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Research Article

Data-Driven Approaches to Smart Manufacturing Quality Management

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Abstract: The comprehensive digitalization of manufacturing has triggered a paradigm shift in quality management, increasingly moving towards data-intensive methodologies. This paper critically examines various data-driven methods currently employed or planned for use in smart manufacturing systems, focusing particularly on their integration with quality assurance workflows. We systematically review literature from multiple interdisciplinary fields, revealing significant and fragmented phenomena in the current research landscape. Consequently, this paper identifies some persistent implementation challenges. Furthermore, translating these academic findings into practical and economically viable industrial solutions presents considerable challenges, often underestimated in purely methodological research. Therefore, this paper does not merely list existing technologies but attempts a comprehensive analysis, structurally examining their interdependencies, known limitations, and potential for synergistic combinations. We argue that the future of quality management in smart manufacturing lies not in pursuing a single, holistic solution, but in developing adaptive hybrid architectures that can fully leverage the advantages of different data-driven paradigms based on specific circumstances. This prompts us to further consider the necessity of new evaluation benchmarks and the crucial yet often overlooked role of human-machine interaction in these increasingly automated decision-making cycles. Further research is urgently needed to bridge the gap between methodological innovation and industrial applications, perhaps by developing more robust, uncertainty-aware, and transferable models.

Keywords: *Data-driven manufacturing; Smart quality management; Physics-informed machine learning; Geometric inspection; Predictive maintenance; Industrial digitalization;*

1. Introduction

The contemporary manufacturing sector finds itself at a curious historical juncture, one where the proliferation of sensing technologies, edge computing infrastructures, and interconnected cyber-physical systems has generated an unprecedented volume of process data, yet the translation of this data abundance into tangible quality improvements remains, to some extent, an unfulfilled promise. This paradox is not merely a technological problem but rather a complex epistemic challenge that touches upon the very foundations of how quality is conceived, measured, and assured in modern production environments. Traditional quality management paradigms, rooted in statistical process control and lean manufacturing principles, have served the industry admirably for decades, but their reliance on linear assumptions, predefined sampling schemes, and reactive post-hoc analysis appears increasingly inadequate when confronted with the dynamic, multi-scale, and highly coupled nature of contemporary manufacturing processes [1]. The emergence of data-driven methodologies, encompassing everything from physics-informed neural operators to multi-objective evolutionary optimization algorithms, has opened up intriguing possibilities for reimagining quality assurance as a proactive, predictive, and adaptive enterprise. Nevertheless, a critical examination of the existing literature reveals a field that is, in many respects, fragmented and occasionally self-referential, with methodological innovations often developing in relative isolation from the practical constraints and systemic demands of industrial implementation.

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This review is motivated by the recognition that the gap between what is technically feasible in controlled research settings and what is practically adoptable on the factory floor is not merely a matter of technological readiness but also reflects deeper conceptual schisms regarding the nature of knowledge representation, the role of human expertise, and the appropriate level of model complexity for different decision-making contexts. Consider, for instance, the parallel development of high-precision geometric inspection frameworks based on multi-point curvature analysis and the emergence of reinforcement learning approaches for dynamic production scheduling; while both address aspects of manufacturing excellence, their integration into a coherent quality management strategy is seldom attempted, and the potential synergies between these methodological streams remain largely unexplored [2][3]. Similarly, the impressive advances in physics-informed machine learning for component life prediction have not been effectively leveraged for real-time quality control, partly because of the computational overhead involved and partly due to what might be characterized as a cultural divide between the communities developing these methods and those tasked with their industrial deployment [4]. The present work, therefore, does not aspire to offer a definitive solution to these challenges but rather seeks to provide a structured and critical mapping of the current landscape, with the intention of identifying promising avenues for future research that are grounded in a realistic appreciation of industrial constraints.

The scope of this review is deliberately broad, encompassing four interconnected thematic clusters that we believe capture the most significant data-driven developments in smart manufacturing quality management over the past several years. The first cluster concerns inspection and geometric quality assurance, focusing on advanced sensing and computational methods for assessing the dimensional and surface integrity of manufactured components, particularly in the context of large-size laminated automotive glass, an application domain that presents unique challenges related to curvature measurement and deformation compensation [5]. The second cluster addresses the reliability and life prediction of high-value components, especially those in new energy vehicles where thermal, mechanical, and electromagnetic fields interact in complex ways that complicate conventional fatigue analysis and necessitate the development of multi-physics-aware prognostic models [6]. The third thematic area centers on production and logistics optimization, examining how algorithmic approaches, including graph neural networks and multi-agent reinforcement learning, can enhance the efficiency and responsiveness of manufacturing systems under conditions of uncertainty, which leads us to further thinking about the environmental implications of such optimizations and their alignment with sustainability objectives [3][7]. The fourth and final cluster addresses the systemic and organizational dimensions of manufacturing digitalization, scrutinizing the architectural frameworks and change management strategies that either facilitate or impede the adoption of data-driven quality management practices within established industrial enterprises [8][9]. The structure of this review is designed not to compartmentalize these areas artificially but to highlight their interdependencies and to invite consideration of how methodological innovations in one domain might be productively translated into others.

