

Artificial Intelligence in Manufacturing Quality: Applications, Challenges, and Emerging Research Directions

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Abstract: Artificial intelligence (AI) is increasingly integral to managing manufacturing quality. Techniques such as machine learning, deep learning, and computer vision are employed for tasks like defect detection, quality forecasting, process surveillance, fault diagnosis, and process enhancement. Recently, large language models (LLMs), retrieval-augmented generation (RAG), and knowledge-graph strategies have introduced innovative methods for utilizing engineering documents and other unstructured manufacturing data in quality assessments. This review analyzes peer-reviewed studies published between January 2021 and September 2026, categorizing the literature by the quality function AI supports rather than by specific algorithms. It explores six domains: automated inspection and defect detection, predictive quality, process monitoring and anomaly detection, explainable AI and diagnosis, quality knowledge management, and integrated decision support. The findings suggest a gradual broadening of AI's functional role, evolving from merely detecting and predicting isolated quality outcomes to interpreting diverse information, aiding diagnosis, supporting engineering decisions, and starting to coordinate quality-related tasks. The review also highlights ongoing challenges related to data quality, rare failures, model drift, explainability, interoperability, industrial validation, and human oversight. Industrial evidence is more mature in inspection, predictive quality, and selected monitoring applications, whereas generative and agentic methods remain at an earlier stage of industrial validation.

Keywords: Artificial intelligence; manufacturing quality; Quality 4.0; predictive quality; generative AI

1. Introduction

Traditionally, decisions regarding manufacturing quality have relied on inspection outcomes, process metrics, equipment information, and structured engineering techniques like statistical process control (SPC), process capability analysis, design of experiments, failure mode and effects analysis, and root cause analysis. While these methods continue to be essential, contemporary production systems produce a significantly larger and more varied array of information. Evidence for a quality investigation can now come from sensors, automated testing systems, machine controllers, vision systems, manufacturing execution systems, quality records, maintenance histories, and engineering documents.

Quality 4.0 describes the extension of established quality management practices through connected data, analytics, automation, and digital technologies. Reviews of Quality 4.0 emphasize that the opportunity is not simply the availability of more data; sustainable deployment also depends on project selection, process redesign, relearning, organizational capability, and data integration (1–3). Broader Industry 4.0 research similarly shows that AI is being applied across production, maintenance, and quality functions; however, implementation maturity varies considerably across use cases (4–6).

Early manufacturing AI applications were dominated by bounded tasks such as image classification, defect detection, and prediction of a product-quality characteristic from process data. Recent literature shows a broader role. Explainable AI (XAI) is being used to identify influential production parameters, virtual metrology is being linked to advanced process-control decisions, and LLM-based systems are being investigated for retrieval and interpretation of engineering knowledge (7–12). This raises a more useful question than whether a particular algorithm achieves higher accuracy: how is the functional role of AI within manufacturing quality changing?

This review addresses three research questions. RQ1 asks which principal manufacturing quality-management activities are supported by AI from 2021 to 2026. RQ2 examines the technical and organizational challenges that constrain industrial deployment and scalability. RQ3 examines how generative AI, LLMs, interoperable manufacturing information, and emerging agentic systems are changing the role of AI in manufacturing quality management. The central argument developed from the literature is that AI is progressing from detection and prediction toward monitoring, diagnosis, knowledge assistance, and decision support. The progression does not imply that newer approaches replace conventional quality methods; rather, AI increasingly extends the amount and variety of evidence that can be used in engineering decisions.

