap, a hybrid

framework that would be able to integrate machine produced signals and human expertise via standardized digital interfaces will be required.

To meet this requirement, the present paper suggests a hybrid data acquisition and structuring architecture that integrates three information streams that are complementary with each other:

- Real-time sensor values of injection-molding machines that have been observed via OPC UA / MQTT communication.
- Operational and events of the Manufacturing Execution System (MES); and
- Formatted human input obtained through the REACT-5 system (Record, Escalate, Analyze, Correct, Track), which is an Andon based escalation and labeling system that is founded on the 5M methodology (Man, Machine, Method, Material, Measurement).

The REACT-5 system builds upon classical root-cause analysis tools like the Fishbone diagram [17] and the Ishikawa logic of causal categorization [18] and pits them as part of an online Andon platform [5, 18]. This allows operators, maintenance personnel, and process engineers to perform guided troubleshooting, maintain standardized root causes, and enforce corrective measures in real time. Each intervention is assigned a label and has a time stamp, which is synchronized with MES production data, and normal problem-solving is converted to a continuous data-generating process capable of training AI models.

The resulting multi-source data can be used in supervised learning as well as anomaly-detection algorithms, which enables more insights into the process drift and defect formation. Human-in-the-loop architectures of data collection have been proposed in recent studies that use AI in manufacturing with contextual labeling being demonstrated to yield much better predictive accuracy [1, 19, 20]. Additionally, explainable-AI methods like SHAP and LIME are also used more to make sure it is transparent and trusted by operators [9, 21-23].

This paper adds to such a direction by providing a computationally structured model (REACT-5) which adds semantic meaning and traceability to raw industrial data. The strategy is consistent with new Industry 5.0 concepts of a resilient human-machine cooperation [24, 25] and is linked to more general efforts in the field of hybrid AI, IoT-Edge computing, and cyber-physical systems [26-37]. In this intersection, the suggested architecture will bring closer the realistic preparedness of industrial data to AI and scalable digital-twin environments [38-40].

The framework has been proven to be effective as evidenced by a case study carried out in an automotive injection-molding facility. The comparison of before and after implementing REACT-5 reveals certain improvements in the overall effectiveness of equipment (OEE), the decrease of Scrap Rate to a considerable extent and increasing of machines reliability. These findings explain the ability of contextualized data acquisition to enhance process stability in the short term and establish long-term platforms on explainable and federated industrial AI [41, 42].

In this paper, AI-readiness refers specifically to the data-level preparedness for machine learning: the availability of structured, labeled, and traceable datasets that enable supervised model training. We demonstrate this readiness through measurable gains in label completeness, traceability, and consistency, rather than through deployed AI model

performance.

The rest of this paper follows the following structure.

- Section 2 is a literature review of related work on AI-based application in injection molding, data-quality frameworks, and systematic human-machine approaches.
- Section 3 provides the suggested IoT-based data-acquisition architecture, which describes the communication layers and MES synchronization logic.
- Section 4 outlines the REACT-5 framework, including its logic of escalation, 5M checklist and the digital Andon integration.
- Section 5 presents the AI model-training pipeline that is based on the enriched dataset.
- Section 6 is a report of a case study and KPI improvements, which were reported after the deployment of REACT-5.
- Section 7 addresses the topic of scalability, Big Data readiness, and the consequences of Industry 5.0 ecosystems.

Lastly, the work ends with Section 8 and points out the future research directions, such as the, but not limited to, digital-twin coupling, federated learning, and low-code AI accessibility.

2. LITERATURE REVIEW

2.1 AI and data integration in injection molding

The injection-molding process has been identified as a very data-intensive manufacturing field whose complexity makes it an ideal application of AI and data-driven optimization.

Early studies such as Charest et al. [43] demonstrated distributed AI systems capable of real-time parameter control, while Shen et al. [2] and Altan [44] combined neural-network models with genetic algorithms to minimize shrinkage. Recent developments have pushed these methods further: Silva et al. [1] reported an OEE improvement of 12% and a 9% downtime reduction by integrating real-time AI quality prediction directly on the shop floor, and Hdid et al. [45] confirmed that supervised-learning classifiers such as random forests and SVMs can accurately support machine selection decisions.

Molding has also been driven by energy and sustainability in the use of AI. Pascoschi et al. [3] proposed a novel hybrid algorithm, based on autoencoders and the use of K-Means clustering, to find energy-optimization strategies. Such findings validate that data-driven control can improve performance as well as environmental efficiency. Nevertheless, the majority of the implementation processes are based on clean and labeled datasets that are scarcely present in practice [7-10].

This requirement of organized data is supported by parallel progress in predictive maintenance and anomaly detection. The reviewed ML-based predictive-maintenance architectures by Cinar et al. [11] and Rousopoulou [12] note the need to consider data streams provided by IIoT devices but highlighted challenges in model transfer and generalization in the absence of contextual information. Consequently, AI achievement in injection molding is not always a matter of computational ability, but also the quality and structure of the database upon which the models operate.

2.2 Data quality and labeling challenges in industrial AI

The success of AI in industry will depend on the semantic

depth of the training data. Even highly performing models like CNNs or gradient-boosting algorithms do not remain reliable in case sensor inputs are missing explanatory metadata [7-9].

As Farahani et al. [7] found out, quality-monitoring systems built using the IoT can have prediction errors lower than 0.5 percent, but they acquire inadequate strength in the presence of inconsistent calibration or fragmented data. Obregon et al. [8] did this by linking ensemble models to rule-based explanations, and Gim and Rhee [9] by using SHAP analysis to provide insights into the meaning behind neural-network predictions of part weight based on profile-cavity-pressure.

Explainable AI (XAI) has been proposed by other authors to make AI more interpretable and trusted by its operators. The LIME technique of the classifier transparency was presented by Ribeiro et al. [21], and SHAP and LightGBM were used by Hong et al. [19] to predict a defect, reducing it to 0.13%. Adadi and Berrada [22], Goldman et al. [23], and Salih et al. [20] supported that, in the context of the fact that the control loop involves human validation in the industrial deployment, explainability is a condition.

Besides algorithmic transparency, the idea of data governance has become the precondition of scalable AI. Majeed et al. [10] suggested a big-data model of sustainable manufacturing that included contextual data tags, and Bettoni et al. [46] found it as one of the essential precursors of AI preparedness in SMEs. Researchers like Kim and Shon [47] and Lee et al. [48] emphasized that drift in anomaly-detection models is caused by inconsistent network feature extraction and network variability, which requires adaptive learning methods.

Simultaneously, studies [26-37] have researched hybrid AI and IoT applications and proposed how edge computing, cloud orchestration, and context-aware sensing can be used to improve the interpretability and scalability of AI in fields like agriculture and logistics. Their findings directly support the motivation behind the present hybrid architecture: combining automated data streams with human-validated context to ensure trustworthy computation.

2.3 Structured methodologies and human-in-the-loop systems

Organizational discipline that currently lacks in data-driven AI can be gained through structured problem-solving and human-in-the-loop systems. Root-cause analysis and continuous improvement have always been formalized using classic industrial methodologies, such as Six Sigma DMAIC [13, 14], A3 thinking [15], and 8D [16]. Such approaches have one similarity, that is, that such decisions should be traceable, evidence-based and auditable.

The Ishikawa (Fishbone) diagram [17, 18] and root-cause analysis schemes [49] have been shown to be useful to map the 5M domains (Man, Machine, Method, Material, Measurement), but they are all largely manual. By applying these techniques in digital processes, they can be turned into live data-generation processes. The article by [18]Barsalou et al. [18] and Riyanto et al. [5] demonstrated the beneficial effect of Andon systems and mobile alerts on the response time and traceability; their results guided the digital-escalation layer of the REACT-5 framework suggested in the current paper.