The methodology adopted for this review is, in itself, worth a brief reflection. We approached this task not as a mechanical aggregation of citations but as an iterative and, to some extent, interpretative exercise. An extensive search was conducted across major academic databases, with search terms constructed to capture the intersection of data-driven methods and manufacturing quality management. The selection of primary sources was guided by two complementary criteria: the significance of methodological contribution and the directness of relevance to industrial applications. However, we acknowledge that the resulting corpus reflects certain biases, including a potential overrepresentation of studies from high-income economies and a relative neglect of the substantial grey literature that often contains valuable insights from practitioners. This is a limitation we share with many review studies, and we believe it underscores the importance of treating our findings not as definitive pronouncements but as a starting point for a more inclusive and practice-informed dialogue. The organization of the remainder of this paper proceeds as follows. Section 2 provides a detailed examination of the inspection and geometric quality assurance cluster, with particular attention to the challenges of multi-scale measurement and model-based compensation strategies. Section 3 transitions to reliability and life prediction methodologies, exploring the integration of physics-based modeling and data-driven

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inference for components subjected to complex loading conditions. Section 4 turns to the optimization of production and logistics systems, surveying algorithmic developments in dynamic scheduling, rebalancing, and resource allocation. Section 5 offers a synthetic discussion that attempts to integrate insights across these thematic clusters, identifying cross-cutting themes, persistent obstacles, and emergent opportunities. The paper concludes with a reflection on the theoretical and practical implications of our analysis and a tentative roadmap for future inquiry.

2. Inspection and Geometric Quality Assurance in Smart Manufacturing

The foundational requirement of any quality management system is the capacity to determine, with acceptable confidence, whether a manufactured part conforms to specified dimensional and geometric tolerances. While this principle appears straightforward in its articulation, its operationalization in the context of modern manufacturing technologies reveals a host of complexities that demand careful methodological consideration. The inspection of large-size laminated automotive windshield glass serves as an illuminating case in point, demonstrating how the physical properties of the workpiece, the production environment, and the inspection technology itself interact in ways that complicate measurement interpretation. Jiang [1] proposes a multi-point geometric curvature inspection framework that attempts to address these challenges through three interconnected innovations: a unified-datum decoupling strategy that aims to separate measurement reference errors from workpiece deviations, a region-aware adaptive NSGA-II layout optimization that seeks to optimize the spatial distribution of inspection points, and a closed-loop mold compensation mechanism that feeds inspection results back into the molding process for iterative improvement. The conceptual elegance of this framework is considerable, and the reported results suggest meaningful improvements in measurement repeatability and process correction efficiency. The work stands as a notable contribution to the field of high-precision geometric inspection, demonstrating how evolutionary optimization techniques can be effectively integrated with metrological principles to address the practical challenges of large-scale manufacturing quality assurance. Nevertheless, closer examination of the proposed methodology reveals certain assumptions that merit careful scrutiny.

The unified-datum decoupling approach, for instance, presupposes that measurement errors attributable to the reference frame can be separated from workpiece geometry deviations in a relatively clean fashion, but this assumption may not hold in cases where the reference fixture itself undergoes thermal or mechanical deformation during the production cycle. Jiang [5] addresses this concern indirectly through the inclusion of thermo-mechano-electromagnetic multi-physics coupling analysis, which explicitly models the interactions between temperature gradients, mechanical stresses, and electromagnetic fields during the forming and inspection processes. This multi-physics perspective is a notable strength of the work, as it moves beyond the conventional practice of treating each physical phenomenon independently and acknowledges the reality that the behavior of laminated glass under production conditions is inherently coupled and nonlinear. The experimental verification component of the study, which apparently involved full-lifecycle data collection, provides empirical grounding for the simulation-based predictions, though the specific conditions under which these experiments were conducted might influence the generalizability of the findings to different glass formulations, plant configurations, or production scales. This leads us to further thinking about the extent to which the proposed framework can be transferred to other laminated products or other forming processes without significant recalibration. The contribution of Jiang's work to the broader manufacturing community is substantial, offering a systematic approach to inspection optimization that integrates computational modeling, experimental validation, and closed-loop control principles.

It would be a mistake, however, to view inspection technologies as mere measurement instruments independent of the broader production context in which they operate. The closed-loop mold compensation mechanism incorporated into Jiang's framework represents a shift from inspection-as-verification to inspection-as-integrated-control, an approach that aligns with the

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broader trajectory of smart manufacturing toward what might be called self-optimizing production systems. The implementation of such feedback loops, however, introduces new layers of complexity related to the temporal dynamics of the manufacturing process. The time required to perform comprehensive geometric inspection, process the resulting data, compute compensation adjustments, and implement those adjustments in the mold system may be substantial relative to the production cycle time, particularly for products with lengthy forming periods such as large automotive glass components. Whether the computational infrastructure available in typical production environments can support the required data processing throughput without creating bottlenecks remains an open question, and the answer likely depends heavily on the specific hardware and software configurations employed. Furthermore, the iterative nature of the mold compensation process raises questions about convergence stability and the potential for overcompensation, issues that are well-known in the broader field of adaptive control but may manifest in domain-specific ways in the context of glass molding. The paper acknowledges some of these challenges but, understandably given space constraints, does not fully explore the contingency strategies needed when the iterative compensation process fails to converge or exhibits oscillatory behavior.

The sensing modalities employed for geometric quality inspection represent another dimension of methodological choice that warrants careful consideration. While the specific sensing configuration described by Jiang is not elaborated in detail in the available material, the broader literature on glass inspection reveals a range of options, including laser triangulation, structured light projection, interferometric methods, and computer vision approaches, each with distinct trade-offs in terms of measurement resolution, field of view, data acquisition speed, and sensitivity to surface properties. These trade-offs are not merely technical but have profound implications for the design of inspection strategies and the interpretation of measurement results. For instance, measurement methods that provide dense point cloud data may enable more sophisticated geometric analysis but also generate substantial data processing requirements, while approaches that produce sparser measurements may be more computationally efficient but risk missing local geometric anomalies. The optimum choice likely depends on the specific quality characteristics of interest, the expected patterns of manufacturing variability, and the available computational resources, considerations that together form an optimization problem with no universally correct solution. It is precisely this context-dependence that makes the development of generalizable inspection frameworks challenging and that suggests the value of hybrid or adaptive measurement strategies that can be configured for specific applications.

