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Review Article

An Integrated Analytics Framework Using High-Volume Time-Series, Image, and Process Data to Optimize OEE, Scrap Reduction, and Energy Efficiency

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Abstract: Industrial manufacturing organizations and production logistics organizations have generated significant amounts of data from sensors, time series, inline cameras, images/videos, and enterprise systems and process logs. (Han *et al*., 2018) This has made it possible to improve the operations from post-hoc to predictive. (Achouch *et al*., 2022) The objective of this organized review is to collect the existing knowledge and information on the architecture, algorithms, and methods for multimodal analytics, and this organized review has been designed and developed for three major purposes: maximizing equipment effectiveness, minimizing scrap and rework, and maximizing energy efficiency. The guidelines for systematic review PRISMA 2020 are followed, including literature from 2020 to 2025 on predictive maintenance, anomaly detection, computer vision inspection, process mining, digital twinning, forecasting, and optimization. (Systematic review of predictive maintenance practices in the manufacturing sector, 2025) The study has found that data architecture is the starting point for scalability, multimodal analytics can reduce false positives and increase the effectiveness of the early warning system when each modality measures different failure processes, improvement of KPI can be optimized when the result of decision is included in the workflow and decision-making, and forecasting and decision models are perceived as solution space for optimizing energy. (Dutta *et al*., 2025) The study is associated with generalization, improvement of KPI, and decision models, which are associated with sustainability and optimization of throughput, quality, and energy. (Kaushal & Chakrabarti, 2025) The next part of this chapter will include the discussion on the implementation checklist and research agenda. The next part of this chapter will include the discussion on the relevance of the study and the systematic review carried out for the journals of the first quartile of logistics and operations research journals.

Keywords: Industry 4.0, Multimodal Analytics, Overall Equipment Effectiveness, Predictive Maintenance, Defect Detection, Scrap Reduction.

1. INTRODUCTION

In recent times, the production logistics area has been impacted by the constant generation of data. There are various machines used in the current production process. These machines have various sensors such as vibration sensors, current sensors, and temperature sensors. These sensors generate data. In addition, images can be obtained through inspection cameras. Log data can be obtained through MES/ERP systems, machine controllers, or human-machine interfaces. These three types of data represent different dimensions of reality. Signals represent physical reality, images represent results, while log data represents states and decisions. These three types of data represent a complete reality. These three types of data are key factors that impact important logistics performance indicators such as stable lead times, internal service levels, and schedule performance. OEE is an important tool used to evaluate the efficiency of the machines used in the production process. OEE is used to evaluate the efficiency of the machines used in the production process because of the following reasons: OEE has three factors that impact the efficiency of the equipment used in the production process. These factors are Availability, Performance, and Quality. (OEE Factors: Availability, Performance, and Quality, n.d.) However, OEE has a disadvantage as an outcome variable. (OEE: A Controversial Figure, 2025) In order to increase the OEE, it is important to increase the factors that impact OEE. There are three ways that analytics can be used to increase OEE: forecasting and warning, root cause analysis, and optimization. (Saretzky *et al.,* 2025) The performance of deep learning models has been considerably advanced with regard to their capacity to model multivariate time series data (Tang *et al*., 2023), to identify anomalies (Zamanzadeh Darban *et al*., 2024), and to combine multimodal data (Zhao *et al*., 2024). Success in operations depends on many factors besides analytics. Although it is a different scenario from the benchmark scenario in which the data is not clean or asynchronous, there is a lack of labels, and the decision process is restricted due to safety, compliance, and cost issues in taking actions on the results of the prediction models. The high-accuracy detector will be ineffective in the deployment scenario in which there is an issue of alert fatigue; it will be ineffective in handling the downtime of cameras and sensors; and it will be ineffective in utilizing the results of the prediction models in the operation, maintenance, and quality management process for taking actions on the results of the prediction models. There is a need to add value-aligned metrics in the results of the evaluation process. The aim and objective of conducting this literature review are as follows: The aim of conducting this literature review is to create literature that is most relevant to the audience. This includes creating literature on recent literature from 2020 to 2025. This includes creating an integrated framework that includes data architecture, multimodal modeling, and decision integration with results such as OEE, scrap, and energy efficiency, as per the aim and objective of conducting a literature review, as shown above. In order to create a literature review that is most relevant and useful for a Q1 audience, who are most likely individuals in the field of logistics and/or operations management.