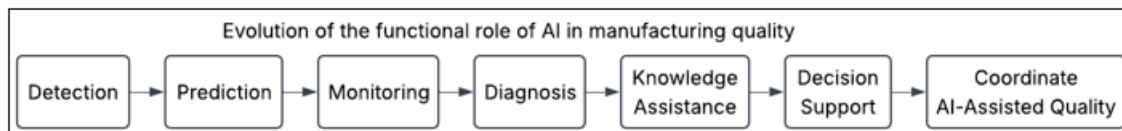


Figure 1: Functional evolution of AI in manufacturing quality synthesized from the reviewed literature

2. Review Methodology

A structured literature review was conducted for work published from January 2021 through September 2026. The review aimed to provide a technical synthesis rather than a formal systematic review or meta-analysis. Literature was gathered through repeated keyword searches using scholarly discovery tools and publisher/indexing databases, with bibliographic details checked against publisher or indexing records when quantitative results were used. Search terms included combinations such as artificial intelligence AND manufacturing quality; machine learning AND quality assurance AND manufacturing; predictive quality; deep learning AND defect detection; anomaly detection AND smart manufacturing; explainable AI AND manufacturing quality; Quality 4.0 AND AI; semiconductor virtual metrology; large language model AND manufacturing; retrieval-augmented generation AND manufacturing quality; and knowledge graph AND fault diagnosis. Backward and forward citation tracking was also used to identify technically relevant studies. Because the review was designed as a structured technical synthesis, it did not use a registered protocol or PRISMA-style screening process.

Studies were included when they were peer-reviewed, published within the review period, used AI or data-driven methods as a substantive part of the work, and addressed a manufacturing-quality function such as inspection, prediction of product or process quality, process monitoring, diagnosis, quality knowledge, or decision support. Predictive-maintenance studies were excluded unless they explicitly

connected equipment behavior to product or process quality or to a quality decision. Review papers were used to establish research trends and recurring gaps; empirical studies were examined for manufacturing context, data, validation approach, reported outcomes, and limitations. English-language work discoverable through the selected scholarly and publisher sources formed the primary evidence base.

For each key study, the review assessed the manufacturing process, data type, sample or dataset description when reported, AI method, evaluation metrics, validation setting, reported outcome, limitations, and relevance to the research questions. Evidence strength was classified by validation context: E1, benchmark or laboratory evidence; E2, retrospective industrial data; E3, industrial trial or pilot; E4, operational deployment; and E5, operational or field evidence with a measured manufacturing-quality outcome. Review articles were identified separately as synthesis evidence. Missing technical details were not inferred. This classification is intentionally simple: it distinguishes model performance from evidence that a method remains useful under production conditions.

The literature was coded into six functional themes: (1) automated inspection and defect detection; (2) predictive quality; (3) process monitoring and anomaly detection; (4) failure diagnosis, explainability, and quality optimization; (5) quality knowledge and generative AI; and (6) integrated quality decision support. Cross-study synthesis focused on what the AI system contributes to the quality workflow, the strength of industrial evidence, and the remaining barriers to deployment.

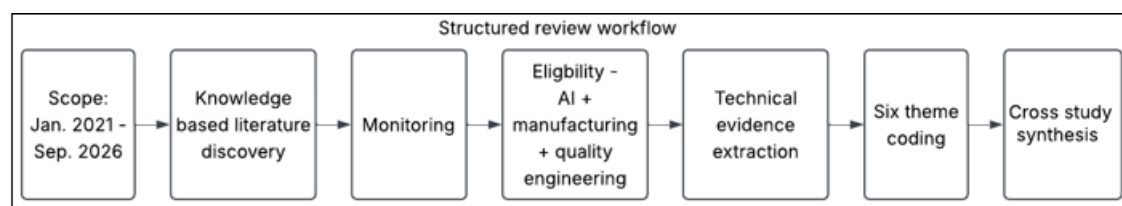


Figure 2: Review workflow used for evidence extraction and thematic synthesis

3. Evolution of AI in Manufacturing Quality

The evolution of AI in manufacturing quality is best understood as an extension of existing quality practice. Inspection established whether a product met requirements. SPC and capability analysis added evidence about process stability and variation. Connected manufacturing then made larger volumes of process, sensor, test, and traceability data available. AI adds the ability to identify complex patterns in those data, but the engineering purpose remains tied to conformance, process control, failure prevention, and improvement.