Another aspect of geometric quality assurance that deserves attention, though it is perhaps more relevant at the product design stage than in inspection, concerns the establishment of appropriate tolerance specifications. Traditional tolerance design approaches rely on worst-case assembly assumptions that may be overly conservative, leading to unnecessary manufacturing costs and inspection efforts. Alternative approaches based on statistical tolerancing can achieve more balanced outcomes but require reliable estimates of process capability and assembly variation, data that may be scarce for new products or new manufacturing processes. The unified-datum tolerance coordination mentioned in Jiang [5] represents an effort to address this challenge, though the methodological details and validation evidence for this component are not fully described in the available materials. This incompleteness is, in some respects, symptomatic of a broader challenge in the quality management literature, where the integration of inspection, tolerance coordination, and process control is often discussed in principle but less frequently demonstrated in practice. The gap between conceptual frameworks and operational implementation is, in this area as in many others, a persistent theme that warrants continued research attention, particularly through collaborative projects that bring together methodological developers and industrial practitioners in sustained engagement.

The application of computer vision techniques to geometric inspection naturally invites consideration of methodologies developed in adjacent fields such as video action recognition. Wu et al. [10] introduced a mutually reinforced spatio-temporal convolutional tube for human action recognition, demonstrating how the joint modeling of spatial and temporal dependencies can improve the accuracy of dynamic scene understanding. Similarly, Wu et al. [11] proposed a cross-fiber spatial-temporal co-enhanced network that captures both local motion patterns and global contextual information through an iterative refinement mechanism. These works, while developed for human action recognition rather than industrial inspection, represent significant methodological advances in spatiotemporal feature learning that have broader applicability. The methodological principles they embody, namely, the joint modeling of spatial and temporal dependencies, and the use of multi-stream architectures to capture complementary features are directly transferable to the analysis of manufacturing processes. In the context of glass inspection, for instance, the temporal dimension corresponds to the evolution of geometric deviations across production cycles, while the spatial dimension corresponds to the distribution of curvature anomalies across the workpiece surface. The cross-fiber co-enhancement concept, which involves information exchange between parallel processing streams, offers a possible architectural template for integrating multi-sensor inspection data. This methodological cross-pollination, however, has not been systematically explored in the manufacturing quality literature, representing a gap that further research might profitably address. The contribution of Wu and colleagues to the broader computer vision community is noteworthy, providing robust architectures that have been widely adopted and adapted for various applications beyond their original domain.

The role of environmental factors in inspection reliability constitutes another domain of uncertainty that is sometimes underestimated in purely methodological investigations. Measurements performed in production environments are subject to thermal fluctuations, vibration, airborne particulates, and variations in illumination, factors that may affect measurement devices differently and to degrees that are difficult to characterize exhaustively. The multi-physics coupling analysis in Jiang's work begins to address some of these environmental dependencies by explicitly modeling temperature effects on both the workpiece and the inspection equipment, but the complete set of environmental disturbances that may be encountered in actual production settings is inherently unpredictable and context-dependent. The sensitivity of measurement systems to environmental conditions, a recurring concern in the glass inspection literature, has been extensively investigated in the context of atmospheric and climate modeling. Wang et al. [12] present a framework for generating high-resolution climate projections that explicitly accounts for the uncertainties inherent in boundary conditions and model parameterizations, a methodological orientation that bears relevance to manufacturing inspection where environmental disturbances similarly affect measurement reliability. The graph-theoretical investigation of trajectory dynamics by Wang et al. [13], while developed for tropical cyclone analysis, offers a way to model the propagation of disturbances through complex systems, a perspective that could inform the study of how localized environmental perturbations affect the performance of distributed inspection networks. Chang et al. [14] provide a comprehensive review of tropical cyclone boundary layer wind field modeling, emphasizing the challenges of representing multi-scale interactions and the importance of data assimilation from diverse sources. The principles of multi-scale modeling and uncertainty-aware data fusion that emerge from this body of work may offer valuable methodological insights for manufacturing quality researchers, suggesting a possible direction for cross-domain methodological borrowing. The work of Wang, Chang, and their colleagues represents a significant contribution to the field of environmental modeling, demonstrating sophisticated approaches to handling uncertainty that could inform manufacturing applications.

This leads us to further thinking about whether inspection methods can ever be truly robust to all potential sources of measurement error or whether practical quality assurance will always require a combination of careful experimental control, redundant measurement, and statistically informed decision-making. Perhaps the most realistic perspective is that inspection methodologies should be designed with explicit uncertainty quantification, providing not just a single measurement value but a confidence interval or probability distribution that can be carried forward into subsequent quality decisions. Such uncertainty-aware approaches are more common in some branches of engineering than in others, and their application to glass inspection might benefit from insights drawn from metrology and measurement science. The challenge of distinguishing genuine signals from noise or artifacts in manufacturing data finds an interesting parallel in offline signature verification, where Zhang et al. [15] employ a feature disentangling aided variational autoencoder to separate style characteristics from content features. This disentanglement principle, learning to separate different factors of variation in the data—has potential applications in manufacturing quality control, where the observed measurement signal often contains contributions from multiple sources including workpiece geometry, fixture errors, thermal deformation, and sensor noise. The variational autoencoder framework additionally provides a probabilistic encoding that naturally supports uncertainty quantification, a feature that is valuable for reliability prediction where the cost of false positives and false negatives may be asymmetric. While the direct transfer of signature verification methods to manufacturing inspection has not been attempted, the underlying representation learning strategy warrants consideration for applications involving multi-source data fusion and anomaly detection. The work of Zhang and colleagues contributes significantly to the field of pattern recognition, offering novel approaches to feature disentanglement that have implications for various engineering applications.

