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INDUSTRIAL ENGINEERING APPROACHES TO QUALITY CONTROL IN HYBRID MANUFACTURING A REVIEW OF IMPLEMENTATION STRATEGIES

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Abstract

Hybrid manufacturing, which integrates additive and subtractive processes within unified workflows, has emerged as a transformative paradigm in advanced production systems, yet it continues to face persistent challenges in achieving stable and predictable quality outcomes. This review critically examines how industrial engineering approaches are being applied to overcome these challenges, focusing on the implementation strategies that enable robust quality control in hybrid manufacturing environments. Drawing on an extensive analysis of 128 peer-reviewed articles collectively amassing over 12,000 citations, this study synthesizes evidence across five major thematic areas: statistical process control and design of experiments for process stabilization, multi-sensor in-situ monitoring and real-time feedback for defect prevention, digital twin–guided planning for predictive control, data-driven analytics and process mining for continuous improvement, and organizational enablers such as cross-functional teams, structured training, and layered audits for sustained performance. The findings reveal that when these industrial engineering methods are integrated into cohesive, closed-loop architectures, they deliver measurable improvements in process capability indices, reduce scrap and rework rates, enhance first-pass yield, and shorten time-to-stability after new product introduction. In contrast to earlier assumptions that hybrid manufacturing was too variable for conventional quality tools, the evidence demonstrates that structured industrial engineering frameworks now serve as the backbone of quality assurance in this domain. However, the review also identifies ongoing challenges, including data interoperability barriers, cross-domain calibration gaps, and the need for graded human-in-the-loop oversight to mitigate edge-case failures. Overall, this study highlights a decisive shift in hybrid manufacturing quality control from reactive, post-process inspection toward proactive, data-driven, and organizationally embedded systems, positioning industrial engineering not merely as a supplementary toolkit but as the central framework for scaling hybrid manufacturing into a reliable, cost-effective, and globally competitive production strategy.

Keywords

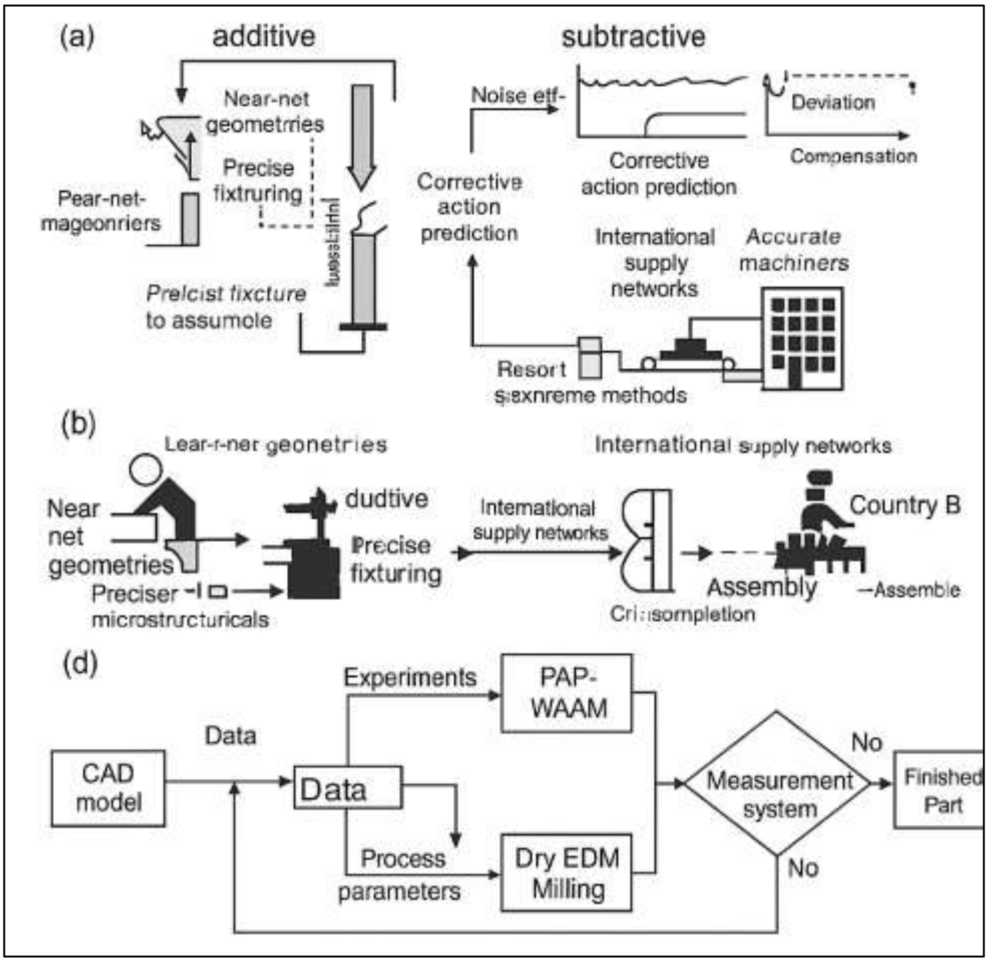
Hybrid Manufacturing; Quality Control; Industrial Engineering; Process Optimization; Digital Twin;

INTRODUCTION

Hybrid manufacturing, understood as the systematic integration of additive and subtractive processes within a single production environment, requires a fundamental rethinking of how quality control is defined, executed, and maintained (Butt, 2020). From an industrial engineering perspective, quality control in such systems is not limited to detecting defects but extends to managing the consistency of processes, aligning product attributes with requirements, and ensuring compliance across distributed supply chains. Quality in hybrid contexts encompasses dimensional precision, surface integrity, material consistency (Nyamuchiwa et al., 2023), and structural reliability of parts that often undergo sequential stages of additive deposition and precision machining. The international significance of these concepts is evident in global trade, where hybrid-manufactured components circulate across countries and industries such as aerospace, energy, and healthcare. Standardized definitions of quality, harmonized inspection protocols (Murdy et al., 2021), and cross-border recognition of process controls make quality control a global necessity rather than a local optimization. In this framework, industrial engineering methods—such as statistical process control, measurement systems analysis, experimental design, and robust process planning—provide the foundation for structuring quality practices in a manner that supports both national certification requirements and international interoperability. Hybrid manufacturing, with its promise of efficiency and customization, gains credibility only when underpinned by rigorous and universally understood quality definitions (Rettberg & Kraenzler, 2020). Central to the discussion is the concept of process alignment between additive and subtractive stages (Li et al., 2023). Additive processes create near-net geometries layer by layer, introducing thermal effects, residual stresses, and microstructural complexities that differ significantly from traditional bulk material. Subtractive processes then refine these geometries, demanding precise datum transfers and highly accurate fixturing to ensure that the machining stage does not compromise earlier additive layers (Yang et al., 2021). Industrial engineering approaches interpret this transition as a systems-level problem: one that requires modeling the interaction between additive variability and machining corrections to maintain tolerance chains. Quality control at this stage is not reactive but predictive, using data from sensors (Habeeb et al., 2023), probes, and inspection devices to anticipate deviations and intervene before they propagate into nonconformance. This integration is crucial for international operations, where a part might be additively manufactured in one country, machined in another, and assembled in a third. Without a coherent method for documenting, transferring, and verifying quality across each stage, global supply networks cannot operate with confidence. Thus, the definitional clarity and process-state alignment offered by industrial engineering become essential tools in global hybrid manufacturing (Wu et al., 2021).