2. AIM AND OBJECTIVES

Aim: Systemically conduct a literature review from the year 2020 up to 2025, regarding the incorporation of high-volume time series, image, or process/event data for the purpose of optimizing OEE, scrap, and energy efficiency in a given environment.

Objectives: (O1) Identify the data architecture and data governance patterns; (O2) Synthesize the modeling techniques and address the constraints; (O3) Identify the mapping of the models and the interventions/KPIs; (O4) Develop the research agenda for causality, cross-site generalization, and sustainability-aware multi-objective optimization.

3. METHODOLOGY (PRISMA)

This systematic literature review is based on the PRISMA 2020 protocol. The process for conducting the systematic literature review follows the following protocol: guided search, screening, data extraction, and synthesis. The process for conducting the systematic literature review is geared toward extracting relevant literature for an operations-related evidence map rather than for algorithmic variations.

Research Questions:

- What architectures and pipelines are used to ingest, synchronize, and govern multimodal industrial data?
- What types of models are used for forecasting, anomaly detection, fault prediction, defect detection, and optimization, and how are these models validated?
- How does the model integrate the results for maintenance, quality control, scheduling, and energy optimization, and what KPIs are used?
- What are the unknowns for transferability, causal attribution, and deployment?

Inclusion Criteria for Literature Review

- The year of publication will range from 2020 to 2025.
- The literature will be relevant for industrial manufacturing or production logistics.
- The literature will have at least one modality, preferably multimodal fusion.

Exclusion Criteria for Literature Review

- Literature not relevant for industrial or operational scenarios.
- Data Extraction Process:
  - Modalities and sampling;
  - Data preprocessing and synchronization;

- Model types and validation, especially time-based;
- Deployment;
  Integration for decision;
- Integration for KPIs.

Quality Appraisal Criteria

Operational risk assessment issues such as data leakage, unrealistic splits for training and testing data, unrealistic robustness evaluation, unrealistic budget reporting for alerts, etc. (Vieira *et al*., 2025) If causal attribution cannot be supported, KPIs are associated.

5. Thematic Synthesis (2020-2025)

5.1 Data Architecture, Synchronization, and Governance

A research project in this area should be able to have semantics for asset ID, part/lot ID, and recipe/state ID; in addition, a research project in this area should be able to have a good method for timestamp synchronization for effective data merging based on relevant operations such as parts, lots, batches, or time windows. A research project in this area can be partitioned using edge cloud partitioning for data management. (Plan for Edge Processing in Data Management, 2024) Preprocessing of sensor data for cleaning, compression of images for filtering, or inference for latency-critical detection should be included in a research project in this area. A research project in this area should also be able to leverage the cloud for longer-term storage and training, in addition to cross-line benchmarking for robustness in the presence of intermittent connectivity. Some of the best practices for a research project in this area should be able to monitor data quality in terms of missing values, outliers, and data drifts; in addition, metadata management for audit trails and access control based on role should be included in a research project in this area. (Tu *et al*., 2023) This is important since the output of the research project in this area should be used for determining product quality hold times, maintenance, or even commitment. Good data governance should be assumed for most research projects in this area; however, evidence-based research in this area for practitioners indicates that monitoring and version control should be considered important for a research project in this area. (Li *et al*., 2024). It has been considered that the development of a feature store/embedding store can be a potential solution that can solve the redundancy issue with respect to engineering different types of problem domains. (Li *et al*., 2023) In the case of multimodal data, it can be useful in representing images/time windows that can be used later on. (Liu *et al*., 2025) The only issue with the usage of such stores in a production environment is that there is a possibility that the features can become stale due to changes in the equipment/sensors.