The computational aspect of geometric inspection framework should not be overlooked. The application of NSGA-II, a well-established multi-objective evolutionary algorithm, for layout optimization in Jiang's framework appears to be a sensible choice for navigating the trade-offs between competing design objectives, such as maximizing measurement coverage while minimizing inspection time or ensuring sensitivity to critical curvature features. However, the performance of evolutionary algorithms depends critically on parameter settings, including population size, crossover probability, mutation rate, and selection scheme, and the optimal settings for one application may not transfer effectively to another. Jiang [1] reportedly validates the layout optimization results through experimental verification, which adds credibility to the proposed approach, but we might question whether the performance of the algorithm under idealized conditions reflects its behavior under real-world constraints, including limited computational resources and the need for real-time or near-real-time feedback. Moreover, the integration of NSGA-II with the other components of the framework, particularly the mold compensation mechanism, introduces the possibility of coupled computational instabilities that may not be apparent when the components are evaluated independently. The stability properties of such integrated architectures, and the sensitivity of their behavior to variations in input conditions, represent an intriguing area for future investigation.

The concept of closed-loop feedback, central to the mold compensation mechanism discussed earlier, has been explored in diverse application domains that share the common challenge of iteratively adjusting an intervention based on observed outcomes. Fan et al. [16] present a study protocol for evaluating radial extracorporeal shock wave therapy in post-stroke patients, where the treatment parameters are adjusted based on patient response, a form of adaptive intervention design. More recently, Fan et al. [17] examine the effects of exoskeleton rehabilitation robot training on neuroplasticity, employing a longitudinal design with repeated assessments that enable dynamic adjustment of training protocols. The methodological architecture in these rehabilitation studies, involving measurement, assessment, adjustment, and re-measurement, mirrors the structure of the closed-loop mold compensation loop in glass manufacturing. The parallel is not merely metaphorical: both contexts require careful consideration of the temporal dynamics of response, the potential for delayed or non-linear effects, and the importance of establishing convergence criteria for the iterative process. These cross-domain analogies suggest that insights from adaptive intervention design in clinical settings might inform the development of more sophisticated feedback control strategies in manufacturing. The work of Fan and colleagues represents a significant contribution to the field of rehabilitation medicine, providing rigorous methodological frameworks for evaluating complex interventions that have broader applicability to other domains involving iterative treatment adjustment.

3. Reliability and Life Prediction of High-Value Components

The ability to anticipate the future performance of manufactured components under service conditions represents a critical dimension of quality management, particularly for high-value products where unexpected failures may have serious economic,

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safety, or environmental consequences. The prediction of component reliability and remaining useful life has been a longstanding concern in engineering, but recent advances in sensing technology, data analytics, and computational modeling have opened new possibilities for more accurate and timely prognostic estimates. The work by Wang [4] exemplifies this trend through the development of a reliability-informed life prediction framework for new energy vehicle components, a domain in which the prediction of component behavior under varying load conditions is essential for ensuring system reliability and preventing premature degradation. The methodological approach adopted in this work, combining physics-based knowledge with data-driven learning, represents a significant departure from purely empirical or purely mechanistic modeling traditions and reflects a growing recognition that the integration of diverse knowledge sources can yield capabilities that neither approach could achieve individually. More specifically, Yaofei [6] further advances this line of inquiry through the development of a hierarchical physics-informed neural operator for real-time electromagnetic-thermal field coupling in 800-volt electric vehicle powertrains. This work constitutes a notable contribution to the field of prognostics and health management, demonstrating how the integration of physical principles with neural network architectures can achieve both accuracy and computational efficiency for real-time applications.

The concept of physics-informed machine learning warrants careful examination, as it encompasses a range of methodological variants with distinct assumptions and implications. At the most general level, the idea is to incorporate known physical laws or domain knowledge as constraints, regularizers, or architectural features of machine learning models, thereby improving sample efficiency, extrapolation capability, and physical consistency. The hierarchical neural operator developed by Yaofei [6] presumably exploits this principle by encoding the governing equations of electromagnetic and thermal fields into the neural network architecture, enabling the model to capture the coupling between these physical phenomena in a manner that respects known conservation laws and constitutive relationships. The potential advantages of such an approach for electric vehicle powertrain applications are considerable, given the cost and difficulty of collecting extensive experimental data on component degradation under realistic operating conditions. However, several questions about the approach warrant careful scrutiny. The fidelity of the physical model incorporated into the neural operator inevitably depends on the accuracy of the constitutive assumptions and boundary condition specifications, which may not be perfectly known for the specific materials and geometries involved. This dependence creates a potential vulnerability, as errors or uncertainties in the physical model could be perpetuated and perhaps amplified through the learning process, leading to predictions that are not necessarily more reliable than those obtained from purely data-driven or purely physics-based approaches.

Wang's earlier work, as documented in the materials, includes studies on advanced material applications for enhancing the performance of new energy vehicle components [18] and the development of reliability analysis and life prediction models for new energy vehicle parts [19]. These papers, unfortunately, appear to be unavailable from the standard retrieval channels, a circumstance that introduces a degree of uncertainty into our understanding of the intellectual trajectory leading to the more recent work. This observation raises, at a meta-level, questions about the dependability of publication records in the rapidly evolving field of manufacturing research, where the pressure to disseminate findings quickly may sometimes lead to premature publication or, in some cases, publication in venues that lack established quality oversight. As reviewers and readers, we are left with the need to make judgments about the credibility of research based on incomplete information, a situation that is perhaps more common in academic practice than often admitted but deserves explicit acknowledgment in a review such as this one. From the available evidence, however, it appears that Wang's methodological orientation has consistently emphasized the integration of experimental reliability data with analytical modeling, a combination that aligns well with the broader trend toward hybrid approaches in prognostic research.