Quality 4.0 literature consistently places data integration and analytics alongside organizational and process redesign (1–3,13,14). Escobar et al. identify project selection, process redesign, and relearning among the issues that determine whether big-data quality initiatives become sustainable (1). Bousdekis et al. similarly position data analytics as a major enabler of Quality 4.0 while highlighting the need to connect analytics to quality-management activities (2). Antonino et al. extend this perspective through an architectural model intended to integrate quality requirements into Industry 4.0 systems (3).

Within this connected environment, predictive quality emerged as a distinct research stream. Tercan and Meisen reviewed 81 publications and found applications across a

wide range of manufacturing processes, with both classification and regression used to estimate product-related quality from process and product data (7). Their review also showed that many studies relied on experimentally generated data and that sparse datasets and lack of benchmark data remained important challenges. More recent reviews continue to report substantial use of neural networks, support-vector machines, random forests, and related methods in manufacturing quality assurance (6).

Higher predictive accuracy is only one part of the development. Monitoring methods attempt to recognize changes in process behavior; XAI methods expose model-relevant variables or regions; and generative approaches retrieve and synthesize engineering knowledge (15–18). The resulting functional progression is therefore Detection → Prediction → Monitoring → Diagnosis → Knowledge Assistance → Decision Support. These functions overlap in practice, and their maturity is uneven, but the progression provides a useful structure for comparing the literature.

4. Automated Inspection and Defect Detection

Automated visual inspection is one of the most established manufacturing AI applications. The quality task may be classification, localization, object detection, pixel-level segmentation, or anomaly detection. The correct formulation depends on the decision required by the manufacturing process. A binary accept/reject station may only require classification, whereas engineering analysis of a surface defect may require its location, size, and geometry.

CNN-based methods remain prominent. Jha and Babiceanu describe deep CNNs as a foundation of modern automated optical inspection and identify supervised classification and segmentation, as well as unsupervised approaches, among the major research directions (9). A broader 2024 survey by Hütten et al. examined 196 open-access publications in manufacturing and maintenance. The authors reported that CNNs remained dominant, approximately 97% of the reviewed work used supervised learning, and the median dataset contained about 2,500 samples; they also noted increasing attention to vision transformers and a gap between computer-vision research and industrial introduction (19). Recent inspection studies also examine transformer-based surface-defect detection, transfer learning, and edge-supported deployment (20–23).

Transfer learning is particularly relevant where manufacturing defect data are limited. Singh and Desai used pretrained ResNet-101 features with a multiclass support-vector machine for surface-defect detection in centerless grinding of tapered rollers. The study reported 100% precision for the Good class and positioned the approach as a way to reduce the training-data and computational burden associated with training deep models from scratch (24). Although this architectural style is advantageous for smaller manufacturers, acknowledging that class-specific precision does not entirely reflect production capability is crucial. For quality engineering, model accuracy is only one part of the inspection system. Rare defects create class imbalance, so a high overall accuracy can coexist with unacceptable defect escapes. Precision, recall, F1 score, localization or

segmentation metrics, false-reject behavior, and defect-escape behavior should be interpreted together with defect prevalence. Production validation should also consider repeatability, camera and lighting variation, product orientation, surface finish, material changes, line speed, and product revision. These factors determine whether a model remains useful outside the dataset on which it was developed. Zero-defect-manufacturing research similarly treats in-line inspection as part of the production-control system rather than an isolated classifier (25).

The literature supports a distinction between model validation and inspection-process validation. A model can perform well on a held-out image dataset while the complete inspection process remains sensitive to optics, fixturing, illumination, data drift, or previously unseen defect modes. This is similar to conventional measurement-system thinking: the algorithm is part of the measurement system, not the entire system.