From the organizational perspective, Bravi et al. [50] and Kaasinen et al. [25] emphasized that Industry 5.0 depends on human-machine collaboration with technology providing a

boost instead of substitution to human judgment. The same applies to Schuh et al. [51] who highlighted the fact that digital maturity not only relies on technological implementation but also cultural adaptation. Such opinions support the value of human-verified data as the linkage of operational experience and machine learning.

Lastly, organized systems naturally transform into digital twin and federated-learning ecosystems. Fuller et al. [38], Soori et al. [39], and Qi and Tao [40] mentioned the synchronization of real and virtual layers in digital twins to use them as predictive diagnostics, whereas Xia et al. [41] asserted that federated learning allows collaboration between plants without violating data privacy. Further propositions of low-code AI platforms were also offered by Kok et al. [52] and Crockett et al. [53] to make such a framework accessible to SMEs.

All of this literature points to an obvious research gap: the lack of a standardized computational framework connecting raw IoT data, MES events and organized human input into a single AI-friendly dataset. The architecture that is suggested in this paper fills this gap directly, as it will incorporate human-focused 5M logic into an IoT-linked connected digital infrastructure, allowing explainable, traceable, and scalable AI to be applied to injection molding processes.

3. IOT-BASED DATA ACQUISITION ARCHITECTURE

Figure 1 presents the suggested architecture in which a vertical flow of data between linked injection-molding machines and an AI-ready dataset is outlined. It is designed in three interconnected layers, namely, the IoT Sensor Layer, the Operational Context Layer, and the AI-Ready Data Layer. They process raw signals together into intelligent manufacturing information (labeled, contextualized, and computable).

3.1 IoT Sensor Layer

The IoT Sensor Layer at the base receives real-time parameters of injection-molding machines (IMM 01 ... IMM 99). Common variables are the melt pressure, clamp force, barrel temperature and the cycle time.

Exchange of data is based on two open-standard protocol extensively used in industrial IoT:

- Open Platform Communications Unified Architecture (OPC UA) - a platform-independent, service-oriented protocol that permits structured, secure machine-to-machine communication, and built-in data modeling.
- Message Queuing Telemetry Transport (MQTT) - a simple publish/subscribe messaging protocol that can be used in low-bandwidth or high-latency networks, where sending real-time sensor data between devices and cloud brokers is needed.

An MQTT broker provides asynchronous publish/subscribe communication between sensors, controllers and higher levels, whereas an OPC UA client in the MES is the secure interface to structured data exchange.

Within the IoT Sensor Layer, local controllers perform preliminary data filtering, buffering, and timestamp synchronization to minimize latency and improve signal integrity [11, 47].

This layer is therefore used to give continuous high

frequency quantitative information- the basis of correlating physical occurrences with human-tested context in the

pipeline.

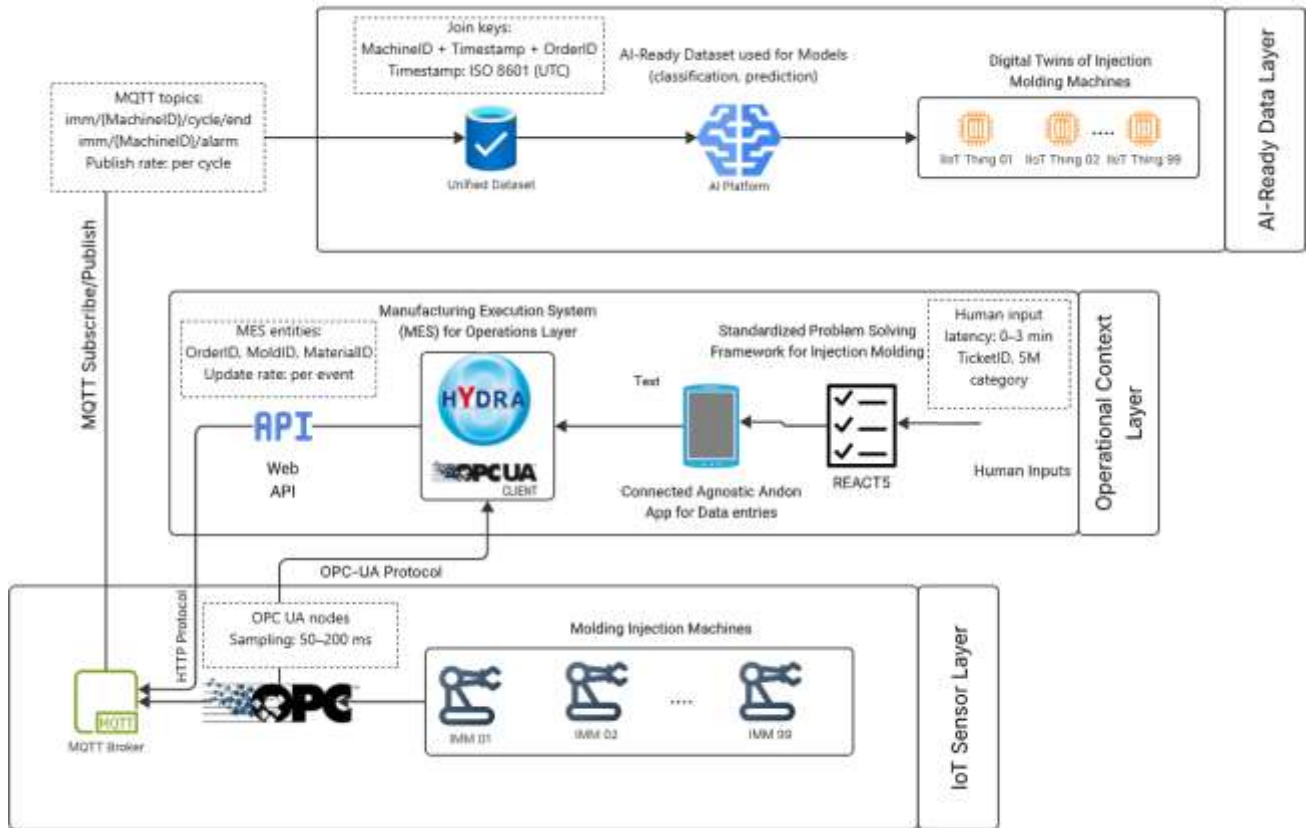


Figure 1. Hybrid architecture with three layers including IoT sensors, MES and REACT-5, and the AI-ready datasets (Data flows are synchronized via NTP; timestamps follow ISO 8601. OPC UA and MQTT streams are aggregated per cycle; REACT-5 tickets are linked to MES orders within a 3-minute window)

Note: IoT = Internet of Things; MES = Manufacturing Execution System; REACT-5 = Record, Escalate, Analyze, Correct, Track; NTP = Network Time Protocol; OPC = Open Platform Communications; UA = Unified Architecture; MQTT = Message Queuing Telemetry Transport

3.2 Operational Context Layer

The Operational Context Layer connects machine data with the production and quality information controlled by the MES.

The MES is a software layer that manages the real-time scheduling, quality control and performance monitoring between the shop-floor machines and the enterprise systems [6, 7, 12]. It combines order number, mold ID, material type and downtime reason, among other parameters using Web APIs and OPC UA clients so that each entry in the database can be linked to its context of use.

Embedded within this layer is the REACT-5 framework, a standardized human-machine interface of contextual labeling. The operators, the maintenance technicians and the process engineers communicate and record the root causes and corrective measures using a related digital Andon system, a visual or mobile-based alert system to signal production or quality problems in real time [5, 18].