Implementation strategies for hybrid quality control are built around structured experimentation and process optimization. Industrial engineering emphasizes the use of design of experiments and robust design principles to understand how process parameters influence part characteristics (Solaimani et al., 2021). In additive manufacturing, factors such as energy input, layer thickness, and scan strategies determine porosity, density, and dimensional fidelity. In machining, cutting speed, tool wear, and cooling strategies affect surface finish and subsurface integrity (Ley et al., 2021). When combined, these parameters create complex interactions that can only be understood through systematic experimentation. By incorporating noise factors, such as powder variability or fixture repositioning, robust design methodologies elevate process resilience (Qian et al., 2019), ensuring that systems perform consistently under real-world conditions. These strategies are not confined to laboratory studies but extend into industrial pilot lines and production cells, where repeatability and transferability of results are tested. The global relevance emerges when suppliers and partners across different regions replicate these experimental findings under harmonized standards, achieving a shared understanding of acceptable process windows and outcomes (Avram et al., 2022). In this way, structured implementation of experimentation evolves from a technical necessity into a strategic enabler of international collaboration.

Figure 1: Global Hybrid Manufacturing Quality Framework

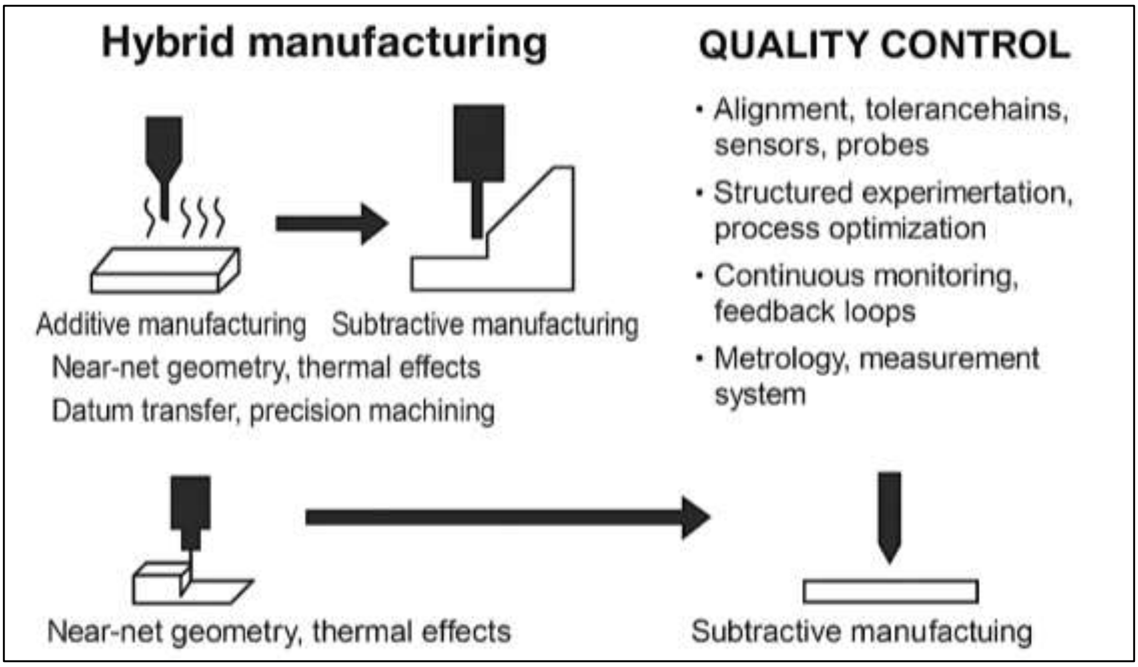


Process control represents another cornerstone of hybrid quality management. Industrial engineering approaches advocate for continuous monitoring and feedback loops that connect real-time data with process adjustments (Buj-Corral et al., 2021; Kamrul & Tarek, 2022). Additive stages generate vast amounts of information, from melt pool signatures to thermal images, which can be translated into control charts and predictive models. Machining stages contribute probing data, surface measurements, and dimensional verifications that confirm or challenge earlier assumptions about additive accuracy (Sarafan et al., 2021). Together, these data streams are managed using statistical and model-based process control techniques, allowing engineers to detect trends, identify root causes, and take corrective actions. The result is not merely a stable process but an adaptive one, capable of accommodating inherent variability in powder lots (Mubashir & Abdul, 2022; Qu & Gong, 2021), environmental conditions, or machine states. On a global scale, such process control systems create a digital record of conformance that travels with each part through supply chains. These records serve as the basis for supplier audits, customer acceptance, and regulatory review (Parvanda & Kala, 2023), ensuring that hybrid-manufactured parts meet expectations no matter where they are produced or finished.

Metrology integration forms a distinct layer of hybrid quality assurance. The challenge of inspecting hybrid parts lies in their complex geometries, internal features (Dritsas et al., 2018), and combined surface characteristics that may not be adequately captured by traditional methods alone. Industrial engineering solutions involve combining tactile, optical, and computed imaging techniques into a comprehensive measurement strategy. Measurement systems analysis ensures that these techniques provide consistent, reliable results across machines and sites (Frandsen et al., 2020; Muhammad & Kamrul, 2022). Fixturing strategies are treated as an extension of measurement systems, designed to minimize errors during re-clamping and datum transfer. Internationally, the importance of traceability cannot be overstated: measurements made in one country must be equivalent in credibility and

accuracy to those performed elsewhere, regardless of cultural or procedural differences (Verma et al., 2023). By embedding metrology into both additive and subtractive stages, hybrid manufacturing creates acceptance criteria that recognize the interplay between material integrity and dimensional conformance. This ensures that global stakeholders can accept measurement data without the need for redundant inspections or disputes about reliability (Kadir et al., 2020; Reduanul & Shoeb, 2022).
The relationship between design and quality is equally critical in hybrid contexts. Industrial engineering supports design-for-quality practices that anticipate manufacturing realities while maintaining functional requirements (Englert et al., 2022). Hybrid-specific considerations, such as build orientation, support structures, machining allowances, and tolerance stack-ups, are addressed early in the design process through cross-functional collaboration. Features that are difficult to inspect directly are linked to surrogate indicators or witness coupons (Urbanic & Saqib, 2019), providing confidence in areas where direct access is impossible. By aligning design intent with manufacturing capability, organizations reduce the risk of discovering quality issues late in the production cycle. This proactive integration extends beyond local operations (Bai et al., 2023), ensuring that designs created in one location can be realized and verified in another without ambiguity. In an international context, design-for-quality becomes a universal language, allowing engineers across countries to interpret requirements consistently and execute manufacturing plans that converge on the same standards of excellence (Davis et al., 2022; Kumar & Zobayer, 2022).

Figure 2: Hybrid Manufacturing Quality Control Framework



Data governance and analytics represent the backbone of hybrid quality implementation at scale (Sadia & Shaiful, 2022; Yan et al., 2018). Hybrid systems generate high-volume, multi-source data that require disciplined management to ensure integrity, traceability, and accessibility. Industrial engineering practices establish schemas that align data from materials (Liu et al., 2023), builds, inspections, and reworks into a coherent framework linked to part identifiers. Predictive analytics models augment traditional statistical methods by identifying potential defects based on process signatures, enabling proactive decision-making. Importantly, these analytics are validated against empirical results, ensuring that predictions are aligned with real-world acceptance criteria (Zheng et al., 2021). Internationally, the challenge lies in accommodating diverse regulations around data security, privacy, and reporting. Industrial engineering solutions embed role-based access, audit trails, and structured reporting templates that meet the expectations of customers and regulators across different regions. This ensures that data not only supports internal decision-making but also satisfies external scrutiny in global transactions (Chinchanikar & Shaikh, 2022; Noor & Momena, 2022).