5. Predictive Quality

Predictive quality moves the quality decision upstream by estimating a product-related quality characteristic from process, sensor, product, or contextual data before conventional inspection is complete. In compact form, the task can be represented as $\hat{y} = f(X)$, where X contains available manufacturing information and $\hat{y}$ is the estimated quality outcome. The value of the prediction is the additional reaction time it creates: a unit can be routed for additional inspection, a process can be investigated, or production can be adjusted before more nonconforming material is produced.

Tercan and Meisen found that predictive-quality studies span primary shaping, forming, cutting, joining, additive manufacturing, assembly, and multistage processes (7). In the 81 publications they reviewed, 51 used numerical prediction and 30 used classification. They also reported that 83% of studies using real manufacturing data generated training data through predefined experiments. This is useful evidence of technical feasibility, but it also shows why production generalization remains a concern: experimentally varied parameters under controlled boundary conditions may not represent the full range of long-term production variation.

Semiconductor manufacturing provides a particularly strong example through virtual metrology (VM). VM estimates quality or metrology characteristics from equipment and process data when physical metrology is sampled rather than performed on every wafer. Maitra, Su, and Shi describe VM as an important advanced-process-control tool but conclude that wider adoption still faces technical and implementation challenges (26). Chien et al. developed a decision-based VM framework that connected machine-learning prediction with confidence assessment and run-to-run control, and validated the approach in a leading semiconductor manufacturer (27).

A 2025 industrial study by Fan and Zheng illustrates the lifecycle problem directly. Their rolling-window, production-maintenance-based VM approach was evaluated on chemical vapor deposition data. Relative to the baseline model operating at the site, the authors reported MAE improvements of 39.99%, 26.26%, and 30.75% across three recipes (28).

The model was designed to update training data around production and maintenance changes rather than assuming that the original data distribution would remain fixed.

These semiconductor studies show why predictive quality should be evaluated in engineering terms. MAE, RMSE, R-squared, precision, recall, and related metrics are useful, but the practical question is whether the error is acceptable relative to the engineering tolerance and the consequence of an incorrect decision. Validation should also reflect intended deployment. Random train-test splits may overestimate future performance when sequential production observations share material, equipment, recipe, or environmental conditions. Temporal, lot-based, machine-based, or revision-based validation can provide stronger evidence of generalization.

6. Process Monitoring and Anomaly Detection

Process monitoring asks whether the manufacturing process is behaving as expected. This differs from predictive quality: a process can become unusual before a labeled defect or downstream quality failure is available. Traditional SPC remains the appropriate baseline for many stable and interpretable processes. AI becomes particularly useful when the process is high-dimensional, nonlinear, time-dependent, or poorly represented by independent univariate charts.

Multivariate statistical methods and machine learning can therefore be complementary. Wang and Liu proposed a multivariate control-chart framework based on Isolation Forest. Their Monte Carlo evaluation reported advantages for detecting small shifts across several distributions and for heavy-tailed conditions, while retaining efficient computation (29). The contribution is notable because the machine-learning anomaly score is incorporated into a familiar SPC concept rather than presented as a replacement for process control.

Autoencoders, one-class methods, and sequence models provide related approaches when normal production data are much more abundant than labeled failures (15,30,31). These methods can learn a representation of normal process behavior and flag observations that deviate from it. The engineering interpretation must remain conservative: an anomaly is not automatically a defect, and an abnormal process state does not by itself identify a root cause.

This distinction is especially important for time-series signatures such as force-displacement curves, torque-angle profiles, current traces, vibration, acoustic signals, and thermal histories. Two cycles can have similar maxima while differing substantially in slope, oscillation, timing, or transient behavior. Monitoring the full signature or meaningful engineered features can expose process changes that a single summary value misses.

Operational monitoring should balance detection rate, false alarms, and detection delay. Excessive sensitivity can produce alert fatigue; insufficient sensitivity can allow continued production after a process shift. A useful system also distinguishes process anomalies from product-quality anomalies and data/system anomalies. Missing packets,

sensor faults, synchronization errors, and unit changes can appear abnormal even when the physical process is stable.