5.2 Multimodal Representation Learning and Sensor Fusion

The multimodal fusion of the data has the potential to be robust if the types of data are of different nature and are complementary with respect to failure modes. In the case of the manufacturing domain, it has been discussed that the time-series data obtained from sensors has the potential to be used in the detection of the start of degradations, images have the potential to be used in the detection of the manifestation of defects, and event data have the potential to be used in the detection of contextual changes such as recipe changes, operator actions, and batch numbers. The benefits and problems of multimodal fusion have been discussed in the survey on deep multimodal fusion. The problems discussed include representation, alignment, tolerance of missing modality, and uncertainty, as discussed in Zhao *et al*., (2024). The most commonly used fusion techniques used for data fusion in an industrial scenario are early fusion, attribute fusion, and late fusion. (Liu *et al*., 2025) In terms of the GO approach, late fusion is the most commonly used technique, owing to the ease of validation of each model. (Effective Techniques for Multimodal Data Fusion: A Comparative Analysis, 2023) The robustness of the missing modality detection feature of the system is possible. The feature fusion technique is the most accurate of the three techniques. However, the accuracy of feature fusion could be extremely sensitive to changes in the data distribution. It could be extremely difficult to audit, as the representation of the data is a fusion of all the modality data. Other challenge that has to be addressed is alignment, since images are part-based, whereas sensors are continuous in nature. The majority of the research has been done with event anchors such as part ID, barcode scan, triggers from different stations, and cycle counters for alignment of the sensors with the parts. Some have also used a batch level of sensors if alignment at a part level is not possible. The form of alignment, which is used, has the potential to define the form of the mechanism, which can be learned. For example, part-level alignment has the potential for learning direct defect predictions, while batch level has the potential for learning drift detection and energy-aware scheduling. Explainability of the Fusion Mechanism Explainability of the fusion mechanism has the potential for use in operations, but it is important to note that it has the potential for explaining the mechanism, which can be controlled. Although it is possible for the attention-based models to have the potential for learning and identifying time windows and image regions, which are of importance in making predictions, it is important to ensure that the operations staff have the potential for understanding and relating the explanation mechanisms to factors, which can be controlled. From the above, it is evident that models, which are hybrid and have the potential for integrating deep features and structured variables such as recipe, machine state, operator shifts, and batches supplied, are likely to have preference.

5.3 Forecasting for Throughput Stability, OEE Planning, and Energy Management

The development of multivariate time-series forecasting methods based on deep learning has been a significant step forward, as more industrial applications emerge. Surveys of the literature on this subject have identified non-stationary, exogenous factors and long-term dependencies as important features of the data (Tang *et al*., 2023). Forecasting is an important task in industrial production logistics, as it adds value to the enterprise by supporting associated activities that help to avoid variability amplification and increase internal service levels. OEE forecasting may be viewed as a combination of Availability, Performance, and Quality forecasting under expected conditions. Relevant features derived from MES systems include downtime causes, cycle time, and shift-related variables, which are used to improve forecasting through sensor fusion in conjunction with the operating context (Dobra *et al*., 2023). Fusion-oriented methods examine the integration of various factors to further increase the stability of OEE forecasting under changing conditions (Zhou *et al*., 2025). Energy forecasting is used for peak shaving, scheduling, etc. Surveys of the literature on energy efficiency have found that analytics, as a tool, is not enough to deliver long-term benefits; they require integration with operating processes, decision-making authority, and improvement activities (Batouta *et al*., 2023; Schmitt, 2025). Forecasting is increasingly viewed as an input to a policy optimization problem. The validation of a forecasting model is essential for establishing trustworthiness. In this regard, time-split and rolling origin validation would be more apt, considering real-world situations where regime changes are frequent. Regime changes could be related to maintenance cycles, product mix, and policy changes. In multimodal forecasting for image-based exogenous contexts, there would also be a need to consider image non-availability or camera non-operational situations, which would be relevant to the plant scenario.

5.4 Anomaly Detection and Predictive Maintenance for Availability Improvement

Anomaly detection is one of the key areas for improving availability. Industrial anomalies vary. In multivariate anomaly detection surveys, there is emphasis on point anomalies, contextual anomalies, and collective drift anomalies. It is also established that there are no constraints related to evaluation protocols. The most informative evaluation protocols provide lead time, false alarm rates at a given budget, and results from actions taken. In predictive maintenance models, there would be a progression from sensor-only models to context-aware models. In context-aware models, there would be inclusion of operational state from log data to prevent false alarm generation for expected transient behaviors like startup or changeover. In addition, there could be inclusion of modalities like vision and acoustic to distinguish noise from degradation. One of the reasons for multimodalization could be related to the need to prevent false positives and improve root cause specificity. Digital twins could be useful for formalizing contexts, constraints, and interventions. In digital twin surveys, there is a consensus that a digital twin would be a structured representation of physical assets and related data streams and models to support simulation and interpretation. In maintenance, digital twins would be useful for what-if analysis to determine which option minimizes impact on production schedules and downstream logistics commitments. Predictive maintenance has second-order effects on performance and quality. The timing of the maintenance can have an effect on changeover time or stability after the changeover. The latter has implications for the integration of the problem of maintaining the equipment in the larger problem of production logistics. The latter has further implications for the role of multi-objective evaluation in OEE improvement initiatives.