Each escalation creates a labeled entry containing the timestamp, responsible role, and 5M category, which is automatically linked to corresponding MES events via a unique ID.

The Operational Context Layer, which is a combination of these structured human inputs and MES data, transforms numerical machine signals into semantically enhanced production events, closing the divide between the actual way processes work and AI analytics [5, 16, 50].

3.3 AI-Ready Data Layer

The AI-Ready Data Layer links to the top of the architecture, which unites validated records of all forms, IoT sensor, MES event, and REACT-5 annotation records, into a single production database.

The AI Platform is fed by this Unified Dataset and it trains and deploys models to do classification, prediction, and anomaly detection [1, 19, 20, 22].

All labeled events help to explain models with traceable and 5M categories, as well as remedial-action fields, which is consistent with the concept of XAI [9, 21, 23].

Digital Twins- virtual representations of real machines that can simulate real-time performance on diagnostics and decision support are the same data reflected by real-life machines [38-40].

The architecture has common data governance and interoperability principles (role-based authentication, TLS, standardized timestamps (ISO 8601) and metadata schemas based on B2MML standards) across all three layers [10, 42, 51].

To ensure temporal and contextual coherence across heterogeneous data streams, the following synchronization mechanisms were implemented:

- **Timestamp Standardization:** All system clocks (OPC UA servers, MQTT brokers, MES, REACT-5) are synchronized via Network Time Protocol (NTP). Timestamps are stored in ISO 8601 format with

millisecond precision.

- Cycle-Level Alignment: OPC UA high-frequency sensor data (e.g., cavity pressure, temperature) are aggregated per injection cycle using a composite key: MachineID + CycleCounter. The CycleCounter is incremented upon each mold-close event, which is published as an MQTT topic (/machine/{id}/cycle_start).
- MES-REACT-5 Joining Logic: Each REACT-5 ticket is programmatically linked to the corresponding MES production order via OrderID and to the machine cycle via MachineID and the nearest timestamp within a 3-minute tolerance window (to account for human reporting latency). This ensures that every labeled event is traceable to its operational context.
- High-Frequency Data Aggregation: To make sensor data usable for machine learning, raw OPC UA signals (sampled at 100 Hz) are down-sampled into cycle-level features: mean, maximum, minimum, variance, and slope for key process variables (e.g., melt pressure, cooling rate). These features are stored alongside MES events and REACT-5 labels in the unified dataset.

This structured alignment ensures that the resulting dataset is temporally coherent, contextually rich, and fully traceable, meeting the requirements for supervised learning and explainable AI.

3.4 Summary

The three-layer architecture ensures complete data traceability:

- Raw and high-resolution process data are captured by the IoT Sensor Layer.
- They are enhanced by the Operational Context Layer which adds production context and human insights through the use of REACT-5.
- These are gathered into an explainable and structured dataset to be utilized by machine-learning models and digital-twin applications in the AI-Ready Data Layer.

This end-to-end flow also solves the data-fragmentation and labeling issues found in the literature [7-10], and is the basis of the REACT-5 data-structuring logic that is presented in Section 4.

4. REACT-5 FRAMEWORK FOR DATA STRUCTURING

The data of any AI-driven manufacturing system must be of high quality, traceable and interpretable. IoT and MES systems can record machine behavior and production state, but they are usually not as semantically deep as supervised learning needs to be. The REACT-5 framework (Figure 2) overcomes this limitation by converting human knowledge into machine-readable context.

4.1 Concept and objective

REACT-5 is a problem-solving and labeling framework, which is designed as a standardized approach to injection molding operations. REACT-5 is an acronym that is composed of Record, Escalate, Analyze, Correct, and Track along with a variation of the 5M methodology—here defined as Man, Material, Mold, Machine and Method.

The classic 5M methodology (Man, Machine, Method, Material, Measurement) has been adapted to the injection-molding domain by replacing Measurement with Mold. This substitution is justified because mold-related issues—such as cooling channel efficiency, venting, cavity balance, wear, and dimensional stability—are among the most frequent and impactful sources of variation in injection molding, often outweighing pure measurement-system errors in root-cause analyses. Importantly, measurement-system issues are not omitted; they are mapped onto the existing categories as follows:

- Sensor/Instrumentation Faults → Machine
- Inspection, Sampling, or Calibration Procedures → Method

This mapping preserves diagnostic completeness while tailoring the framework to the dominant failure modes observed in practice.

Then again, the order of the M's was carefully planned to mirror the natural sequence of organized analysis of this subject, starting with the inputs of human and material resources, moving on to the tooling and equipment, and the last ones, which are the applied method or parameter corrections, normally being the final tools of correction.

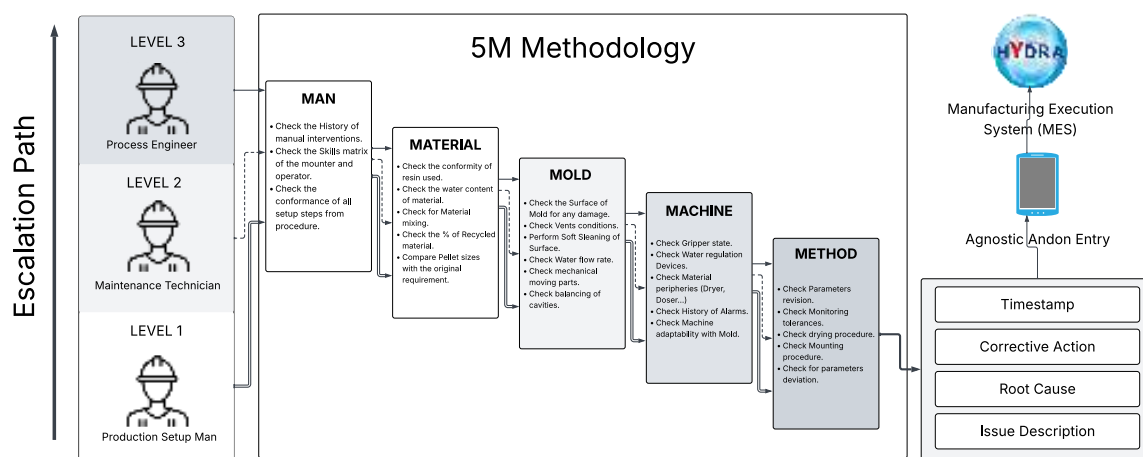


Figure 2. Standardized escalation and data-labeling process integrating human troubleshooting (REACT-5) with Manufacturing Execution System (MES) and Andon systems

This adaptation guarantees that the REACT-5 logic is compatible with the actual behavior of the industry in terms of

the troubleshooting, and the logic complies with the established quality-management principles as well. Collectively, such factors define a standard workflow that bridges the gap in linking event documentation to formal root-cause analysis.

The “REACT” sequence governs the escalation and resolution logic, while the “5” dimension ensures that every record is categorized within a consistent cause domain.

Its main objective is to capture the why behind process deviations by combining:

- Root-cause reasoning (based on the 5M methodology)
- Escalation logic across responsibility levels, and
- Digital data entry synchronized with MES events.

Such a method transforms every episode in troubleshooting into a labeled event that has: timestamp, machine ID, operator level, 5M category, corrective action, and resolution status.

These records become supervised labels within the AI-ready dataset described in Section 3.