7. Explainable AI, Failure Diagnosis, and Quality Optimization

Prediction and anomaly detection become more useful when engineers can understand why a model produced a result. XAI methods such as SHAP, Grad-CAM, Integrated Gradients, saliency analysis, and feature-importance methods can expose influential variables or image regions. Their value is not that they prove causation; rather, they can reduce the search space for engineering investigation and reveal whether a model is relying on physically plausible evidence (17,32,33).

Senoner, Netland, and Feuerriegel provide one of the strongest industrial examples in the review period (8). They combined nonlinear modeling with Shapley additive explanations to relate production parameters to process quality in high-power semiconductor manufacturing. The authors developed a process-importance measure, selected improvement actions, and then evaluated those actions through a field experiment on a transistor-chip product. The experiment produced a 21.7% reduction in yield loss relative to the average yield loss in the study sample, and the authors reported significant improvements during post-experimental rollout. The strength of this evidence is that the explanation was connected to an intervention and production validation, not only retrospective interpretation.

The semiconductor example also clarifies the difference between feature attribution and root cause. A model can identify variables associated with quality variation, but correlated production parameters, recipes, material characteristics, and equipment states can create plausible but noncausal relationships. AI-assisted root-cause analysis is therefore a more defensible description than autonomous root-cause determination. Data-driven and knowledge-driven RCA studies support a workflow in which screening narrows the investigation, engineering develops the hypothesis, and controlled evidence determines whether the proposed cause is accepted (16,34).

The same principle applies to optimization. A predictive model can identify combinations of settings associated with improved outcomes, but a statistically favorable recommendation must remain within equipment, process, material, safety, and specification constraints. AI can accelerate the search for candidate adjustments; engineering review and controlled validation determine whether those adjustments become process changes.

8. Generative AI, LLMs, and Quality Knowledge

A large portion of manufacturing-quality knowledge is not stored in sensor tables. It exists in nonconformance reports, corrective actions, work instructions, specifications, engineering-change records, maintenance histories, supplier reports, troubleshooting guides, and lessons learned. LLMs introduce a way to interact with this unstructured information

through natural language, extending AI from numerical analysis toward knowledge assistance.

Retrieval-augmented generation is particularly relevant because a general-purpose LLM does not contain an organization's current specifications, process instructions, or failure history. RAG retrieves relevant information from an external knowledge base before generating a response. Heredia Álvaro and González Barreda developed an advanced RAG system for ceramic-tile quality control that retrieved specialized sources to diagnose defects and propose corrective actions. Their architecture also used tailored preprocessing and post-processing rather than relying on direct prompting alone (10).

Manufacturing quality also benefits from structured relationships. Zhou et al. proposed CausalKGPT for cause analysis of quality defects in aerospace thin-walled-shell manufacturing (11). The approach constructed a causal quality-related knowledge graph from manufacturing documents and used it to augment an LLM. The authors report that the resulting system produced more domain-specific and reliable quality-problem responses than the commercial baseline models used in their case study. This is an important direction because manufacturing investigations often depend on relationships among product revision, process, material, equipment, defect, and corrective action rather than isolated text passages (35–37). Knowledge-graph-driven diagnostic work on intelligent production lines provides an additional example of structured manufacturing knowledge being used for fault reasoning (36).

The main limitation is trust. An LLM can generate a technically plausible statement that is not supported by manufacturing evidence. Quality applications therefore require source traceability, controlled retrieval, authorization, auditability, and human validation. Recent smart-manufacturing literature on LLMs and human-in-the-loop systems similarly identifies validation, uncertainty, hallucination, and real-time integration as unresolved issues (12,38,39). Generative AI should therefore be treated as an evidence-retrieval and reasoning assistant, not as an unrestricted authority for product disposition or process change.