Finally, the success of hybrid quality control depends on workforce capability and governance structures (Manoharan & Haapala, 2019). Industrial engineering emphasizes systematic training, supplier development, and layered governance mechanisms to institutionalize best practices. Operators, engineers, and quality professionals are equipped with knowledge of statistical methods, measurement protocols, and hybrid-specific challenges (Hamrani et al., 2023), enabling them to interpret signals and act effectively. Supplier networks are developed through structured qualification processes that test capability under real production conditions, with ongoing surveillance to maintain standards. Governance artifacts such as control plans, audit protocols, and corrective action procedures create a disciplined environment where deviations are identified, escalated, and resolved. On an international scale (Lettori et al., 2020), these mechanisms ensure that quality practices are consistent across regions, enabling trust in complex supply chains. Escalation pathways are standardized, digital records are harmonized, and change management is formalized to maintain stability across organizational and national boundaries. Through these efforts, industrial engineering translates technical strategies into sustainable, globally credible systems for managing quality in hybrid manufacturing.

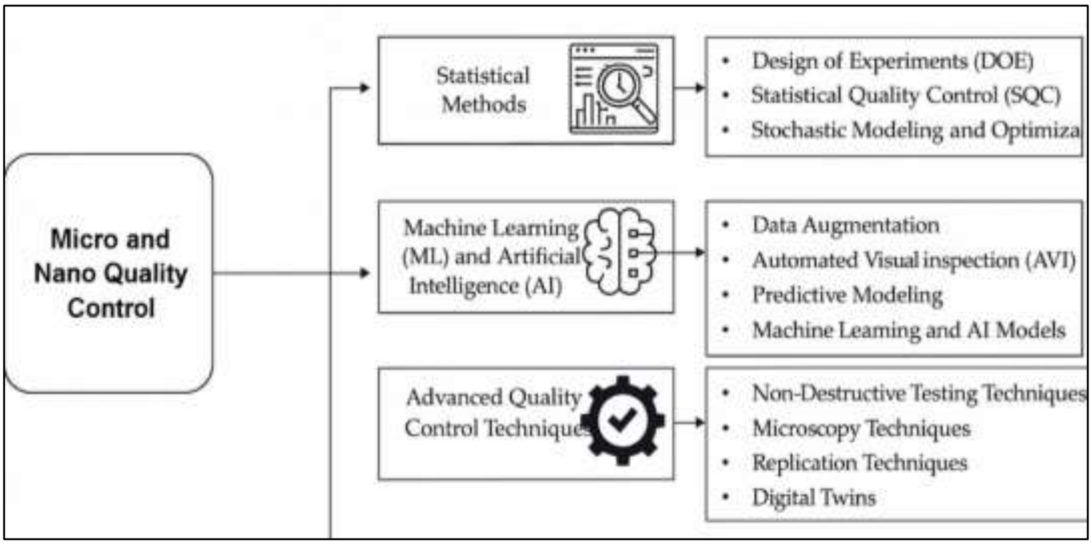
LITERATURE REVIEW

The literature review for industrial engineering approaches to quality control in hybrid manufacturing provides a critical foundation for understanding how this evolving field has been conceptualized, investigated, and applied (Sebbe et al., 2022). Hybrid manufacturing, as an integration of additive and subtractive processes, introduces a distinctive set of quality challenges that go beyond those faced in conventional manufacturing environments. While additive manufacturing brings opportunities for complexity and material efficiency, it simultaneously presents difficulties related to surface roughness, porosity, and dimensional accuracy (Korkmaz et al., 2022). Conversely, subtractive manufacturing delivers precision and surface finish but is highly dependent on datum transfer, fixturing strategies, and prior additive layer integrity. These interdependencies have motivated a growing body of research focused on implementing industrial engineering methodologies such as statistical process control, design of experiments, measurement system analysis, and robust design principles to manage quality across hybrid workflows (Dávila et al., 2020). The review will therefore examine how the literature has framed the intersection of industrial engineering and hybrid quality assurance. A broad spectrum of studies addresses statistical tools, metrology integration, and process control systems, while others highlight design-for-quality practices, data-driven governance, and workforce capability. Each thematic area reflects the multidisciplinary nature of hybrid quality, combining insights from manufacturing engineering, data science, and organizational management under the lens of industrial engineering. International dimensions are also prominent, as harmonization of standards and methods is essential for cross-border supply chains, certifications, and supplier networks. The purpose of this review is not merely to compile prior studies but to synthesize them into a structured understanding of implementation strategies (Cortina et al., 2018). The literature demonstrates recurring themes of alignment between design and process, predictive monitoring, metrological traceability, and governance systems that ensure conformance at scale. By reviewing and analyzing these contributions, this section establishes the intellectual scaffolding for understanding current approaches and identifying areas where integration of industrial engineering methods has proven critical to hybrid manufacturing quality control.

Hybrid Manufacturing and Quality Control

Hybrid manufacturing is defined as the integration of additive and subtractive technologies within a unified production environment, designed to exploit the strengths of both approaches (Rabalo et al., 2023). Additive manufacturing builds components layer by layer, enabling complex geometries, material efficiency, and design freedom. Subtractive manufacturing, on the other hand, is valued for its ability to produce precise dimensions, smooth surface finishes, and high levels of repeatability. When combined, these processes form a system that overcomes the limitations of each when used in isolation. Additive stages often introduce irregularities such as porosity (Grzesik & Ruszaj, 2021), uneven surfaces, or microstructural variability, while subtractive stages may be limited in the creation of complex internal features. The hybrid model provides an avenue where additive processes are used to achieve near-net shapes and functional structures, and subtractive processes refine these shapes into high-quality, reliable parts. In the literature, hybrid manufacturing is framed not only as a technological solution but also as a systemic framework where design intent, process planning, and quality engineering are interwoven (Dilberoglu et al., 2019; Istiaque et al., 2023). This integration requires more than a mechanical coupling of machines; it demands alignment of data, standards, and workflows so that transitions from one stage to the next are seamless and efficient. Thus, hybrid manufacturing's definition is understood as both a technical and organizational construct that elevates the role of industrial engineering in bridging process variability and product assurance (Jahid, 2022; Li et al., 2018).