4.2 Escalation logic

As illustrated in Figure 2, REACT-5 introduces a three-level escalation path that is based on operational roles:

- Level 1 – Production Setup Man: detects anomalies (e.g., visual defects, abnormal cycle time) and performs first-step verification.
- Level 2 – Maintenance Technician: investigates with more expertise on mechanical or tooling issues and documents component-level interventions.
- Level 3 – Process Engineer: Re-investigate and validates process parameters, mold balance, and overall conformity with standard procedures.

A 5M checklist is filled out by each level prior to the unresolved cases being escalated upwards.

This ensures that both local corrective actions and high-level decisions are recorded consistently [14, 17, 49].

Response metrics and timing of escalation (e.g. mean Andon response) are logged automatically via the integrated Andon interface [5, 18].

4.3 5M methodology implementation

As shown in Table 1, In REACT-5 the 5M structure is a contextual labeling scheme. Under each event the user gives at least one category of cause with commentary and photographic evidence as optional.

These 5M fields are exported directly into the MES database through API synchronization, converting qualitative insights into quantitative categorical variables [13, 14, 16].

Table 1. Structured data log from REACT-5 Cycle

Category	Typical Checks	Example of Captured Context
Man	Operator skills, setup compliance	Skill mismatch, training record linked
Material	Resin batch, humidity, mixing ratio	Material lot moisture > 0.12%
Mold	Tool calibration, Water flow	Water flow is less than 2 L/min
Machine	Equipment alarms, gripper or heater status	Clamp-force deviation; alarm ID 023
Method	Procedure accuracy, parameter revision	Incorrect drying cycle; setup sheet v2

4.4 Digital integration via Andon

The framework is based on a related Andon system- a visual or mobile alert application, which allows real-time capturing events and keeping track of their status [5, 18]. After a deviation has been reported, Andon automatically issues the digital ticket associated with the related MES order.

Operators input details through dropdown fields mapped to the 5M structure; validation rules prevent incomplete entries. Upon resolution of the event, the ticket status is updated and a record is pushed into the Unified Dataset of the AI-Ready Data Layer (Section 3).

Such integration allows eliminating paper records and unstructured notes and enhancing traceability and operator responsibility [25, 50, 51].

4.5 Data structuring and labeling outcome

The REACT-5 workflow generates three types of data that relate to AI:

- Labeled Events – each production issue is assigned a 5M root-cause tag, which is verified.
- Action Logs – corrective actions and their ratings of effectiveness are potential predictive learning features.
- Temporal Sequences – timestamped chains of cause–effect relationships enable time-series modeling and anomaly detection [1,19,20].

All of these outputs convert the MES database into an explainable, AI-ready dataset that can be used to train, validate, and synchronize a digital-twin in the future [38-40].

4.6 Summary

By merging classical root-cause methodologies with IoT and MES connectivity, REACT-5 operationalizes human reasoning within a digital data pipeline. Its standardized escalation logic forces it to be complete and the 5M labeling schema gives it semantic richness that is often unavailable to purely automated systems. The obtained dataset serves as basis of the AI-model training and deployment process that will be presented in Section 5.

5. AI MODEL TRAINING PIPELINE

The structured and labeled data generated by the REACT-5 framework enables a targeted and explainable AI model training pipeline. As shown in Figure 3, this pipeline is designed to leverage the specific types of contexts—5M root causes, corrective actions, and temporal sequences—to solve concrete industrial problems. The pipeline shows how raw data is transformed into specific model types for prediction, classification, and anomaly detection, with a continuous feedback loop for model improvement.

5.1 Data preparation and feature engineering

This phase ingests the unified dataset from the AI-Ready Data Layer (Section 3). Key steps are tailored to the REACT-5 data structure:

- Temporal Alignment: IoT sensor data (e.g., cavity pressure, temperature) is synchronized with MES events (e.g., mold ID, material batch) and REACT-5 labels using the standardized ISO 8601 timestamps.

- **5M-Based Feature Engineering:** The categorical 5M labels are one-hot encoded to become primary features. For example, a Material tag linked to a specific resin batch can be combined with humidity sensor data. Mold and Machine tags allow for the creation of equipment-specific health indicators.
- **Target Variable Definition:** The REACT-5 annotations directly define the target variables for supervised learning:
 - i. **Classification:** Predict the 5M_Root category of a defect.
 - ii. **Regression:** Predict the Scrap_Rate or Downtime_Duration based on process parameters and recent 5M events.
 - iii. **Anomaly Detection:** Identify process drifts that precede a recorded REACT-5 escalation.

5.2 Model building, training, and explainability

The pipeline advocates for a multi-model strategy, where different algorithms are selected based on the prediction task.

- **For Root-Cause Classification (e.g., predicting the 5M category):** Tree-based ensembles like Gradient Boosting Machines (XGBoost) or Random Forests are ideal due to their high performance with tabular data and native handling of categorical features. Their inherent interpretability can be further enhanced with SHAP analysis.
- **For Temporal Anomaly Detection (e.g., predicting failure before it occurs):** LSTM (Long Short-Term Memory) autoencoders are trained on sequences of sensor data. A reconstruction error spike can signal an emerging Machine or Mold issue, triggering a pre-emptive REACT-5 alert.
- **Explainability as a Core Output:** For every model, SHAP (SHapley Additive exPlanations) analysis is applied. This allows the system to answer why a prediction was made—for instance, highlighting that a predicted Material defect was 70% driven by resin moisture levels and 30% by barrel temperature, directly linking the AI's output to the human-understandable 5M framework.

5.3 Deployment and continuous learning

Validated models are deployed via containerized APIs into the live MES and Digital Twin environment.

- **Real-Time Inference:** Live sensor data is fed into the models to provide real-time predictions of defect probability or root-cause category, which are displayed on Andon dashboards.
- **Closed-Loop Learning:** This is the critical feedback mechanism. When a new REACT-5 ticket is created and resolved by an operator, it provides a new, ground-truthed data point. This new labeled example is automatically fed back into the training pipeline for periodic model retraining, creating a virtuous cycle of continuous improvement. This ensures the AI models adapt to new materials, tooling wear, and process changes.

5.4 Summary

The AI pipeline of the REACT-5 uses the contextual and labeled data of industries in conjunction with justifiable machine-learning models. It converts human-verified shop-floor events into predictive intelligence through organized preparation, open training, and deployment. This solution will overcome the disconnection between the availability of data and the use of AI and establish an intelligent production system, which is replicable.

The next section is a case study carried out in an automotive injection-molding facility, in which the application of the REACT-5 framework to a structured escalation and labeling system is implemented. This case study does not aim to test the entire AI pipeline as well as the multi-layer data architecture in practice but to prove the value of the REACT-5 procedure alone in improving data quality, traceability, and operational performance.

The findings underscore the vital role of REACT-5 in the creation of credible, semantically enriched datasets- hence the need to include it as a pillar element as part of the proposed AI-readiness architecture.