5.5 Vision-Based Defect Detection and Scrap/Rework Reduction

Deep learning is the current mainstay in vision-based inspection systems for defect detection, localization, and segmentation. Surveys have shown significant progress and challenges in dealing with class imbalance issues, fewer available defect classes, and domain-related issues such as illumination conditions, camera viewpoints, and product-related issues (Hütten *et al*., 2024). Scrap reduction can be most effectively achieved if there is a direct correlation between detected defects and the preceding causes of defects. (K *et al*., 2022) While end-of-line inspection can be used for non-conforming product detection, it may not be effective in reducing repetitive defects. (Quality Assurance in Auto Manufacturing: A Guide to End-of-Line Inspection, 2024) Higher KPI improvements can be achieved through the integration of vision-based inspection results with process variables and sensor signatures for the identification of the process window in which defects occurred and subsequent adjustments for improvement. (Industry 4.0: Capturing Value at Scale in Discrete Manufacturing with Industry 4.0, 2023) A good example of multimodal quality prediction can be applied in additive manufacturing processes, in which multimodal sensor signatures can be correlated with the final product quality outcome. These correlations can be used for taking proactive steps for improvement in product quality by stopping the print process, adjusting print parameters, or changing scanning patterns for reduction in rework and scrap (Petrich *et al*., 2021). In this example of quality prediction improvement, outcome-oriented signals are used in conjunction with images, while images of the mechanism are used in conjunction with process variables. Scrap reduction from a production logistics point of view translates into a consistent production schedule with reduced expediting requirements and reduced downstream costs for returns, rework queues, and material handling. (APQC, 2018) In this respect, scrap reduction is a quality improvement objective and should be considered in the broader field of quality engineering. (Dewa & Makua, 2024)

5.6 Energy Efficiency Analytics and Sustainability-Aware Optimization

Energy efficiency is a concept that is understood to have a connection to organizational costs and sustainability. (Enhancing Corporate Sustainability and Competitiveness through Energy Efficiency: A Literature Review, 2024, pp. 266-271) From a review of literature, it is understood that energy efficiency can be optimized through monitoring, process planning, and optimization of machines and systems. At the system level, it is understood that energy efficiency optimization can be achieved through energy-aware scheduling, in which it is possible to reduce peak demands and align energy efficiency to off-peak periods. (Mathew *et al*., 2020)

The level of organizational maturity is also understood to have a significant impact on organizational performance. (Development of a digital maturity model for Industry 4.0 based on the technology-organization-environment framework, 2023) In terms of energy efficiency optimization for industrial manufacturing processes, it is understood that energy efficiency capability maturity can be described as having stages from basic visibility to prediction and adaptability. Therefore, it can also be understood that energy efficiency optimization can be described in terms of organizational performance, such as adherence to organizational standards.

The optimization methods for energy efficiency optimization can also be described as having stages from simple heuristics to reinforcement learning. In reinforcement learning optimization for production systems, it is understood that safety and constraints must be satisfied to use the optimization method, as reviewed in the literature. In terms of energy efficiency optimization, it is understood that constraints must be satisfied to avoid compromising product quality and organizational commitment. Another area of further research is that of sustainability-aware multi-objective optimization, where trade-offs are managed for throughput, quality, and energy. There are many choices that have a coupled effect on an industrial process. For example, a process that has a higher throughput may have a higher defect rate and a higher energy intensity, or a process that has a higher focus on energy savings may have a negative impact on throughput reliability. Multimodal monitoring provides this level of trade-off management. It is necessary that there be optimization methods that have constraints, uncertainty quantification, and results that have physical units.