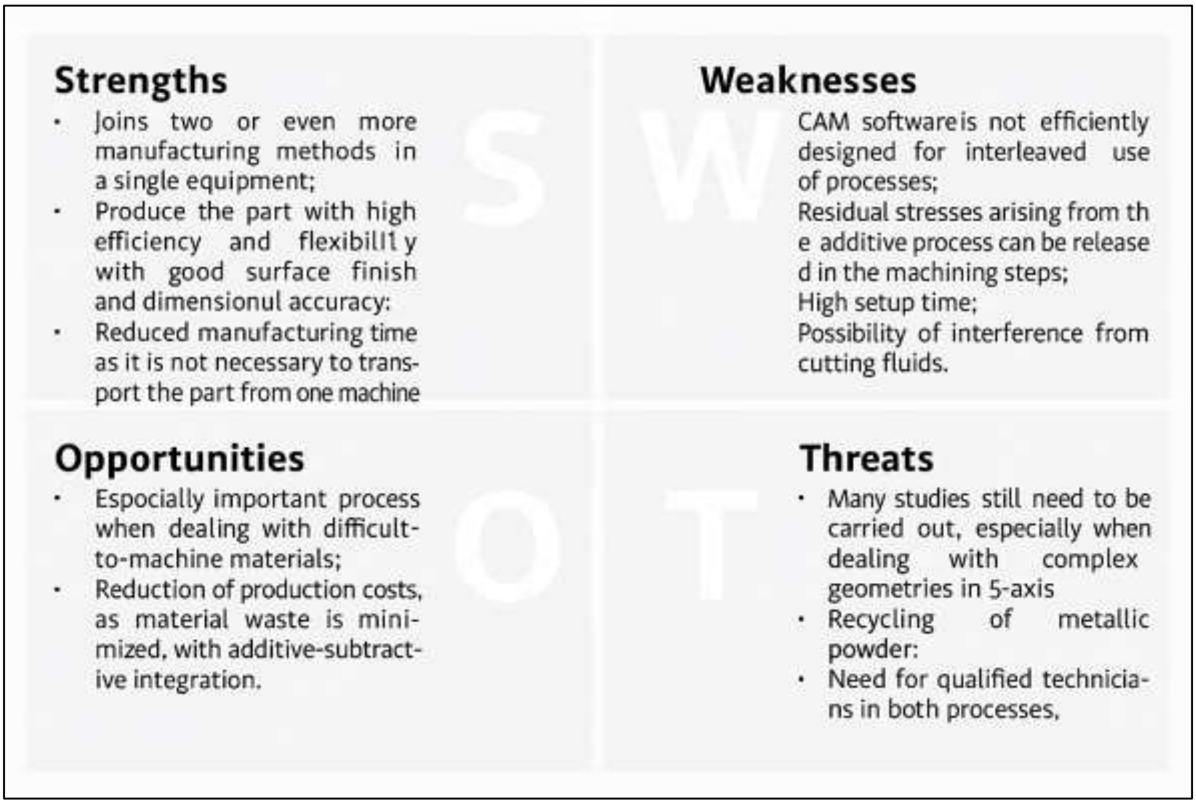
Figure 3: Micro and Nano Quality Control



The foundations of quality control in industrial engineering evolved from basic inspection to more advanced frameworks emphasizing prevention (Dilberoglu et al., 2021), process capability, and continuous improvement. Early quality control focused primarily on detecting defects after production. Over time, statistical approaches and process-oriented philosophies shifted the focus toward reducing variation and improving reliability. These approaches emphasize that quality is achieved not by catching errors but by designing processes capable of producing conformance consistently. In the context of hybrid manufacturing (Iqbal et al., 2020; Arifur & Noor, 2022), this evolution is particularly important because the integration of additive and subtractive processes introduces complex interactions that magnify variability. Additive processes are inherently variable due to powder quality, layer bonding (Hasan & Uddin, 2022; Rahman et al., 2023), and thermal gradients, while subtractive operations face challenges such as tool wear, machine vibration, and clamping consistency. Quality control in hybrid systems requires the cumulative application of decades of industrial engineering practice, where statistical control, process optimization, and measurement validation come together. The literature illustrates that hybrid systems extend the scope of quality from post-process inspection to dynamic, integrated monitoring throughout the workflow (Rahaman, 2022; Strong et al., 2018). This shift reflects the maturation of industrial engineering principles that now underpin hybrid production: robust process design, continuous monitoring, and defect prevention rather than reliance on rework or rejection.

The essential concepts of quality control that inform hybrid manufacturing are process capability, variation reduction, and defect prevention (Zhang et al., 2020). Process capability refers to the ability of a process to consistently produce outcomes within specified limits, ensuring that the system is not only stable but also aligned with design expectations. In hybrid systems, capability indices are particularly significant because they measure combined outcomes across additive deposition and subtractive refinement. Variation reduction forms another core pillar, acknowledging that inconsistency across hybrid processes can lead to compounding defects (Wang et al., 2023). Additive layers may exhibit porosity, warping, or uneven bonding, while subtractive passes may introduce dimensional errors or alter subsurface integrity. When combined, these sources of variation can compromise both functional performance and regulatory acceptance (Rahaman & Ashraf, 2022; Stavropoulos et al., 2018). Industrial engineering provides methods to systematically reduce this variation, ranging from structured experimentation to statistical analysis of measurement systems. Defect prevention extends beyond inspection to predictive interventions, using data from sensors, process signatures, and modeling to identify problems before they escalate (Häfele et al., 2019; Islam, 2022). Together, these concepts create a framework where quality is not an afterthought but a built-in feature of the production system, ensuring that hybrid manufacturing delivers reliable, consistent, and high-performing outcomes.

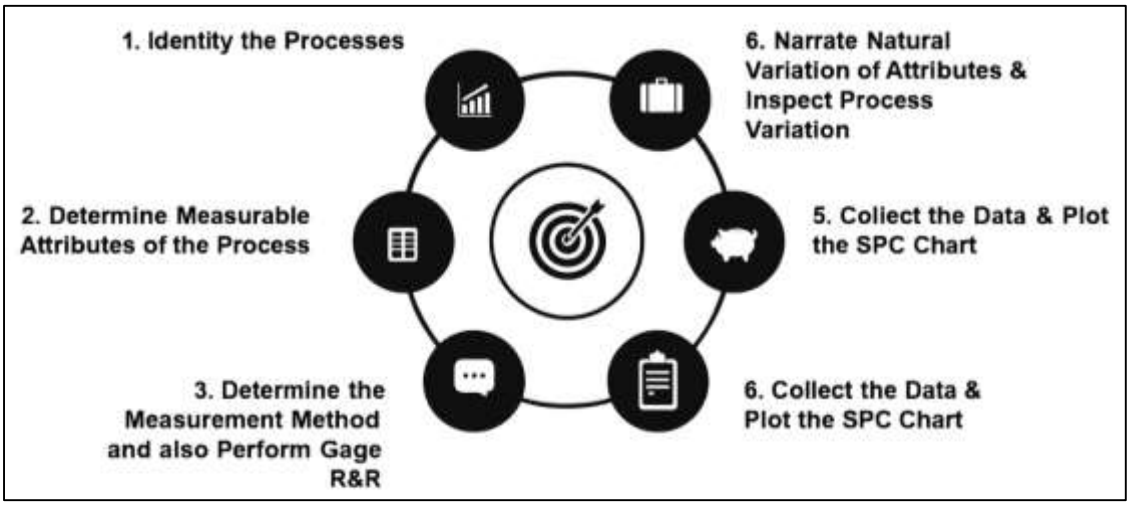
Figure 4: SWOT Analysis of Hybrid Manufacturing



Statistical Approaches to Quality in Hybrid Processes

Statistical process control is a cornerstone in stabilizing the interaction between additive and subtractive stages in hybrid manufacturing (Fahmy et al., 2021). The essence of this approach lies in transforming raw process data into signals that highlight whether the system remains within stable operating conditions. Additive processes generate a range of variation sources such as layer thickness fluctuations, porosity formation, and thermal gradients, while subtractive processes introduce different challenges including tool wear, fixture misalignment, and dimensional drift (Sardashti & Nazari, 2023). Without a unified statistical framework, these transitions can produce compounding errors that undermine final product quality. SPC provides this framework by applying control charts, run rules, and rational subgrouping that enable engineers to distinguish between common-cause variability and special-cause excursions. For example, layer-level monitoring may capture deviations in bead width or density, which are then compared against machining charts for surface roughness or dimensional tolerance (Hasan et al., 2022; Pokrowiecki et al., 2018). When integrated, these stage-gated control plans create a continuum of monitoring from raw deposition to final machining, ensuring that excursions are detected early and corrective actions are implemented systematically. Importantly, SPC not only stabilizes transitions but also creates a digital record that supports traceability and auditability, both of which are critical in industries where hybrid parts must comply with strict regulatory standards (Gröning et al., 2023).