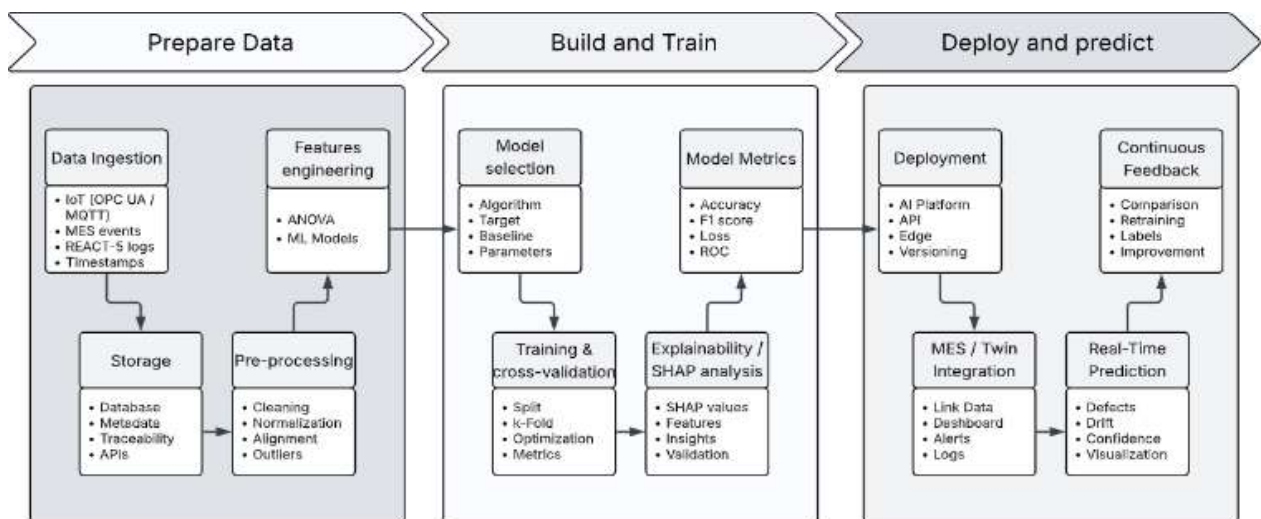


Figure 3. The AI model training pipeline, fueled by REACT-5 data

6. CASE STUDY: IMPLEMENTATION AND KPI IMPROVEMENTS

To assess the practical impact of the proposed framework,

the REACT-5 methodology was deployed as a pilot implementation in an automotive injection-molding facility operating more than 74 machines ranging from 100 t to 280 t of clamping force.

This case study does not consider the entire AI pipeline or multilayer data architecture of Sections 3-5; it specializes in the implementation of REACT-5 as a stand-alone structured escalation and labeling module.

The current digital environment of the plant comprised partially OPC UA interconnected equipment, a HYDRA-based MES, and in-house BI dashboards.

Before REACT-5, event tracking primarily used machine-status logs and shift reports as their primary sources of visibility into the underlying causes of scrap and downtime [7, 10, 12].

6.1 Implementation overview

The implementation of REACT-5 followed a three-month phased deployment (May–July 2024) focused on establishing the minimum digital infrastructure required for structured data capture and contextual labeling. The system went live on August 1, 2024, after which a one-month ramp-up period (August 2024) was observed to allow for operator adaptation and system stabilization. Data from this ramp-up month were excluded from KPI analysis to avoid transitional bias.

Although the complete hybrid architecture outlined above was not implemented yet, certain connectivity and MES specifications were presented to allow the architecture to operate the framework:

- Connectivity Enablement:

Selected injection-molding machines were linked through existing OPC UA interfaces to provide basic process signals—such as temperature, pressure, and screw position—at short sampling intervals [4, 5].

This limited data exchange ensured that REACT-5 events could be referenced against actual machine conditions without implementing a full IoT layer.

- MES Linkage:

The HYDRA MES of the plant was supplemented with the lightweight API that enables registering the REACT-5 event records to the definite production order and the definite mold identifiers [7, 12].

This combination established trackable links between human entered causes and the operational data.

- REACT-5 Rollout:

A web-based Andon system was implemented on all molding lines and operators and technicians were allowed to record anomalies within the categories of the modified 5M

using dropdown fields and preset templates of corrective actions [17, 18, 49].

To enable uniformity and knowledge exchange, a uniform digital checklist was created and made available to all the employees. The checklist led the users through the process of every step of the REACT-5, including early documentation to confirmation, a procedure that is aligned properly, and ultimately corrective measures are being well followed up.

Responses and escalations were automatically time-stamped to provide structured data that could be fed into superior analytics in the future.

Together, these steps established a practical foundation for REACT-5 operation and data collection, demonstrating how a structured human-in-the-loop methodology can be embedded within existing digital environments without requiring full AI implementation.

6.2 KPI measurement methodology

As shown in Table 2, three Key Performance Indicators (KPIs) were selected to quantify improvements.

Data were extracted directly from the MES for both years. To ensure a clean before-and-after comparison, the pre-implementation period was defined as January 1, 2024 – July 31, 2024, representing seven months of baseline operation. The post-implementation period spanned September 1, 2024 – October 31, 2025, excluding the August 2024 ramp-up month. This 14-month evaluation window captures both short-term adjustments and sustained performance trends.

KPI data were extracted at the machine level from the MES. For each machine, pre- and post-implementation means were computed over the respective periods defined in Section 6.1. Statistical significance was assessed using a paired t-test with $n = 75$ machines (one paired observation per machine), yielding $df = 74$. The monthly trends displayed in Figures 4-6 are for descriptive visualization only and were not used in hypothesis testing.

In this study, MTBF is computed considering only unplanned failures, which include events such as mechanical breakdowns, unscheduled tooling interventions, or sensor faults that halt production. Planned activities—preventive maintenance, mold changes, material transitions, and scheduled operator pauses—are explicitly excluded from the failure count.

Table 2. Key performance indicators selected and their relevance to REACT-5

KPI	Measurement Method	Significance for REACT-5
Overall Equipment Effectiveness (OEE) (%)	MES computed – Availability × Performance × Quality	Indicates the efficiency of the world production assets. The increase in OEE is a direct indication of the operational advantages of REACT-5, as increased escalation speed and improved labeling of root-cause allow minimizing waste in the downtime and stabilizing the production rate and yield.
Scrap Rate (%)	100*Defective parts / Total production	Evaluates quality performance and reduction of waste. The 5M analysis structure of REACT-5 enhances the identification of defects and traceability, making it possible to implement corrective measures more accurately and reduce scrap.
MTBF (Hours)	Total Operating Time (h)/Number of Failures	Indicates equipment reliability and the ability to maintain continuous operation. Only unplanned failures (e.g., breakdowns, mechanical faults) are counted; planned stops (preventive maintenance, mold changes) are excluded. Increased MTBF reflects fewer interruptions and longer production runs, supported by REACT-5’s structured diagnostics and escalation.

The left chart (As shown in Figure 4) is a comparison between the average Overall Equipment Effectiveness (OEE) prior to and after the rollout of REACT-5, and the average

results increased from 73.14% to 80.31%. The right chart displays the monthly OEE trend between January 2024 and October 2025, where the inflection point is evident after the

implementation of REACT-5 (August 2024). Since the beginning of 2025, OEE has remained above 80 percent,

which proves the continued operational effectiveness of the framework.