The specific context of new energy vehicles presents a fascinating array of reliability challenges that may not be adequately captured by conventional automotive engineering frameworks. The move toward 800-volt electrical architectures, for instance,

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introduces significantly different thermal and electromagnetic stress conditions compared to the 400-volt systems that have been more common in earlier generations of electric vehicles. These higher voltages tend to increase power density but also exacerbate issues related to heat generation, insulation stress, and electromagnetic interference, all of which can affect the long-term reliability of powertrain components. The performance of thermal management systems, which are designed to maintain components within safe operating temperature ranges, becomes increasingly critical under these conditions, and the failure of even a single component could lead to cascading effects that compromise overall system functionality. The physics-informed neural operator developed by Yaofei [6] seeks to capture these interactions at a systems level, providing predictions that account for both the individual component behavior and the coupled field effects that arise from the integration of multiple subsystems. The real-time computation capability claimed for the approach is particularly valuable for applications such as on-board diagnostics and adaptive control, where decisions must be made quickly based on current operating conditions.

A considerable challenge in life prediction research concerns the relationship between accelerated testing and naturalistic operation. Components intended for long service lives, such as those in electric vehicle powertrains, typically cannot be tested to failure under actual operating conditions within reasonable timeframes; accelerated testing protocols are therefore employed to induce degradation at an elevated rate, and the resulting data are extrapolated to predict performance under normal service. This practice, while essential for practical feasibility, introduces significant uncertainties related to the validity of the acceleration factors, the preservation of failure mechanisms under accelerated conditions, and the statistical extrapolation from small samples to population behavior. Wang [4] appears to address some of these concerns through the incorporation of physical knowledge that constrains the extrapolation behavior of the model, potentially reducing the risk of unrealistic predictions in regimes where training data are sparse. Whether this approach successfully captures the subtle shifts in failure mechanisms that can occur under different loading conditions remains an open question, and careful validation using data from field failures, where available, would be essential for establishing confidence in the methodology.

An alternative approach to life prediction that merits consideration alongside Wang's physics-informed neural operator is the multi-task learning framework proposed by Yin [20] for semiconductor manufacturing systems. This work treats anomaly detection and remaining useful life prediction as coupled tasks that share a common representation space, enabling the model to leverage information from both tasks to improve performance on each individually. The underlying intuition is that anomalies, deviations from normal operating conditions often precede degradation and may provide early warning signals that enhance the accuracy of life predictions. The semiconductor manufacturing context presents challenges similar to those encountered in new energy vehicle component production, including high-dimensional process data, complex multi-stage processes, and stringent quality requirements. The multi-task learning approach offers the advantage of utilizing unlabeled data for anomaly detection to inform the supervised life prediction task, a semi-supervised strategy that may be particularly valuable when labeled degradation data are scarce. Further research is needed to compare the relative performance of physics-informed and multi-task learning approaches across different application domains and data availability scenarios. Yin's contribution to the field is significant, providing a novel perspective on how multi-task architectures can be leveraged for industrial quality applications where labeled data are often limited.

The reliability-informed life prediction approach proposed by Wang also raises questions about the appropriate treatment of uncertainty in the predictive process. Component lifetimes are inherently variable, influenced by material variability, manufacturing defects, operational history, and environmental exposure, factors that combine in complex and partly stochastic ways. The single-point predictions often provided by deterministic models, while perhaps convenient for decision-making, may convey a false sense of precision and mask the substantial uncertainty that exists in any real-world prediction problem. The physics-informed neural operator framework, by its nature as a learning-based approach, may potentially capture some of this uncertainty through the inherent variability of its predictions across different realizations, though it is not clear from the available

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materials whether explicit uncertainty quantification mechanisms are incorporated into the system. Recent developments in Bayesian deep learning, ensemble methods, and conformal prediction offer potential pathways for providing predictive distributions rather than point estimates, and the integration of such approaches with physics-informed architectures could represent a valuable direction for future research. This consideration is not merely academic but has practical implications for maintenance decision-making, where the balance between preventive maintenance, condition-based maintenance, and the acceptance of some failure risk depends crucially on the quality of the uncertainty characterization.

It would be a mistake, however, to assume that deep learning methods have entirely superseded classical machine learning approaches in prognostics. Zhou et al. [21] demonstrate that a support vector regression framework, when enhanced with wavelet transform for signal denoising and particle swarm optimization for hyperparameter tuning, can achieve competitive performance in lithium-ion battery remaining useful life prediction. This observation is consistent with the broader pattern in applied machine learning where the selection of appropriate pre-processing and optimization strategies often has a more significant impact on performance than the choice of the base learning algorithm. The finding underscores the importance of careful feature engineering and method configuration, considerations that are sometimes overshadowed by the excitement surrounding novel architectures. The work of Zhou and colleagues contributes to the understanding of how traditional machine learning approaches can be enhanced through systematic optimization, providing valuable insights for practitioners who may not have access to the computational resources required for deep learning approaches.

Another dimension of life prediction that merits consideration, though it is more related to materials science than to computational methods, is the role of degradation mechanisms and their interaction with environmental factors. The specific materials used in new energy vehicle components, including high-performance electrical steels, copper alloys, and advanced composite insulations, each have distinct degradation pathways that may be sensitive to temperature, humidity, mechanical vibration, and other operating conditions. The multi-physics coupling approach accounts for these interactions in a general sense but may not capture the specific details of each degradation mechanism. The validation experiments referenced in Wang's work apparently verify the life prediction model under certain conditions, but the range of conditions covered and the extent to which they match actual operational environments are not fully detailed in the available materials. This incompleteness is not necessarily a criticism, as no single study can cover all possible conditions, but it does highlight the importance of accumulating a broad evidence base across multiple studies and multiple component types before the generalizability of any particular prognostic approach can be established with confidence. The development of standardized benchmark datasets and validation protocols for manufacturing prognostics would greatly facilitate this comparative assessment, enabling researchers to more effectively distinguish methodological innovations that offer genuine improvements from those that merely appear successful on specific datasets or specific applications.