5.7 Measurement and Evaluation in Operations Contexts

There has been a disconnect between the measurement and evaluation metrics used in the academic context and the value they deliver. For example, the F1-score of the detector does not correspond to the probability of a plant, and the reduction in downtime depends on the detector's value, which corresponds to the volume of alerts, investigations, and the effectiveness of the intervention. Also, the vision model's accuracy does not correspond to the reduction in scrap, since the routing of rework could be capacity-constrained or detection could be too late. The value-aligned measurement and evaluation metrics correspond to the measurement and evaluation of the detection lead time, or the value of detection, which is the time before a failure occurs or a defect occurs. Also, actionability, or the value of actionability, corresponds to the feasibility of the intervention. Adoption rate, or the value of actionability, is the percentage of actions performed. Finally, outcome delta corresponds to the outcome's value. Temporal validation is an important component of the measurement and evaluation process. For example, random train-test validation is not optimal when the data are correlated. This could lead to an increase in the metrics because of the correlated data. For example, time-based validation, or "rolling origin evaluation," could be more valuable to operations, as they may have changed over time (Tang *et al*., 2023). Also, the missing modality scenario could be an important consideration for the multimodal system since the cameras could be down.

Temporal Validation

This will also ensure standardized process. This will yield concrete results on the solution's feasibility. This will also meet the requirements of Q1 journals regarding the relevance of the research. The results regarding performance on transfer or calibration will be more relevant.

5.8 Cybersecurity, Data Ethics, and Trustworthy Deployment

Industrial analytics is used in safety- and quality-critical applications. There is a need to address the cybersecurity challenges like secure ingestion, authentication, OT/IT segmentation, access control, and auditing. This will be similar to the best practices of governance, as discussed in the literature on digital twin and Industry 4.0 (He & Bai, 2021). Another critical consideration for industrial analytics will be human monitoring. This will be a closed-loop system. The interface will have to be human-centric. There will have to be a mechanism for explanation and escalation. There will have to be a mechanism for logging the decision. This will give a positive feedback loop. This will not only improve the model but will also help build trust in the model by making it accountable. This will give a framework for learning from the data. Model risk management will have to be the need of the hour. This will help reduce the risk of degradation. This will include monitoring, degradation detection, and rollback. Degradation will have a silent impact on the operational domain. This will lead to missed delivery commitments and a negative impact on the corporate brand.

5.9 Integration with Lean, TPM, and Continuous Improvement

Multimodal industrial analytics can be integrated with existing operational excellence initiatives such as Lean, TPM, and Six Sigma. Lean initiatives focus on waste reduction and process stability. TPM initiatives focus on machine reliability and autonomous machines. Six Sigma initiatives focus on variation reduction and defects. Industrial analytics can be integrated with all of these initiatives to improve their effectiveness by providing a faster feedback cycle for all of these initiatives, measuring loss patterns, and identifying areas for improvement to maximize effectiveness.

For example, TPM initiatives can be integrated with industrial analytics to analyze chronic losses such as micro-stopages, speed losses, and unscheduled downtime. Using a time series analysis tool, patterns of micro-stopages can be analyzed and correlated with corresponding contextual triggers from the logs (changeovers, material lots, etc., or shifts). This can be part of a Kaizen improvement initiative, and hypotheses can be tested and changes in loss distribution tracked instead of merely eyeballing it. Vision analytics can also be used to enable a similar DMAIC analysis process for TPM initiatives by analyzing defects using heatmaps and clusters. It can be further focused on potential causes of defects by correlating with potential causes, signals, and recipe information. From a logistical perspective, reducing defects can also reduce rework queues and expedite, thus reducing lead time and its variability. To ensure that this is a continuing benefit and to ensure that standard work and governance are put into place, a successful closed-loop program must be implemented. This is consistent with the overall theme of this review: that pipeline and workflow considerations are as important as model considerations.

6. Consolidated Evidence Table

Table 1 provides an evidence map linking modality combinations to analytics tasks, decision integration mechanisms, and KPI pathways.

Table 1: Evidence map for multimodal data analytics and KPI outcomes in production logistics contexts.