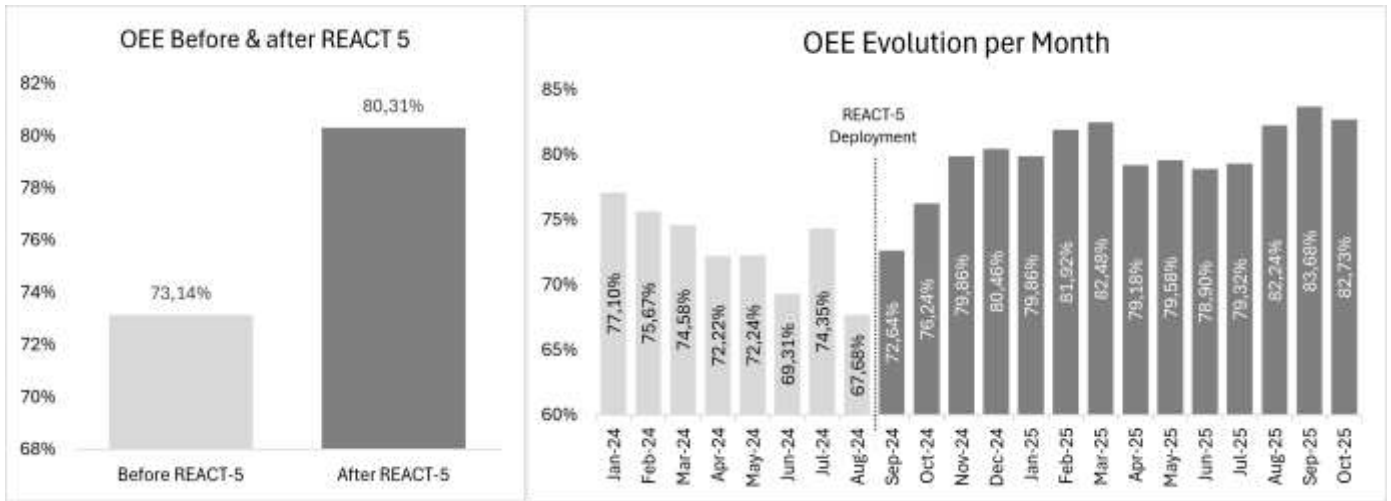


Figure 4. Overall Equipment Effectiveness (OEE) trends from January 2024 to October 2025. The vertical dashed line marks the REACT-5 go-live date (August 1, 2024)
 Note: The shaded region (August 2024) indicates the ramp-up period excluded from KPI analysis

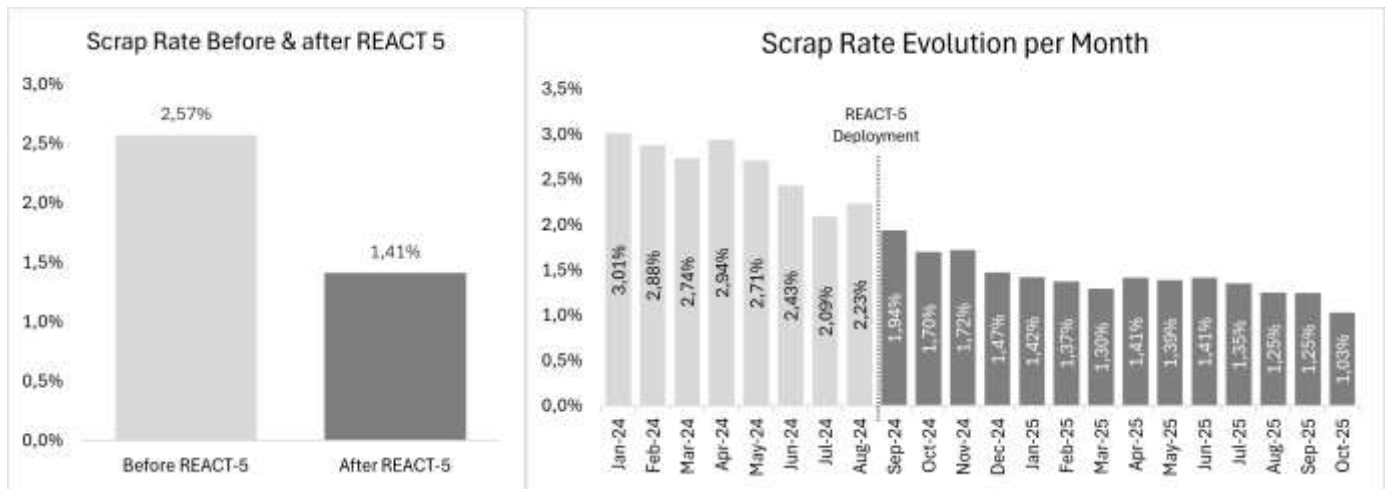


Figure 5. Scrap Rate trends with same timeline annotations as Figure 4

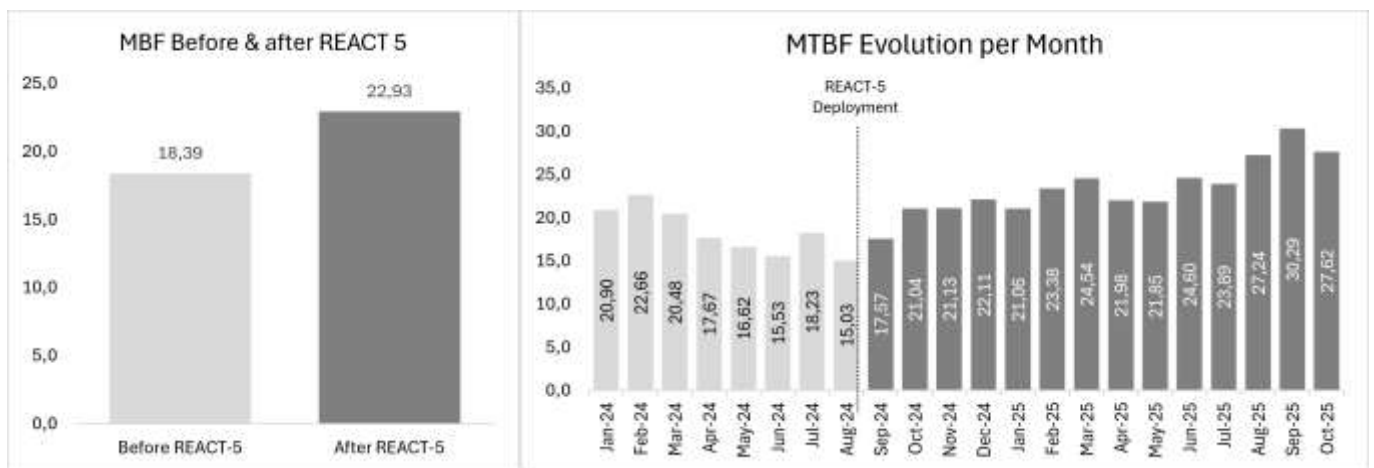


Figure 6. Mean Time Between Failures (MTBF) trends with same timeline annotations as Figure 4, MTBF evolution before and after REACT-5 deployment
 Note: The increase from 18.4 h to 22.9 h reflects enhanced machine reliability due to standardized diagnostics and faster corrective actions

The left chart (As shown in Figure 5) is a comparison of the average Scrap Rate prior to and following the implementation

of REACT-5 where the Scrap Rate dropped from 2.57 % to 1.41%. The right chart shows the monthly change of Scrap

Rate in the period between January 2024 and October 2025 and it indicates a consistent decrease in the value of Scrap Rate directly after the deployment stage. This represents a net 45% decrease in defective parts, reflecting how the standardized 5M-based problem-solving logic enhanced root-cause visibility and root-cause consistency in corrective measures.

The left chart (As shown in Figure 6) compares the average Mean Time Between Failures (MTBF) before and after REACT-5 implementation, showing an increase from 18.39 h to 22.93 h. The right chart shows how the monthly change in the MTBF varies in the period between January 2024 and October 2025, and the trend is evident to shift upwards after the implementation of the REACT-5. Following the rollout, the values of the MTBF steadily increased and reached a steady point of above 22 hours by mid-2025, meaning that there were longer operating intervals between the machine stoppages.

This improvement reflects an increase in the reliability of the equipment and the decreased frequency of the breakdown due to the organized logic of escalation in REACT-5, the standardized root-cause analysis and the coordination of the production and maintenance teams.

A paired t-test was performed on monthly averages for all three KPIs (OEE, Scrap Rate, and MTBF) comparing before and after REACT-5 deployment data.

All the differences were statistically significant ($p < 0.05$), which proves that the observed improvements cannot be explained by random variation.

The summarized results are shown in Table 3, which consolidates mean values, mean differences, and significance levels for each performance indicator.