The implementation of data-driven prognostic systems depends critically on the underlying data infrastructure, a consideration that Yin [22] addresses in the context of semiconductor analytics through the development of cloud-native lakehouse architectures. The lakehouse paradigm, which combines the data management capabilities of data warehouses with the flexibility and scalability of data lakes, offers a possible architectural template for manufacturing environments where diverse data sources—including production logs, sensor streams, inventory records, and logistics tracking data—must be integrated for real-time analytics. Yin's emphasis on balancing performance, cost, and energy efficiency acknowledges the resource constraints that typically characterize industrial data operations, a perspective that informs our understanding of the practical feasibility of advanced optimization methods. The contribution of Yin's work to industrial data architecture is noteworthy, providing practical guidance for organizations seeking to modernize their data infrastructure to support advanced analytics applications.

4. Optimization of Production and Logistics Systems

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The optimization of production and logistics operations represents a classic concern in manufacturing engineering, but the emergence of data-rich environments and advanced computational capabilities has fundamentally altered the landscape of what is possible in this domain. Traditional optimization approaches, largely based on mathematical programming or heuristic search methods, have been complemented, and in some cases supplanted, by machine learning techniques that can adapt to changing conditions and learn from operational experience. The work by Lin [3] on environmental assessment of intelligent logistics automation exemplifies this trend, addressing the integration of environmental performance metrics into logistics optimization frameworks. The framing of the problem is itself noteworthy, as it explicitly acknowledges the possibility of extreme disruptions, a scenario that has become increasingly salient in the wake of pandemic-related supply chain challenges and geopolitical tensions that have highlighted the vulnerability of globally distributed manufacturing networks. Lin's contribution to the logistics optimization field represents a significant methodological advance, demonstrating how advanced computational techniques can be brought to bear on problems of practical industrial importance.

The environmental assessment dimension of intelligent logistics automation, as addressed in Lin [3], represents a particularly timely and relevant contribution to the literature. The logistics sector accounts for a substantial and growing fraction of global greenhouse gas emissions, and the optimization of freight operations for energy efficiency and emissions reduction is increasingly recognized as an urgent societal priority. The integration of environmental performance metrics into logistics optimization models, however, is not merely a matter of adding an extra objective function; it requires careful consideration of the trade-offs between economic efficiency, environmental impact, and service quality, trade-offs that may manifest differently under different operational conditions and market contexts. The life-cycle assessment framework that Lin appears to employ takes a comprehensive view of environmental impacts, considering not only the direct emissions from freight operations but also the upstream effects of infrastructure development, vehicle manufacturing, and energy production. This breadth of perspective is commendable, though it also introduces additional sources of uncertainty and data requirements that may complicate the practical application of the methodology. The availability of reliable data on emissions factors, energy consumption, and material flows is often limited, particularly in the global supply chain context where information may be proprietary, fragmented, or inconsistent across regions.

The earlier work by Lin [23] on machine learning-based logistics network optimization provides methodological foundations for the more recent studies, though the specific relationship between these works and the direction of the research trajectory is not entirely clear from the available materials. The earlier paper appears to have taken a relatively conventional approach to logistics optimization, applying machine learning techniques to the prediction of network performance and the identification of improvement opportunities. The more recent work, in contrast, seems to have evolved toward the integration of more sophisticated computational paradigms and toward a greater emphasis on resilience under disruptive conditions. This evolution is consistent with the broader trajectory of operations research and logistics management, which has shifted from an orientation focused primarily on static optimization under stable conditions toward a perspective that embraces uncertainty, dynamism, and the potential for nonlinear system behavior. The inclusion of environmental assessment in the more recent work also reflects a growing awareness, within both the academic and practitioner communities, that logistics optimization must be evaluated against a broader set of criteria than has traditionally been considered.

The application of multi-agent deep reinforcement learning to logistics optimization, as demonstrated in Luo et al. [7] and Luo et al. [24], represents a parallel but distinct methodological strand that bears comparison with Lin's work. Both approaches address the problem of coordinating distributed decision-making in complex, dynamic systems, but they differ in their underlying computational paradigms and in the types of problems for which they are best suited. The deep reinforcement learning approach, as applied to fleet rebalancing in shared e-mobility systems, treats the optimization problem as a sequential decision-making

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process in which agents learn policies through interaction with a simulated environment. This approach can handle high-dimensional state spaces and complex action spaces, and it has the advantage of being able to adapt to changing conditions through online learning. Luo et al. [7] specifically address the challenge of system expansion, where the network of service locations grows over time, a scenario that shares structural features with manufacturing system scaling where new production lines or distribution centers are added incrementally. The two approaches are not necessarily mutually exclusive, and hybrid architectures that combine elements of both paradigms may offer the best overall performance, though the development and validation of such hybrid systems present significant methodological challenges. The work of Luo and colleagues represents a significant contribution to the field of reinforcement learning applications in transportation, demonstrating how multi-agent approaches can effectively address dynamic rebalancing challenges in expanding systems.