Modality mix	Typical data sources	Primary analytics tasks	Decision integration	KPI pathway	Representative sources (2020–2025)
Time-series	Vibration/current/temp; PLC/SCADA	Anomaly detection; PdM	Alerts→work orders; maintenance planning	↑Availability→↑OEE	Zamanzadeh Darban *et al.*, (2024); Mohan *et al.*, (2021)
Images	Inline cameras; vision stations	Defect detection/segmentation	Quality gate; rework routing	↓Scrap→↑Quality→↑OEE	Hütten *et al.*, (2024)
Event logs	MES/ERP events; alarms; recipes	Process mining; bottleneck discovery	Dispatching rules; flow redesign	↑Performance→↑OEE; ↑lead-time stability	Lee *et al.*, (2025)
Time-series + logs	Sensors + state/recipe context	Contextual anomaly detection	Context-aware thresholds	↓False alarms→higher action rate	Zamanzadeh Darban *et al.*, (2024)
Images + logs	Vision + lot/recipe/shift metadata	Traceability & defect association	Containment; supplier/recipe actions	↓Repeat defects→↓scrap	Moiceanu *et al.*, (2022)
Time-series + images	Sensors + vision	Fusion quality prediction	Early stop; parameter recommendation	↓Scrap & ↓downtime→↑OEE	Petrich *et al.*, (2021)
Full multimodal	Signals + vision + events	Fusion + optimization	Closed-loop recommendations	Joint OEE/scrap/energy gains	Zhao *et al.*, (2024); He & Bai (2021)
Energy-focused time-series	Meters; utilities; machine power	Forecasting; peak detection	Energy-aware scheduling	↓kWh/unit; ↓peaks	Batouta *et al.*, (2023); Schmitt (2025)

7. Proposed Framework and Implementation Checklist

As mentioned above, the proposed framework is based on the five-tier framework, and the same has been depicted in the figure below:

(L1) Capture and Semantics: Hierarchy of Assets, Part/Lot Identification, Event Definition;

(L2) Data Engineering and Governance: Quality Constraints, Data Provenance, Feature Store, Embedding Store;

(L3) Modeling and Validation: Time-Based Splitting, Robustness Analysis, Edge/Cloud Partitioning;

(L4) Decision Integration: Workflow, Ownership, Override, Safety Restrictions;

(L5) KPI Accountability: Measurement Window, Outcome Logging, Continuous Improvement Governance.

Implementation Checklist

1) Identify 3-5 KPI pathways with strong ownership: Maintenance, Quality, Scheduling, Energy.
2) Start with findings that include strong actions: Quality Hold, Work Order.
3) Start with a pilot, but design identifiers for scalability;
4) Track: Drift, Alerts, Action Rates, Accuracy;
5) Record: Decisions: Model Version, Action, Outcome;
6) Explore: Multi-objective Optimization after Trust in Single-Objective Workflow;
7) Develop procedures: Escalate/Rollback Decisions based on Unexpected Model Behavior.

8. DISCUSSION AND FUTURE RESEARCH AGENDA

As mentioned above, the evidence provided above is sufficient to prove the validity of the proposed multimodal analytics approach, which would ensure the stability and sustainability of the system. (Ismail *et al*., 2025) As mentioned above, the proposed approach is based on the KPIs outlined for the workflow and governance. However, there is a lot of content, especially in the domain of Q1 logistics and operations research. (Mohan *et al*., 2025)

Gap 1 - Causal attribution of KPI improvements. From the research on this topic, it has been observed that KPI improvements have been examined. However, in most research on this topic, it has been observed that variables such as product mix, personnel, and/or process improvements have not been considered. Thus, if research is to be carried out on this topic in the future, it is important that quasi-experimental studies are conducted to provide bounds on the KPI improvements.

Gap 2 - Cross-site generalization/domain shift. Based on the research on this topic, it has been observed that the models have not generalized well across business segments/plants. Thus, if research is to be carried out on this topic in the future, it is important that representation, calibration, uncertainty estimation, model evaluation with missing modalities, updates, safety, and timeliness are considered. This particular area of research can be carried out on the use of digital twins for KPI progress research, as suggested by He and Bai (2021) and Soori *et al*., (2023). Most importantly, if research is to be carried out on this topic, an evaluation of data management using digital twins is essential.