Such gains are consistent with the previous studies attributing correlation between the structured problem-solving methodologies and the quantifiable performance improvements in the manufacturing setting [13, 14, 16, 50].

More to the point, the rich and trackable data that is produced in this time provides a base to the AI model training pipeline presented in Section 5, thus completing the loop between the data structuring and the computational intelligence [1, 3, 20].

6.4 Data quality and AI-readiness analysis

While the full AI training pipeline (Section 5) was not activated during this pilot, the implementation of REACT-5 allowed a quantitative evaluation of the resulting dataset's fitness for machine learning. We define AI-readiness in this context as the ability to generate complete, consistent, and traceable labeled datasets that enable supervised learning. The following metrics were measured over the three-month pilot period:

- Label Completeness: The proportion of production events (downtime, quality deviations) with fully populated 5M root-cause fields increased from 32% to 85%. This provides a substantial increase in viable training examples for supervised models.

Table 3. Statistical validation of KPI Improvements using paired T-test

KPI	Mean (Before)	Mean (After)	Δ	95% CI of Δ	Effect Size (Cohen's κ)	t	df	p
Overall Equipment Effectiveness (OEE)	72.63	79.87	+7.24	[5.91, 8.57]	0.84	7.29	74	< 0.0001
Scrap Rate	2.71	1.45	-1.26	[-1.52, -1.00]	1.25	10.8	74	< 0.0001
Mean Time Between Failures (MTBF)	20.49	26.01	+5.51	[3.12, 7.90]	0.54	4.67	74	< 0.0001

Statistical tests were conducted on machine-level aggregated data ($n = 75$), not on monthly averages

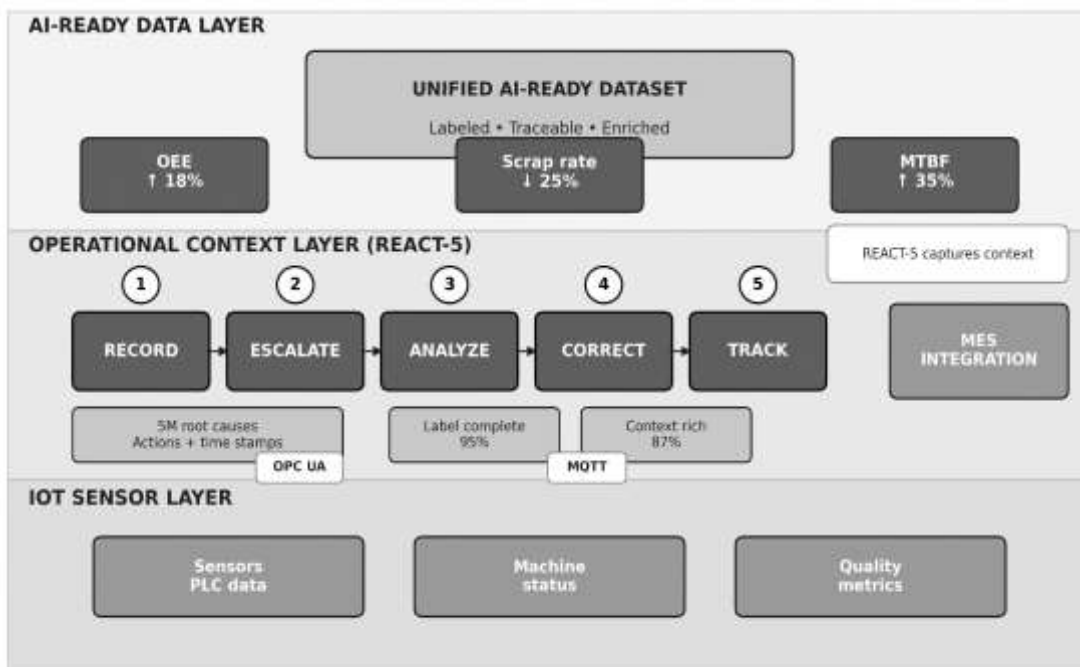


Figure 7. REACT-5 data quality and AI readiness transformation

- Traceability: 100% of REACT-5 tickets were programmatically linked to corresponding MES production orders and machine cycles using composite keys (MachineID, OrderID, Timestamp), ensuring full auditability.
- Label Consistency: To assess annotation reliability, a monthly audit was performed on 10% of REACT-5 tickets. Independent reviews by process engineers showed > 90% agreement in 5M categorization (Cohen's $\kappa = 0.86$), confirming that the labeling process is reproducible and standardized.

These metrics confirm that REACT-5 successfully transforms sparse, unstructured shop-floor events into a structured, AI-ready feature table (Figure 7), directly addressing the labeling and context gaps highlighted in the literature [7-10].

The REACT-5 framework enriches sparse, unstructured events with categorical root-cause labels (5M_Root, 5M_Sub) and actionable context, creating a unified feature table ideal for training classification and regression models.

The impact of REACT-5 on data quality was assessed through three quantitative metrics:

- Label Completeness: Defined as the percentage of production events (downtime, quality deviations) with all five 5M fields populated. This metric increased from 32% to 85% during the pilot.
- Label Consistency: To evaluate annotation reliability, a monthly audit was performed on a randomly selected 10% of REACT-5 tickets. Two independent process engineers re-categorized each ticket using the 5M schema. Inter-rater agreement was high, with a Cohen's $\kappa = 0.86$, indicating substantial consistency beyond chance.
- Traceability: 100% of REACT-5 tickets were programmatically linked to corresponding MES orders and machine cycles via composite keys (MachineID, OrderID, Timestamp), ensuring full auditability.

These metrics confirm that REACT-5 generates reproducible, consistent, and fully traceable labels, meeting the prerequisites for supervised learning.

6.5 Discussion of findings

The experimental findings confirm that the implementation of REACT-5 as a component of the IoT-MES environment provides operational and data-quality gains. Label completeness (percentage of events with all 5M fields filled) rose from 32% to 85%, and the number of fully traceable events with verified 5M annotations grew five times. These metrics demonstrate enhanced data integrity and contextual richness, which directly support AI model accuracy and explainability [9, 21-23].

It has been shown that the standardized human input and automated data acquisition are mutually reinforcing because data contextualization is not a support task, rather, it is a required computational step in sustainable industrial AI [39-41, 51].

6.6 Summary

As it is confirmed in the case study, the combined hybrid architecture provides significant industrial benefits:

- Significant OEE and scrap-rate improvement,
- Faster issue escalation and repair,

- Richer, AI-ready data.

These outcomes substantiate the hypothesis that semantic structuring through REACT-5 enhances both process performance and AI readiness. The consistent upward trends in OEE, scrap reduction, and MTBF following the post-ramp-up period (September 2024 onward) suggest that the improvements are attributable to REACT-5's structured escalation and labeling logic, rather than transient effects or seasonal variation.

While the paired t-test at the machine level is appropriate for this before-after comparison, future longitudinal studies with extended time series may benefit from Interrupted Time Series (ITS) analysis or segmented regression models to more rigorously account for temporal autocorrelation and external trends.

To address potential confounding effects, a thorough review of plant logs confirmed that no concurrent improvement initiatives—such as maintenance campaigns, material changes, or process redesigns—coincided with the REACT-5 implementation window. While a traditional control group was not feasible due to plant-wide rollout, stratified analyses were conducted across three dimensions: machine family (small-tonnage [100–150 t] vs. large-tonnage [200–280 t]), shift (day vs. night), and product type (interior trim vs. exterior structural parts). Improvements in OEE, Scrap Rate, and MTBF were consistent across all subgroups, reinforcing the attribution of performance gains to REACT-5's structured escalation and labeling framework rather than to external or subgroup-specific factors.