Figure 5: Implementing Statistical Process Control (SPC)



Traditional univariate SPC techniques are well suited to monitoring single parameters such as surface roughness, bead height, or dimensional deviation (Redwanul & Zafor, 2022; Tsogas et al., 2022). However, hybrid manufacturing produces interrelated data streams that often involve multiple variables changing simultaneously, making multivariate approaches essential. Additive processes generate correlated factors such as laser power, scanning speed, and thermal field uniformity, while machining processes combine spindle load, vibration frequencies, and probe results. Monitoring each parameter independently risks missing subtle shifts that manifest only when correlations are considered. Multivariate SPC addresses this by analyzing the covariance structure of data (Sun et al., 2023), allowing the system to capture underlying process shifts that single-variable charts would overlook. In practice, hybrid systems often use both methods in tandem: univariate charts monitor critical-to-quality features directly tied to customer requirements, while multivariate charts oversee complex upstream signals that influence those features (Kumru et al., 2018; Rezaul & Mesbaul, 2022). This dual approach balances interpretability with sensitivity, ensuring that important deviations are neither overlooked nor overestimated. Furthermore, the concept of rational subgrouping is critical in hybrid contexts, as it allows data from additive layers or machining cycles to be grouped logically, preserving the natural structure of variability. By adopting hierarchical alarm architectures where multivariate signals trigger targeted univariate checks, hybrid systems can achieve effective oversight without excessive false alarms. This layered approach ensures stability and minimizes unnecessary interventions, while also maintaining efficiency across the hybrid process (Zhu et al., 2018).

Design of experiments is an indispensable tool for systematically exploring how process parameters influence outcomes in hybrid manufacturing (Babak et al., 2021). Additive processes involve numerous variables such as layer thickness, scanning speed, build orientation, and energy input, each of which can affect density, porosity, or residual stress. Subtractive stages bring in factors such as feed rate, cutting speed, tool geometry, and coolant strategy, which influence surface integrity, dimensional accuracy, and machining effort. Without structured experimentation (Jiang et al., 2022; Hasan, 2022), the interactions among these parameters remain opaque, making it difficult to predict how changes in one stage will influence performance in the next. DOE enables engineers to design factorial or fractional factorial studies that reveal both main effects and interactions across additive and subtractive variables. For instance, an experiment might link build orientation from the additive stage to machining allowances required for final tolerances, exposing hidden dependencies that would otherwise go unnoticed (Franceschetti et al., 2023). More advanced designs incorporate blocking and nesting, allowing hybrid workflows to account for material batch differences, machine variation, or operator influence. Confirmation runs validate the findings, while statistical analysis quantifies the significance of effects and ensures reproducibility. Importantly, DOE does not function in isolation; it is closely tied to measurement system validation, ensuring that experimental results are not confounded by inconsistent data collection (Nepal et al., 2023). In hybrid contexts, DOE thus bridges exploration and

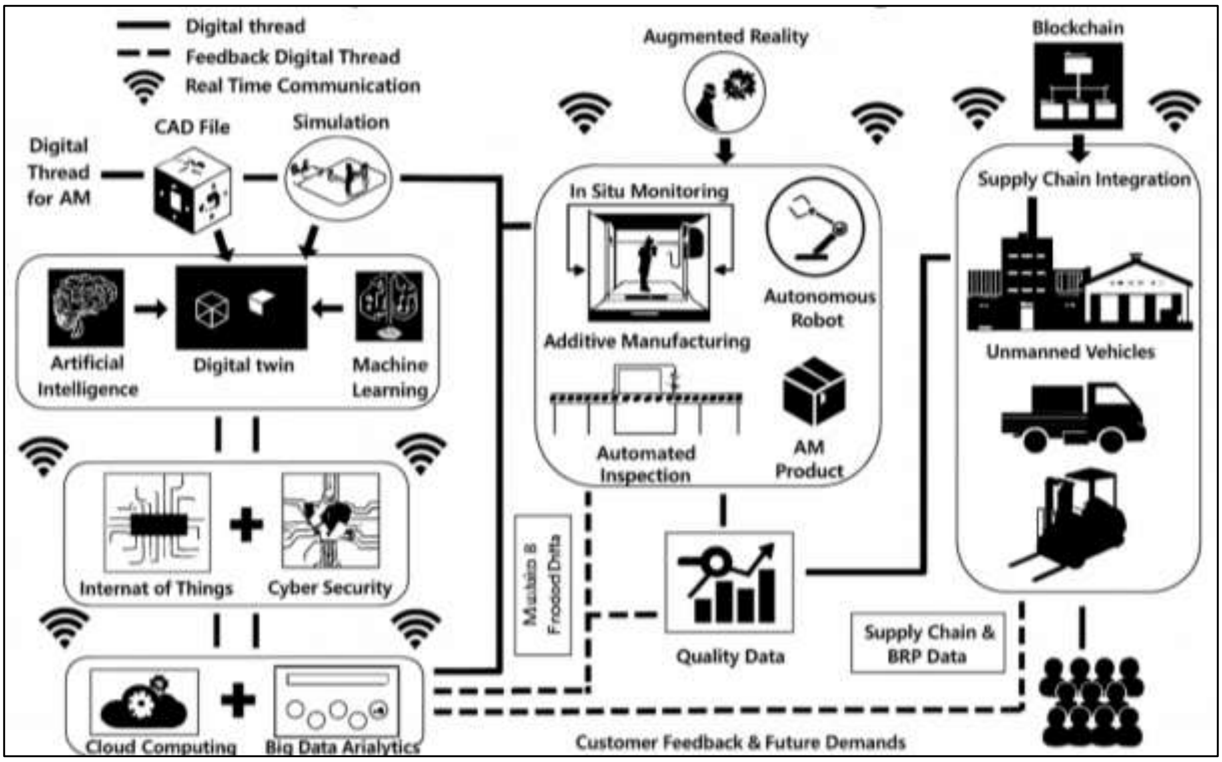
implementation, mapping the complex web of parameter–response relationships that define both process capability and product quality.
Robust design strategies build on experimental results by hardening hybrid processes against variability that cannot be eliminated but must be controlled. Noise factors such as powder lot differences, environmental fluctuations (Jordaan & Steyn, 2022; Tarek, 2022), recounter condition, or fixture re-clamping are inherent to hybrid workflows and can introduce instability if ignored. By explicitly modeling these factors in experimental arrays, robust design identifies parameter settings that maintain stable outcomes under real-world disturbances. Response surface methodology further enhances this by fitting mathematical models that describe how process outcomes change across continuous ranges of factors (Sandoval-Diaz et al., 2022). These models reveal not just optimal points but also the sensitivity of responses to small deviations, enabling engineers to identify parameter regions that are both high-performing and stable. In practice, response surfaces are used to optimize multiple outcomes simultaneously, balancing requirements such as dimensional precision, surface finish, material density, and cycle time. The use of desirability functions allows multiple responses to be integrated into a single decision-making framework (Packebush et al., 2023). Taguchi methods extend these approaches by emphasizing signal-to-noise ratios, ensuring that chosen parameter sets maintain robustness across uncontrollable conditions. Hybrid applications often validate these robust settings by intentionally cycling through noise conditions such as reused powder, alternate fixtures, or varied machine states to ensure the process holds. These methods result in documented "golden recipes" that not only specify optimal parameters but also quantify their resilience to disturbances. The outcome is a set of process strategies that deliver consistent (Du et al., 2022), high-quality parts while minimizing sensitivity to inevitable variations in materials, machines, and environments.