9. Integrated AI Quality Decision Support

The reviewed applications are often studied separately, but actual quality investigations cross system boundaries. A design change may require an engineer to determine which serial numbers contain the revision, whether FPY changed, whether a process characteristic shifted, whether a new failure mode appeared, and whether similar events occurred previously. The evidence may be distributed across MES, QMS, ERP, PLM, test databases, maintenance systems, and engineering documents.

This creates the motivation for integrated quality intelligence. The central contribution is not necessarily a new algorithm; it is the connection of detection, prediction, monitoring, context, explanation, and engineering knowledge into a decision workflow. Reviews of integrated production, maintenance, and quality AI identify information integration and interoperability as central requirements for this next stage (5).

For high-consequence quality decisions, the current evidence supports human-in-the-loop architectures more strongly than unrestricted autonomy. AI can detect, predict, retrieve, explain, and recommend; engineers validate evidence, assess consequences, authorize actions, and update the quality system. The appropriate level of automation should depend on decision risk and validation evidence. When a model is thoroughly validated, it can autonomously direct a unit to undergo retesting. However, alterations in specifications, product handling, or process adjustments necessitate more stringent oversight.

Agentic AI builds on this concept by enabling AI elements to access data, utilize tools, and manage various subtasks. In the future, a high-quality agent could recognize a change in yield, pinpoint impacted units, evaluate modifications, examine failure trends, access records of corrective actions, and compile an investigation dossier. Presently, the evidence from manufacturing does not support considering this as a fully developed autonomous practice (40,41). Agentic quality systems remain a research direction requiring explicit access controls, audit trails, error recovery, validation, and human override.



Figure 3: Proposed synthesis architecture for integrated AI-assisted quality decision support

10. Cross-Study Synthesis and Deployment Challenges

Sector coverage is not uniform. Semiconductor manufacturing contributes several of the strongest industrial examples in this review, particularly for virtual metrology and explainable process-quality improvement (8,26–28). Evidence from machining and roller inspection (24), ceramic-tile quality control (10), aerospace manufacturing (11),

surface inspection (20–23), and zero-defect manufacturing applications (25,42) broadens the sectoral base, but the depth of production validation differs across these domains. Findings from semiconductor environments should therefore not be assumed to transfer directly to manufacturing settings with different data availability, process dynamics, or quality-control regimes.

Across the literature, technical maturity is uneven. Automated inspection has a large evidence base and established industrial use cases, with recent work extending from CNN-based classification toward attention- and transformer-based detection and localization (19–23). Predictive quality and process monitoring have strong research foundations, with semiconductor VM providing examples of industrial implementation and maintenance-aware model updating

(7,26–31,42). XAI and data-driven root-cause methods have growing evidence for connecting prediction to engineering investigation and action, although explanation alone does not establish physical causation (8,25,33,34,43). Generative AI, RAG, causal knowledge graphs, and agentic systems are newer and have a smaller industrial validation base (10–12,32,35–41,44–46). Novelty should therefore not be interpreted as deployment maturity.

Table 1: Functional synthesis of AI in manufacturing quality.

AI role	Quality question	Representative methods	Evidence pattern
Detection	Is the product defective?	CNNs, detection, segmentation	Large research base; industrial use exists (19–22,23)
Prediction	What quality outcome is expected?	RF, SVM, boosting, ANN/DL, VM	Strong research base; selected industrial deployment (7,26–28,42)
Monitoring	Is process behavior changing?	SPC+ML, Isolation Forest, autoencoders	Strong research base; deployment depends on context (29–31)
Diagnosis	What factors are associated with the problem?	XAI, SHAP, diagnostic models	Growing evidence; causal validation still needed (8,25,33,34,43)
Knowledge assistance	What prior knowledge is relevant?	LLM, RAG, knowledge graphs	Emerging industrial evidence (10,11,35–37,45,46)
Decision support	What action should be considered?	Integrated analytics, XAI, RAG	Emerging; human validation important (8,10–12,32,38,39,44–46)
Coordinated action	Can AI organize multiple quality tasks?	Agentic/multi-agent systems	Early-stage manufacturing evidence (40,41)