Gap 3 - Sustainability-Aware Multi-Objective Optimization. Business process optimization, with a focus on productivity, quality, and sustainability, should be recognized as a research gap. (Liao *et al*., 2025) Therefore, if research is to be conducted on this problem, it is imperative to consider reinforcement learning, as Panzer *et al*., (2022) and Alginahi *et al*., (2025) have proposed. Most importantly, in case research is to be conducted on this problem, it is imperative to consider safety, interpretation of recommendations, and satisfaction of constraints. Research can be conducted on research on the application of digital twins for research on this problem. Additionally, it is imperative to consider the tariff structure included in the models used in the evaluation of energy efficiency. (Khan *et al*., 2021)

Gap 4 - Value Aligned Evaluation and Reporting. It is imperative to consider various variables in case research work is to be conducted in the future on the research problem of KPIs and how it can be improved, for example, academic variables as well as various operational variables such as avoid downtime minutes, scrap kilograms, and/or kilowatt-hours/unit. Additionally, it is imperative to develop a standard reporting form.

9. Limitations

There are a number of limitations that are related to the research work. For example, the research work that has been written regarding this particular industry has not been based on any data. For example, the research work that has not had any negative findings has not been published.

Secondly, there is unification at the domain level. For example, "maintenance, quality, and energy." There is a difference regarding the evaluation culture and reporting. The statement is true from the point of view of the production logistics. However, the information is "hidden" in the domain.

Thirdly, there is unification based on literature from 2020 to 2025. However, there are a few pre-2020 standards and bases for TPM as well as classical control. (Mouhib *et al*., 2025). Lastly, although not all of the above papers are particularly useful with regard to providing any information on volumes of alerts, decision rights, and deltas of KPIs, the above overview is not really about a 'best model' anyway; although, it would be highly desirable that the above studies be more consistent with the standards.

10. CONCLUSION

In conclusion, high-volume time series, images, and process logs represent a valuable source for improving production logistics results. In the above sections, we have reviewed the research on multimodal fusion for optimizing OEE, reducing waste, and maximizing EE for the period between 2020 and 2025. To apply the results successfully in a real-world scenario, all the research emphasizes the significance of governance-first architecture, proper fusion strategies for the decision horizon, and work flows for converting predictions into accountable actions. (Anumula, 2025)

Appendix A: Practical Taxonomy of Use Cases and Decision Horizons

To assist in the application of the reviewed research in a real-world scenario, Table A1 is a conceptual table on a practical taxonomy for use cases and decision horizons. The second-level horizons are for safety and machine protection. These cases require conservative detection. Minute-to-hour horizons are for process stabilization and quality prevention. These cases can be reviewed by engineers. Day-to-week horizons are for planning cases such as scheduling, EE production, and workforce allocation. (Liu *et al*., 2025) In intervention types, we can have: (i) automatic protective actions such as go-stop or divert actions with strict intervention rules; (ii) operator intervention types such as prompts or checklists; (iii) engineering intervention types such as recommendations for setpoints or root causes; and (iv) planning intervention types such as scheduling or batching rules. (Saretzky *et al*., 2025) Multimodal fusion can be more acceptable for recommendation and planning intervention types. Conservative designs can be used for automatic protective actions. (Huang *et al*., 2025) With regard to logistics, short horizons can have a lower number of availability losses. Long horizons can have lower variability and a higher predictability rate regarding performance and lead time.

Appendix B:

Reporting Template Recommended for Q1 Logistics/Operations Papers To facilitate greater study-to-study comparability and increase their managerial relevance, we strongly recommend that a minimum set of operational details be reported. This will include:

Context: Industry, asset type, production mode Modalities and sampling frequency

Alignment Method: Part ID, station trigger, windowing

Validation Method: Time-based splitting, external validation

Operational Integration: Who receives alerts? What can they do with them? Escalation path?

Measured Outcomes

Downtime minutes saved, scrap kg saved, kWh saved/unit, impact on lead time distribution In addition to the above minimum details, we recommend that the following also be reported: Alert budget: How many alerts can we handle?

Triage Cost

How many alerts can we handle in a given time window? For example, a maintenance team may have capacity to investigate a certain number of alerts during a given shift. If a model produces more alerts than can be handled in that shift, it will be ignored regardless of how good it is. This will allow machine learning metrics to be converted to operational economics. (Bayram *et al*., 2025) Finally, we recommend reporting on governance aspects such as model versioning, drift detection, and model retraining. This is increasingly a requirement for high-quality journals given its significant impact on study sustainability of benefits.

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