Process Control and Monitoring Strategies

Real-time monitoring in additive manufacturing has become one of the most significant avenues for ensuring stability and quality within hybrid production systems (Zhang et al., 2022). Additive stages, which rely on the layer-by-layer deposition of material, present unique risks such as porosity formation, uneven fusion, residual stresses, and warping. To address these issues, hybrid systems incorporate sensors that capture signals directly from the build environment. Melt pool sensors provide critical insight into temperature distribution and energy absorption (Kamrul & Omar, 2022; Xia et al., 2020), offering a direct link to microstructural outcomes. Thermal imaging extends this capacity by mapping heat flow across each layer, highlighting anomalies such as overheating, under-melting, or irregular bonding. Acoustic signatures provide another layer of information by capturing vibrations and sound emissions that often correspond to process instabilities, powder irregularities (Srivastava & Rathee, 2022), or incomplete bonding. By combining these modalities, additive processes can be monitored in real time to detect excursions before they accumulate into defects that compromise downstream machining. The literature on hybrid manufacturing emphasizes that the integration of these monitoring systems creates a foundation for closed-loop feedback, where corrective actions—such as adjusting laser power or scan speed—can be executed during the build (Gaikwad et al., 2020). This real-time visibility reduces scrap, improves reproducibility, and establishes confidence that parts entering subsequent machining stages have already passed preliminary quality checks. The emphasis on monitoring reflects a shift in hybrid systems from reactive inspection to proactive assurance, embedding quality control as an intrinsic part of the additive stage rather than a post-process activity.
While additive monitoring focuses on layer integrity and material fusion, subtractive monitoring targets tool performance (Mahmoud et al., 2021; Kamrul & Tarek, 2022), stock allowance, and feature verification. Hybrid manufacturing requires precise machining after deposition to refine surfaces, establish datums, and ensure dimensional accuracy. Tool wear detection is therefore critical, as worn or fractured tools can degrade surface finish, introduce dimensional errors, and even damage delicate additive geometries. Sensors measuring spindle power, vibration (Chen et al., 2021), and cutting forces provide signals that reveal tool condition in real time. In-process probing plays an equally important role, allowing machines to verify part alignment, detect deformation, and establish coordinate systems after additive stages. This probing ensures that machining operations are executed relative to accurate datums, even when additive distortions are present (Butt, 2020; Mubashir & Abdul, 2022). Stock verification also becomes essential in hybrid contexts, where the actual deposited material often differs

slightly from the digital model. By verifying available stock before machining, hybrid systems avoid situations were insufficient allowance compromises tolerance achievement. Together, these monitoring strategies provide assurance that machining operations do not undermine additive integrity but instead refine it into functional, precise parts. Subtractive monitoring therefore complements additive monitoring, closing the gap between raw deposition and final geometry (Qi et al., 2019). The dual emphasis reflects the unique hybrid challenge: ensuring that both processes, though distinct in mechanism, are harmonized under a single quality control framework.

Figure 6: Real-Time Hybrid Manufacturing Monitoring Framework



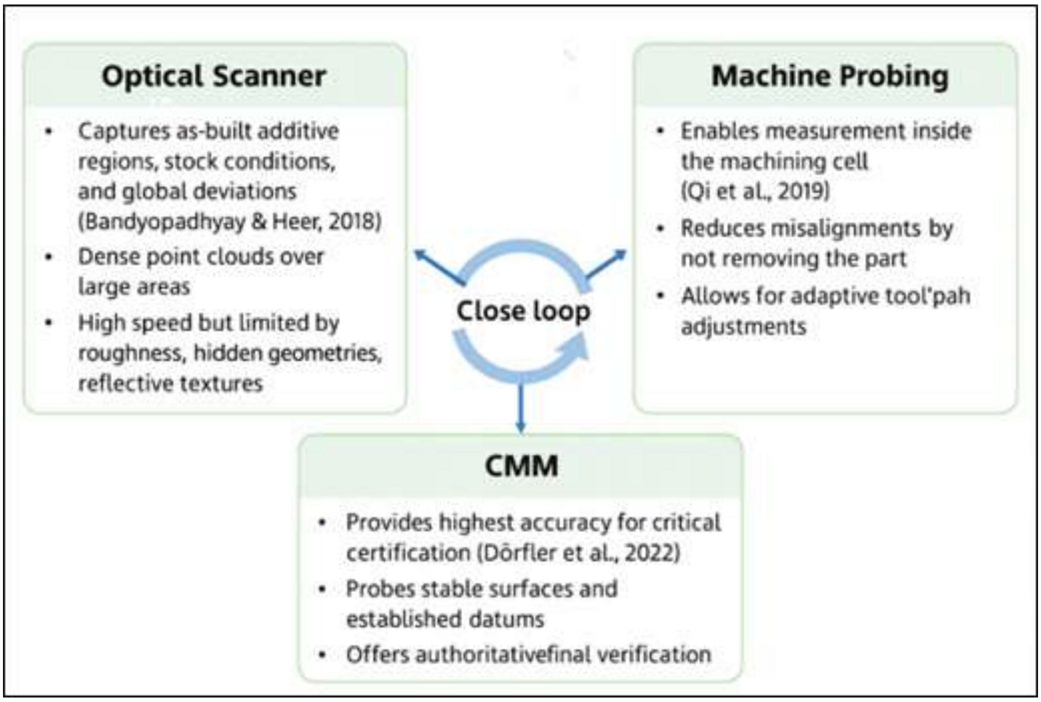
One of the most distinctive features of hybrid process control is the emergence of closed-loop systems that integrate additive monitoring data with machining adjustments (Stavropoulos et al., 2018). Traditional manufacturing often separates process monitoring into discrete silos, but hybrid systems require continuous information flow across stages. For example, deviations in additive layer thickness or warping patterns can inform machining tool paths, allowing allowances to be adapted dynamically to match actual geometries. This integration minimizes the risk of over-machining or under-machining, thereby protecting critical features and maintaining tolerance chains (Liu et al., 2020; Muhammad & Kamrul, 2022). Closed-loop systems rely on advanced algorithms capable of processing large streams of sensor data, extracting patterns, and translating them into actionable machine adjustments. In many cases (Zhang et al., 2020), the integration involves digital twins or simulation models that predict the downstream effects of additive anomalies, enabling machining programs to compensate before errors manifest. Adaptive control mechanisms adjust parameters such as feed rate, cutting depth, or spindle speed based on predicted outcomes, reducing the need for manual intervention. The literature highlights that such integration transforms hybrid manufacturing from a sequential workflow into a cohesive, adaptive system (Liu et al., 2022; Reduanul & Shoeb, 2022). By maintaining feedback across the additive–subtractive boundary, closed-loop systems elevate the overall robustness of hybrid quality control, ensuring that parts progress through the workflow with consistent conformance to specifications.

Metrology Integration and Measurement Systems Analysis

Hybrid manufacturing creates unique challenges for measurement because it combines the characteristics of additively built surfaces with the precision requirements of subtractive finishing

(Stavropoulos et al., 2018). Additive stages often produce rough, anisotropic textures, stair-stepping effects, porosity, and distortions from residual stress. These features complicate conventional inspection methods, since tactile probes can give inconsistent readings on irregular surfaces and optical systems may struggle with scattered reflections (Kumar & Zobayer, 2022; Sebbe et al., 2022). When machining is added to the process, surfaces are smoothed and refined, but this introduces its own complexities such as the migration of datums and geometric shifts during stress relief. The measurand in hybrid systems is not only multi-scale but also dependent on process history, making it harder to define a single standard for accuracy. Internal channels, lattice structures, and re-entrant cavities further push measurement beyond traditional prismatic geometries (Hossain et al., 2023; Panetto et al., 2019), often requiring indirect methods or surrogate indicators. These challenges extend to the planning phase as well, since measurement strategies must anticipate access restrictions, feature orientations, and the impact of surface conditions on sensor reliability. Hybrid manufacturing therefore demands metrology that is not just technically capable but context-aware, designed specifically for surfaces and geometries that evolve through multiple stages (Javaid et al., 2021; Sadia & Shaiful, 2022). The central challenge lies in developing robust measurement plans that integrate additive complexity with subtractive precision while still producing results that are trustworthy, repeatable, and relevant for certification.