10.1 Data quality, traceability, and interoperability

AI performance depends on data that are correctly labeled, synchronized, revision-controlled, and traceable to the product and process state. In practice, identifiers and timestamps may differ across equipment controllers, MES, QMS, ERP, PLM, spreadsheets, and engineering documents. The practical difficulty is often missing context rather than missing data alone. As AI moves toward decision support, consistent product genealogy, material-lot traceability, equipment state, software or firmware revision, and engineering-change history become increasingly important.

10.2 Rare failures and representativeness

Stable manufacturing processes naturally generate fewer defective than conforming units. This limits labeled examples for the failures that quality systems are expected to detect. Augmentation, transfer learning, anomaly detection, self-supervised learning, and synthetic data can reduce the limitation but cannot replace representative validation. Performance on common defects should not be assumed to extend to new or rare failure modes.

10.3 Drift and lifecycle control

Manufacturing systems change through maintenance, tooling replacement, supplier changes, engineering revisions, firmware updates, process adjustments, and continuous improvement. A model validated at one production state can therefore become less reliable. Production AI requires model versioning, monitoring, revalidation triggers, retraining criteria, and rollback capability. Fan and Zheng's semiconductor VM work is a useful example because maintenance and changing production conditions were explicitly incorporated into the model-update strategy (28).

10.4 Explainability, causality, and human oversight

Model explanations can identify variables or regions associated with a prediction, but they require engineering interpretation. The strongest evidence occurs when explanations lead to testable hypotheses and controlled interventions, as in the semiconductor field experiment reported by Senoner et al. (8). Human oversight becomes more important as AI moves from bounded classification toward recommendations that affect process settings, product disposition, or specifications.

Table 2: Representative studies, validation context, and evidence strength

Study	Domain / task	Method or contribution	Evidence relevant to this review	Evidence class
Tercan & Meisen (7)	Predictive quality	Review of 81 studies	Maps processes, data sources, learning tasks, and research gaps	Synthesis
Hütten et al. (19)	Visual inspection	Survey of 196 papers	Shows dominant supervised CNN use and dataset constraints	Synthesis
Singh & Desai (24)	Tapered-roller inspection	ResNet-101 + multiclass SVM	Manufacturing case; class-specific precision reported	E2
Chien et al. (27)	Semiconductor VM	Clustering + ML + confidence for APC	Semiconductor validation and implementation	E4
Fan & Zheng (28)	Semiconductor CVD VM	Rolling-window / maintenance-aware ML	Industrial case; MAE improvement across three recipes	E4

Senoner et al. (8)	Semiconductor yield	Nonlinear model + SHAP + decision model	Field experiment; measured yield-loss reduction	E5
Wang & Liu (29)	Multivariate SPC	Isolation-Forest control chart	Simulation evidence for small-shift/heavy-tail monitoring	E1
Heredia Álvaro & González Barreda (10)	Ceramic-tile quality	RAG quality-control system	Defect diagnosis and corrective-action assistance	E3
Zhou et al. (11)	Aerospace shell quality	Causal KG + LLM	Aerospace quality cause-analysis case study	E3
Shang et al. (20)	Surface-defect detection	Defect-aware transformer	Transformer-based visual surface-inspection evidence	E1
Leberruyer et al. (42)	Zero-defect manufacturing	AI-supported industrial application	Industrial zero-defect manufacturing application	E3
Jang et al. (30)	Industrial process monitoring	Adversarial autoencoder	Unsupervised process fault-detection evidence	E1
Ma et al. (34)	Quality root-cause analysis	Big-data + ML RCA system	Data-driven quality RCA framework	E2
Wan et al. (45)	Smart-manufacturing knowledge	Hybrid RAG + LLM	Domain-centric Q&A with grounded retrieval	E2
Cai et al. (35)	Intelligent manufacturing	Knowledge graph fault diagnosis	Knowledge-graph-driven diagnostic reasoning	E2

11. Emerging Research Directions

Across the reviewed studies, the next stage of AI-enabled manufacturing quality appears to depend less on isolated gains in classification accuracy and more on connecting data, models, knowledge, and engineering decisions (32,38,39,44). Five research directions are particularly important.