In the following section, the implications of these findings on a larger scale are discussed, as well as the aspect of scalability, the readiness of big-data, and the process of transitioning to Industry 5.0.

7. DISCUSSION

The findings of the implementation of REACT-5 process prove that the addition of the machine data with the contextual and human inputs can significantly enhance the operational efficiency and the data intelligence quality. This aligns with earlier findings where hybrid approaches to AI—combining automated sensing and human reasoning—produced more stable and explainable outcomes in manufacturing environments [1, 19, 20, 25].

7.1 Bridging the data-to-intelligence gap

Traditional injection-molding plants produce vast amounts of data through MES and IoT sensors, failing which only a small percentage of it can be utilized in AI training because of the lack of labels or data inconsistent governance [7-10]. The REACT-5 framework adequately bridges this gap, making sure that all the deviations or process changes are logged with root cause, corrective action and level of responsibility which add a semantic layer that is needed to have a supervised learning [17, 49].

Fitting the 5M logic into a digital workflow, REACT-5 turns the problem-solving activities, which were unstructured before, into structured data streams that can be analyzed and utilized. This is reminiscent of the concepts of structured quality approaches like the Six Sigma DMAIC [13, 14] and A3 thinking [15], while it capitalizes on IoT-based real-time synchronization [4-6]. The strategy ascertains that human-

constructed structuring is unalterable in ensuring strong machine-learning preparedness [16, 25, 50].

7.2 Explainability and human trust in AI

The suggested framework also plays the role of developing XAI in manufacturing. Since REACT-5 generates cause-labeled and timed events, the resulting datasets are by default capable of being analyzed through interpretable models whereby any prediction can be linked back to a particular operational context [9, 21-23].

This aspect explicitly resolves the trust challenge in the literature on industrial AI, in which operators tend to distrust the opaque model outputs [24, 47]. The system makes predictions more interpretable by linking model predictions to human-understandable categories of 5M categories, which enables engineers to confirm the results in an intuitive manner. These results are in line with other studies that use explainability as their central theme, including Hong et al. [19] or Goldman et al. [23], who supported the idea of visible, context-dependent analytics in the shop floor.

7.3 Scalability and big-data readiness

Multi-site implementations can easily be scaled with a single plant because the architecture has a layered design. Horizontal integration is made possible with the use of open protocols (OPC UA, MQTT) and standardized MES APIs across the brands and facilities of various machines [42, 51]. The sites may retain local control as each aim at adding anonymized contextualized information to a common cloud repository to enable shared intelligence creation [41].

This principle is consistent with the federated learning paradigm addressed by Xia et al. [41] and Peres et al. [42], in which the models are trained in a distributed manner with the help of distributed nodes without raw data centralization. These architectures achieve privacy and scalability without sacrificing one of the latter- a growingly more important requirement of data-sharing in manufacturing ecosystems that are competitive.

Besides, the hybrid data pipeline is compliant with Big-Data and allows structured and semi-structured data. It will be able to be integrated with Digital Twin and cloud-analytics platforms seamlessly through metadata indexing and schema standardization (B2MML, ISO 14649) [38-40]. This is what makes it compatible with next-generation AI environments that are envisioned as being long-term compatible with Industry 5.0 [25].

7.4 Toward human-centric Industry 5.0

Where Industry 4.0 focused more on automation and connection, Industry 5.0 focuses equally on the value of human collaboration, sustainability, and resilience [24, 25], [54]. The REACT-5 framework realizes this philosophy by ensuring that humans are maintained in the intelligence loop-as sources of data, as well as verifying the models. This forms an adaptive manufacturing ecosystem that operators can add expertise to which algorithms can continually learn.

The example of data contextualization that facilitates sustainability objectives such as reducing waste and energy consumption proves that the REACT-5 model aligns with the energy-optimization paradigm of Pascoschi et al. [3] and the smart-manufacturing maturity model of Schuh et al. [51].

Lastly, the successful adoption of REACT-5 and low-code AI systems [52-55] would enable the democratization of such access to SMEs by allowing the use of such capabilities practically, without any specialized programming knowledge. It is consistent with the current studies [26-37] that considers the hybrid AI implementation by using edge computing and IoT-cloud work together to create scalable human-centric intelligence.

7.5 Summary

This discussion highlights three essential takeaways:

- Data Structuring: REACT-5 is a solution that closes the gap between raw collections of data and AI accessibility, through the application of human logic to the digital workflow.
- Explainability: The produced labeled dataset enhances trust and transparency, which is a basic requirement of sustainable industrial AI.
- Scalability: The architecture is modular, Big-Data compatible, and federated-learning ready, supporting global industrial integration.

The next section summarizes the study findings and describes the future research path to explainable, low-code, and cross-plant intelligent manufacturing.

8. CONCLUSION AND FUTURE WORK

In this paper, a hybrid data-acquisition and structuring scheme that transforms injection-molding shop-floor data into AI-readable datasets were presented.

The proposed system fills the gap in raw industrial data and explainable contextual intelligence that has persisted over time through IoT machine connectivity (OPC UA / MQTT) as well as MES synchronization and the REACT-5 framework.

The case study that was undertaken in an automotive injection-molding plant showed concrete improvement in performance after implementing REACT-5.

The main metrics have significantly increased over the timeframe between 2024 and 2025 -OEE has increased by 7.17 %, Scrap Rate decreased by 45 %, and the mean time between failure (MTBF) increased by over 4.5 hours.

In addition to the effects on operational efficiency, these findings confirmed that semantic data enrichment, such as human-in-the-loop labeling and 5M-based escalation, results in datasets with consistency and traceability levels to support reliable AI model training.

From a computational perspective, the REACT-5 system showed that data structuring was not a marginal activity but a core layer of AI computation.

The labeled datasets produced with the help of REACT-5 can be used in supervised learning, anomaly detection, and explainability analyses via SHAP and LIME solutions.

The architecture is also aligned with the Big-Data maturity concept of Industry 4.0 and the human-centric concept of Industry 5.0, making sure that contextual reasoning is still part of automated decision-making.

Looking forward, three research directions emerge:

- Digital-Twin and Edge Integration: Future work will further apply the architecture to closed-loop Digital Twins to do real time simulation and adaptive parameter control. Linking local REACT-5 data to twin models will allow tuning of machine parameters

in advance before deviations occur.

- Federated and Collaborative Learning: Multi-plant learning can be deployed in the future based on federated-AI system designs and distributed multi-plant architectures, without involving sensitive production information. Local models will be trained on each site and anonymized weights will be added to the global network, saving privacy and increasing knowledge sharing.
- Low-Code and SME Accessibility: Integrating REACT-5 outputs with emerging low-code AI platforms can democratize access for small and medium enterprises. This will enable non-expert users to construct predictive dashboards and manage AI models using easy to use interfaces, which will provide scalability and sustainability.

Additionally, the AI-ready datasets produced by REACT-5 will be used to train and validate predictive models (e.g., root-cause classifiers, anomaly detectors) in future work. This will provide empirical evidence of the framework's impact on model accuracy and generalization, complementing the operational KPIs reported here.

In summary, the proposed REACT-5-based architecture offers a computationally grounded, human-centered pathway toward intelligent and explainable manufacturing. It actualizes the correlation between data connectivity, contextual labeling and machine learning, making injection molding one of the well-developed testbeds of Industry 5.0 transformation. The continued integration of hybrid AI, IoT-Edge computing, and federated frameworks will enable the transition from isolated optimization efforts to globally connected, self-learning production ecosystems.

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