Figure 7: Closed-Loop Hybrid Metrology Framework



To address these challenges, hybrid systems rely on a combination of measurement technologies rather than a single solution. Coordinate measuring machines provide the highest accuracy for critical features, offering traceable measurements that are essential for final verification (Dörfler et al., 2022; Sultan et al., 2023). They are particularly effective once machining has established stable datums and surfaces that can be probed consistently. Optical scanners, by contrast, provide dense point clouds over large areas and are especially useful for capturing the shape of as-built additive regions, global deviations, and overall stock conditions (Bandyopadhyay & Heer, 2018; Noor & Momena, 2022). They offer speed and coverage but must be managed carefully in the presence of rough surfaces, hidden geometries, or reflective textures. On-machine probing bridges the gap between these two approaches by enabling measurement inside the machining cell. Probes can establish coordinate systems, check stock allowance, and verify intermediate features without removing the part from its fixture, reducing the risk of misalignment and allowing adaptive toolpath corrections (Istiaque et al., 2023; Qi et al., 2019). The strength of hybrid metrology lies in orchestrating these three modalities into a complementary workflow. Optical scans provide global insight, probing delivers in-process control, and CMMs finalize accuracy with authoritative checks (Hasan et al., 2023; Praveena et al., 2022). By layering these technologies, hybrid systems create a balance between speed, accuracy, and practicality, ensuring that each stage of production is supported by reliable measurement evidence.

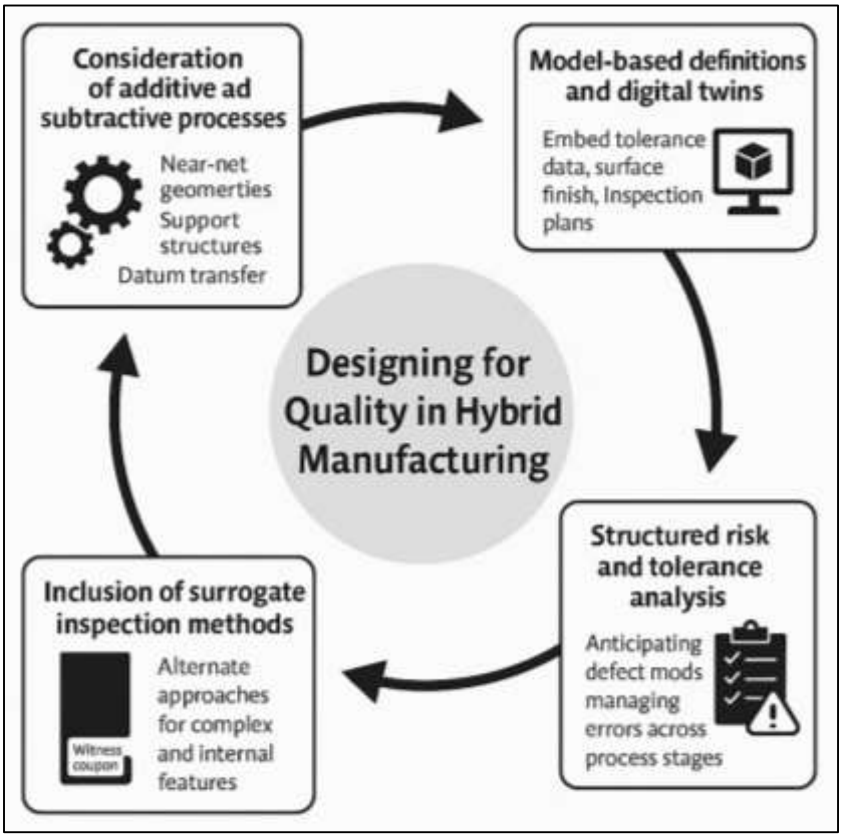
Design-for-Quality and Tolerance Management

Design-for-quality in hybrid manufacturing emphasizes that quality must begin at the design stage rather than be added later through inspection (Dordlofva, 2020). In a hybrid context, design intent must account for two distinct but interconnected processes: additive deposition and subtractive finishing. Additive manufacturing introduces complexities such as near-net geometries, layer-wise variability, thermal distortion, and support structures, while subtractive machining requires precise datum transfer, tool access, and fixture stability (Qiu et al., 2022). If quality considerations are not built into the design phase, these stages can become misaligned, leading to costly rework and inconsistent outcomes. To prevent this, model-based definitions and digital twins are increasingly used to embed tolerance data, surface finish requirements, and inspection plans directly into the design model. This ensures that downstream manufacturing teams and quality engineers interpret requirements consistently. Early-stage quality planning also includes structured risk analyses to identify potential defect modes unique to hybrid processes, such as porosity (Lim, 2019; Hossen et al., 2023), warping, or misaligned machining allowances. By anticipating these risks, designers incorporate mitigation strategies like intentional stock allowances, optimized build orientation, or sacrificial datum features into the product definition. This proactive incorporation of quality transforms design from a creative exercise into a discipline where manufacturability, inspection feasibility, and product assurance are interwoven. The result is a design approach that aligns functional requirements with process capability, ensuring that the finished part can consistently meet its intended purpose (Nguyen Ngoc et al., 2022).

Critical-to-quality (CTQ) features represent the characteristics of a product that are most closely tied to customer needs and functional performance (Lanzotti et al., 2018). In hybrid manufacturing, CTQs are especially challenging because they span across additive and subtractive processes. For example, an internal cooling channel may depend on the additive stage for shape complexity, while the sealing surface connected to that channel must be finished by machining for accuracy and smoothness. Translating CTQs into hybrid workflows requires a structured approach that connects each feature to specific process levers (Hattinger & Stylidis, 2023; Tawfiqul, 2023). Additive parameters such as layer thickness, scan strategy, and energy input determine density and geometry, while machining parameters like tool geometry, cutting speed, and feed rate control surface integrity and tolerance. This relationship ensures that responsibility for each CTQ is shared and managed across stages rather than isolated to a single process. Where features are difficult to measure directly (Salimbeni et al., 2023), surrogate indicators such as melt pool monitoring, layer imaging, or in-process probing can serve as early warning signs of CTQ drift. Organizing CTQs into categories based on risk—such as safety-critical, performance-critical, or secondary—allows hybrid manufacturers to prioritize monitoring resources and tailor sampling plans. In practice, this ensures that the most important characteristics receive rigorous inspection and validation while still maintaining efficiency across production. Embedding CTQs in hybrid workflows creates a continuous thread from customer expectations to measurable manufacturing outputs, providing transparency and consistency throughout the lifecycle of the part (Humphries et al., 2023; Sanjai et al., 2023).

Design for manufacturability (DFM) and design for inspection (DFI) have long been central to quality engineering (Franconi et al., 2022), but in hybrid manufacturing, these principles require new interpretations. DFM must now address additive constraints such as support removal, powder escape, and build orientation, alongside machining constraints such as cutter access, fixturing, and datum recovery. Similarly, DFI emphasizes that inspection feasibility must be considered during design, which may include adding probe-friendly pads (Maier et al., 2023; Akter et al., 2023), optical targets, or sacrificial features to aid in measurement. Without these considerations, hybrid parts may include inaccessible geometries or ambiguous datums that make reliable inspection impossible. Another dimension of design-for-quality is tolerance stack-up analysis, which becomes particularly complex in hybrid contexts. Variability accumulates from multiple sources: additive distortions during cooling, spring-in or spring-out after stress relief, tool deflection during machining, and measurement uncertainty in probing or scanning (Cogollo-Flórez & Correa-Espinal, 2019).