First, multimodal manufacturing intelligence should combine process measurements, images, time-series signals, test results, engineering documents, and product genealogy. Quality investigations already use these sources together; current AI studies often analyze them separately. Second, domain-grounded language models require better manufacturing ontologies, knowledge graphs, retrieval architectures, evaluation datasets, and measures of factual grounding. Third, XAI research should connect model explanation more directly with causal inference, designed experimentation, and physical process knowledge. The objective is not only to identify which variable influenced a prediction, but whether changing that variable produces a repeatable quality improvement.

Fourth, continuous validation should become part of the AI lifecycle. Future work should define drift-monitoring methods, model-revalidation triggers, engineering-change integration, and criteria for retraining or removing a model from production. Fifth, human-AI collaborative quality engineering requires explicit allocation of responsibilities. AI is well suited to continuous monitoring, retrieval, pattern detection, and preparation of candidate explanations; engineers provide physical understanding, challenge model output, assess consequences, and authorize high-impact actions.

Agentic quality systems integrate these directives but demand more rigorous evidence. Assessment must go beyond merely finishing tasks to include defect recall, the rate of incorrect actions, source grounding, traceability, adherence to access-control, recovery from data or tool failures, human intervention, and performance in previously unencountered manufacturing scenarios. A successful demonstration by itself is insufficient. An agentic quality system must operate

reliably and auditably under changing production conditions (40,41).

12. Limitations of the Review

This review has several limitations. It is a structured technical review rather than a registered systematic review or meta-analysis and therefore does not provide a PRISMA-style screening record or formal risk-of-bias assessment. The literature search was bounded to January 2021 through September 2026 and emphasized English-language peer-reviewed work discoverable through scholarly search and publisher/indexing repositories; these choices may underrepresent domain-specific, non-English, or less readily indexed industrial work. The breadth of manufacturing AI also means that sector coverage is uneven, with semiconductor manufacturing contributing several of the strongest industrial-validation examples. The E1-E5 evidence classification provides a consistent validation lens but is not a formal study-quality score. Quantitative results were retained only where they could be verified from the available source records, and missing sample sizes or validation details were not inferred. Direct numerical comparison across studies remains limited because datasets, defect prevalence, manufacturing processes, validation strategies, and performance metrics differ substantially.

13. Conclusion

Across the papers analyzed, AI has increasingly become an important element in managing manufacturing quality. Research in this area addresses automated inspection, predictive quality, process monitoring, failure diagnosis, engineering knowledge retrieval, and new integrated decision-support systems. The most notable advancement goes beyond merely improving algorithmic precision. AI's functional scope is broadening from merely identifying and forecasting isolated quality results to interpreting process behaviors, aiding in diagnosis, retrieving engineering insights, and facilitating decision-making. The robustness of evidence varies among these functions. Applications like inspection, predictive quality, and certain monitoring tasks have relatively solid technical bases. In semiconductor manufacturing, virtual metrology and explainable process-

quality enhancement offer particularly valuable industrial evidence. Generative AI, RAG, causal knowledge graphs, and agentic methods further expand AI's potential role, though their evidence base in manufacturing quality is still in its early stages. Ongoing challenges include fragmented manufacturing data, infrequent failures, model drift, limited industrial validation, distinguishing between association and causation, system interoperability, and human oversight. Consequently, future quality systems are unlikely to rely on a single AI model. The trend is moving toward interconnected systems that integrate detection, prediction, monitoring, diagnosis, engineering knowledge, and decision support while maintaining traceability and human validation.

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