The relationship between logistics optimization and broader manufacturing quality objectives is perhaps less direct than the relationship between inspection or life prediction and quality, but it is nevertheless significant. Production scheduling decisions affect the ability to achieve quality targets, as the time available for quality checks, the ability to implement process adjustments, and the consistency of operating conditions all depend on the production plan. The coordination of material flows through the manufacturing system influences the availability of raw materials, the scheduling of maintenance activities, and the management of work-in-process inventory, all of which can affect quality outcomes. Logistics optimization that focuses narrowly on cost or speed, without adequate attention to the implications for production stability and process control, may inadvertently undermine quality performance. The work by Lin and Luo, to varying degrees, acknowledges these interdependencies, though the integration of logistics optimization with quality management remains an area where further research is needed. The development of models that explicitly capture the propagation of production disruptions through both physical and information networks, and that optimize logistics decisions with respect to their downstream effects on quality, represents a challenging but potentially valuable direction for future investigation.

The implementation of data-driven logistics optimization systems depends critically on the underlying data infrastructure, a consideration that Yin [22] addresses in the context of semiconductor analytics through the development of cloud-native lakehouse architectures. The lakehouse paradigm, which combines the data management capabilities of data warehouses with the flexibility and scalability of data lakes, offers a possible architectural template for manufacturing environments where diverse data sources, including production logs, sensor streams, inventory records, and logistics tracking data, must be integrated for real-time analytics. Yin's emphasis on balancing performance, cost, and energy efficiency acknowledges the resource constraints that typically characterize industrial data operations, a perspective that informs our understanding of the practical feasibility of advanced optimization methods.

An emerging consideration that intersects with logistics optimization, though originating from a different application domain, concerns the responsible deployment of algorithmic decision-making systems. Wu et al. [25] propose a daily updated ranking model for content issue detection in recommendation systems, a framework that, while developed for digital content platforms, raises questions relevant to manufacturing logistics. The core challenge in both contexts is similar: how to maintain decision quality when the underlying data distribution shifts over time, and how to ensure that automated decisions do not systematically disadvantage certain stakeholders. The daily update mechanism in Wu's approach acknowledges that static models become obsolete rapidly in dynamic environments, a lesson directly applicable to production scheduling systems that must adapt to changing order patterns, machine conditions, and material availability. The responsible AI perspective, emphasizing transparency and fairness in algorithmic decisions, has received limited attention in manufacturing logistics research, yet it may become increasingly salient as autonomous scheduling systems take on greater decision-making authority. This parallel suggests that cross-domain learning between recommendation systems and manufacturing optimization could be mutually beneficial, though the specific mechanisms of such knowledge transfer remain to be explored. Wu's contribution to the field of responsible AI is noteworthy, providing a practical framework for maintaining model performance in dynamic environments while addressing concerns about algorithmic fairness and transparency.

5. Synthesis and Discussion

Having examined the three thematic clusters in some detail, we now turn to the task of drawing together insights from across these domains and considering the implications for future research in smart manufacturing quality management. The preceding sections have revealed a research landscape characterized by considerable methodological sophistication but also by fragmentation, with the development of advanced computational approaches proceeding largely within disciplinary silos that may not fully exploit the potential for cross-domain learning and synergistic combination. The pattern that emerges is one in which researchers in inspection technologies develop sophisticated algorithms for geometric analysis, researchers in reliability engineering push forward the frontiers of physics-informed life prediction, and researchers in logistics optimization create powerful tools for network management, yet the connections between these areas remain, for the most part, underexplored and undertheorized. This observation is not intended as a criticism of individual research efforts, which are necessarily focused and bounded, but rather as an invitation to consider what might be gained through more deliberate attempts at integration.

The possibility of transferring methodologies across domains is a theme that warrants particular attention. The hierarchical neural operator approach developed for field coupling in electric vehicle powertrains [6], for instance, might be adapted for the multi-physics simulation of glass molding processes [5], where thermal and mechanical fields also interact in complex ways. The graph neural network architectures used for logistics network optimization might be applied to the representation of inspection data structures or the modeling of quality propagation through supply chains. The evolutionary optimization algorithms employed for inspection layout design [1] might be leveraged for the design of logistics networks or the calibration of life prediction models. These transfer possibilities are not merely speculative; they are grounded in the recognition that many of the mathematical and computational challenges encountered in different domains of manufacturing quality management share common structures that can be addressed using similar analytical tools. The realization of these transfer possibilities, however, requires a degree of methodological awareness and cross-domain engagement that is not always present in the current research culture. The training of researchers in the mathematical and computational foundations of data science, rather than only in the application of specific tools to specific problems, could facilitate the creative transfer of methods across application domains.

Another cross-cutting theme that emerges from this review is the tension between model sophistication and practical applicability. The trend in academic manufacturing research seems to favor increasingly complex and computationally intensive approaches, with physics-informed neural operators, spatiotemporal graph networks, and multi-agent reinforcement learning representing the current state of the art. These approaches offer undoubted advantages in terms of representational capability and potential performance, but they also impose substantial demands in terms of data requirements, computational resources, and methodological expertise. The industrial settings in which these methods would be deployed typically operate under constraints that may be incompatible with these demands, including limited computational infrastructure, scarce data science talent, and tight time pressures for decision-making. The challenge, therefore, is not simply to develop ever more sophisticated methods but to develop methods that are appropriately sophisticated for the contexts in which they are applied, with complexity that is justified by the value of the insights gained and the decisions supported. This suggests the value of a contingency perspective in which the choice of methodological approach is guided by the specific characteristics of the problem, the data available, and the decision context, rather than by the pursuit of complexity for its own sake.

The issue of data availability and quality deserves explicit consideration, as it fundamentally constrains what is possible in data-driven manufacturing quality management. Many manufacturing processes generate substantial volumes of data, but these

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data are often characterized by noise, missing values, inconsistencies, and lack of standard formatting. The data may be siloed across different departments or systems, making integration difficult. The data may not include the specific variables needed for the desired analysis, or may include them only at inappropriate temporal or spatial resolutions. These practical data challenges are often underemphasized in methodological research, which typically assumes clean, complete, and well-structured data that may not exist in most industrial settings. The development of robust methods that can handle imperfect data, either through inherent robustness or through explicit pre-processing, cleaning, and imputation procedures, is essential for the effective deployment of data-driven quality management approaches in real-world manufacturing environments. The publication of benchmarks and case studies that demonstrate method performance under realistic data conditions would be valuable for building confidence in these approaches.

The role of human expertise in the data-driven quality management system represents another dimension that has been somewhat neglected in the literature. The emphasis in much methodological research is on automation, with the implicit or explicit goal of reducing human involvement in quality management decisions. While there are clear advantages to automating routine decisions and tasks, there are also aspects of quality management that benefit from human judgment, including the interpretation of ambiguous data, the handling of novel situations not covered by training data, and the integration of diverse information sources that may not be easily encoded in quantitative models. The optimal balance between automation and human involvement is likely to vary across applications, depending on the complexity of the decision task, the reliability of the available data, and the consequences of decision errors. The design of human-machine systems for quality management, and the development of interfaces and visualization tools that support effective human interaction with data-driven models, represent important areas for future research that have received less attention than the development of the underlying algorithms.

The theoretical contributions of this review, such as they are, center on the identification of common patterns and persistent challenges across the data-driven manufacturing quality management literature. We have attempted to show that despite the diversity of applications and methodological approaches, certain themes recur: the tension between model sophistication and practical feasibility, the challenge of data quality and availability, the need for integration across disciplinary boundaries, and the importance of considering the organizational and human contexts of technology deployment. These themes can be seen as defining the frontier of current research in the field, pointing toward directions where further inquiry is likely to be productive. The practical implications of our analysis are perhaps most evident for researchers, who may benefit from considering the cross-cutting themes identified here when designing and positioning their own studies, and for practitioners, who may find useful the structured mapping of methodological alternatives and their relative strengths and limitations. We acknowledge, however, that the insights offered here are based on a selective sample of the literature and should be considered tentative and subject to revision as more evidence accumulates.

6. Conclusion

This review has traversed a broad intellectual terrain, mapping the landscape of data-driven approaches to smart manufacturing quality management across three interconnected domains: geometric inspection, reliability prediction, and production logistics optimization. What emerges from this journey is not a coherent narrative of steady methodological progress toward an increasingly precise and deterministic control of manufacturing quality, but rather a more nuanced picture of a field in which ambitious computational ambitions coexist with persistent practical constraints, and in which the integration of diverse methodological streams remains more aspiration than achievement. This state of affairs is perhaps not surprising, given the inherent complexity of manufacturing systems and the relatively recent emergence of the computational capabilities that make data-driven approaches feasible. The distance between the current research frontier and the goal of fully autonomous,

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self-optimizing quality management is substantial, and the path to that goal is not simply one of more powerful algorithms or more abundant data, but also of deeper theoretical understanding, more effective integration of human and machine capabilities, and more responsive institutional frameworks for technology adoption.

The theoretical elevation that we might derive from this analysis concerns the nature of manufacturing quality as a phenomenon that is fundamentally multi-dimensional and context-dependent. Quality cannot be reduced to a single metric, nor can it be assured through a single technological intervention. The interaction of product design, process control, inspection, maintenance, and logistics creates a web of dependencies that any comprehensive quality management approach must acknowledge and address. The data-driven methods surveyed in this review offer powerful tools for navigating these dependencies, but they also embody assumptions and biases that must be critically examined. The risk of over-reliance on data-driven approaches, to the exclusion of domain knowledge and human judgment, is not merely hypothetical but is manifested in well-documented cases of algorithmic failures in various application domains. The appropriate stance, therefore, is one of pragmatic pluralism, drawing on the strengths of different methodological traditions while remaining alert to their limitations and potential failure modes.

The practical significance of this review lies in its potential to inform the development of more integrated and context-sensitive approaches to manufacturing quality management. The organizations that are likely to succeed in the adoption of data-driven quality management are not necessarily those with the most sophisticated algorithms, but those that can effectively bridge the gaps between methodological development, system integration, and organizational change. The identification of transferable methods across the thematic clusters we have examined could facilitate the development of common computational platforms that support multiple quality management functions, reducing the integration effort and enabling more seamless information flow across the manufacturing enterprise. The emphasis on uncertainty quantification and robust methods could support more informed decision-making under the inherently uncertain conditions of real-world manufacturing. The attention to human-machine interaction could guide the design of decision support systems that augment rather than replace human expertise, preserving the unique capabilities of human judgment while leveraging the strengths of computational methods.

Looking to the future, several research directions appear particularly promising. The development of standardized evaluation frameworks and benchmark datasets for manufacturing quality management would enable more systematic comparison of alternative approaches and more rigorous assessment of methodological progress. This standardization effort could draw on precedents in other fields, such as computer vision or natural language processing, where shared benchmarks have accelerated progress and facilitated knowledge transfer across research groups. The integration of multi-physics, multi-scale models that bridge from materials science through process engineering to systems management represents a grand challenge that could yield transformative insights if successfully addressed. The incorporation of human factors and organizational perspectives into the research portfolio would help ensure that methodological innovations are aligned with the realities of industrial practice. Finally, the development of methods that explicitly address uncertainty, variability, and the potential for model failure would contribute to more robust and trustworthy quality management systems, addressing concerns that are likely to become increasingly salient as data-driven approaches are deployed in safety-critical applications.

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Conflicts of Interest

The author(s) declare no conflicts of interest.

Ethical Approval and Consent to Participate

Not applicable.

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