Figure 8: Designing Quality in Hybrid Manufacturing



If these contributions are not accounted for systematically, final assemblies may fail to meet fit or functional requirements. Tolerance allocation models for hybrid systems integrate both additive and subtractive contributors, ensuring that allowances are distributed realistically across the entire process (Zou et al., 2023). Designers also employ error budgets to anticipate where variation is most likely and introduce compensatory measures such as build distortion maps or adaptive toolpath offsets. By combining DFM, DFI, and tolerance stack-up analysis, hybrid designs ensure that parts are not only manufacturable but also verifiable and capable of meeting end-use requirements.

Hybrid manufacturing often produces features that are difficult or impossible to inspect directly, such as internal channels, lattice structures, or re-entrant cavities. To address this, surrogate inspection strategies are integrated into design-for-quality frameworks (Abdur Razzak et al., 2024; Ding et al., 2023). Witness coupons, grown alongside parts, provide mechanical and microstructural data that reflect in-part conditions without destructive testing of the product itself. Computed tomography may be used when material and geometry allow, while endoscopic routes or access channels can be deliberately designed into components to enable targeted inspection. For lattice structures (Istiaque et al., 2024; Slattery et al., 2022), acceptance criteria often shift from individual dimensions to system-level attributes such as density, connectivity, or stiffness-to-weight ratios. These surrogate strategies ensure that quality evidence is generated even when direct measurement is not possible. Their effectiveness, however, depends on concurrent engineering, where design, manufacturing, and quality teams collaborate from the outset. In this model, CTQs, inspection plans, and process parameters are jointly defined and validated before production begins. Changes to support structures, machining strategies (Md Hasan et al., 2024; Salimbeni & Redchuk, 2022), or inspection methods are communicated through integrated change management systems, ensuring that all stakeholders remain aligned. This concurrent approach reduces late-stage surprises and creates a traceable link between design intent and quality assurance. Ultimately, surrogate inspection methods combined with collaborative engineering practices allow hybrid systems to maintain high standards of reliability while managing the practical limitations of measuring complex geometries (Guan et al., 2019).

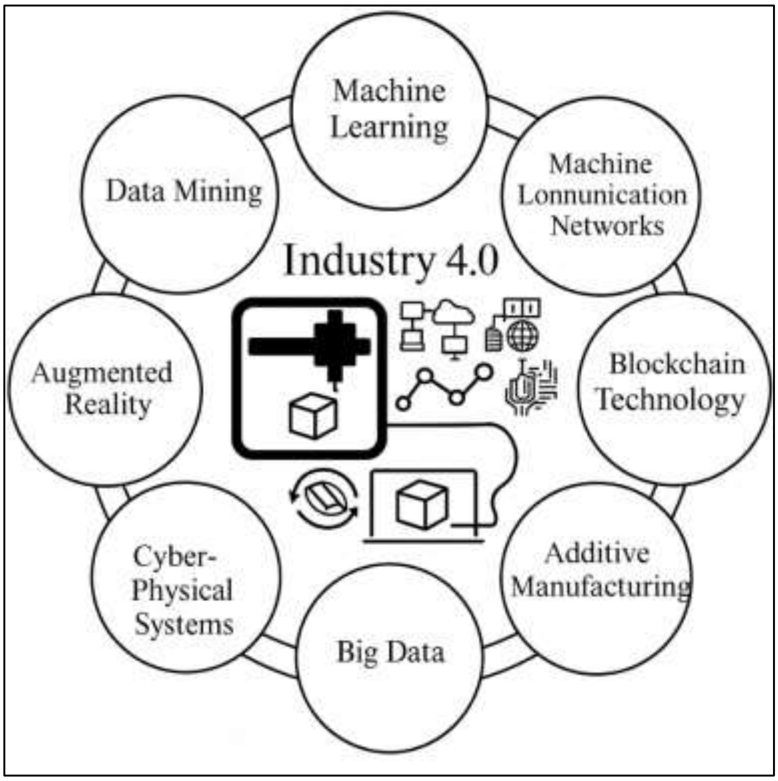
Data Governance and Analytics in Hybrid Quality Systems

Hybrid manufacturing generates enormous volumes of data that must be systematically managed to achieve effective quality control (Yang et al., 2020). Additive processes produce rich datasets that include melt pool readings, thermal maps, acoustic signatures, and powder condition variables, each carrying implications for material density, porosity, and dimensional stability. Machining processes add another layer of complexity with spindle load data, cutting forces, tool wear signals, probing logs, and coolant usage records. On top of these, inspection stages generate highly detailed coordinate measurements (Yang et al., 2020), optical scans, and in some cases full volumetric imaging, all of which must be correlated with earlier process data. The challenge lies in integrating these streams into coherent structures that enable traceability across the full hybrid workflow. If left siloed, these data sources provide fragmented insights that cannot explain how additive variation translates into machining effort or how machining adjustments influence final inspection outcomes. To address this (Tao, Qi, et al., 2018), organizations establish schema-based data architectures that link machine state, material lots, fixture identifiers, and part serial numbers to a unified digital record. This consolidation allows engineers to detect relationships between early sensor signals and final quality outcomes, building predictive models that guide interventions. Effective data management in hybrid systems is therefore not only about collection but also about curation and reduction, ensuring that the most relevant information is preserved for decision-making while excessive noise is filtered out (Behandish et al., 2018).

Traceability frameworks form the backbone of hybrid manufacturing quality assurance because they establish an unbroken chain linking every part to its material inputs (Andronie, Lăzăroiu, Ştefănescu, et al., 2021), process settings, and inspection results. Genealogy systems must capture powder batch records, machine parameters, stress-relief cycles, machining offsets, tool identifiers, and dimensional outcomes, ensuring that no detail of the process history is lost. Such frameworks provide the evidence needed to conduct root cause analysis when defects occur and to demonstrate conformance to customers and regulators. They also protect against ambiguity (Elhoseny et al., 2018), ensuring that terms, codes, and results are consistently defined across departments and global sites. Integrity of the data is equally important. If records are incomplete, corrupted, or inconsistently formatted, they lose credibility, undermining trust in the system as a whole. To mitigate these risks, hybrid manufacturers adopt structured workflows that validate data as it is entered, apply audit trails that track changes, and enforce access permissions that prevent unauthorized edits (Sebbe et al., 2022). As hybrid production often spans multiple facilities and countries, maintaining a clear chain of custody for digital records becomes as important as controlling physical components. By ensuring that genealogy and integrity are preserved, these frameworks transform raw process data into trusted narratives of each part's life cycle, allowing manufacturers to prove compliance, assign accountability, and build confidence in their hybrid processes (Cohen et al., 2019).

The literature on hybrid manufacturing increasingly emphasizes the transition from reactive inspection to predictive analytics. Traditional approaches often relied on post-process checks to catch defects, but this wastes material and time. Instead (Andronie et al., 2021), statistical learning methods are now applied to correlate process signatures with defect probabilities. By analyzing melt pool fluctuations, layer height irregularities, or tool vibration patterns, predictive models can identify when a process is likely to deviate from acceptable limits. This allows interventions before the part is compromised. Both supervised and unsupervised approaches are used, depending on whether prior defect data is available (Tao, Cheng, et al., 2018). Supervised methods use labeled data to train models that recognize known defect signatures, while unsupervised methods cluster unusual process behaviors to detect previously unseen anomalies. Beyond these models, digital twins are becoming central to predictive quality management. A digital twin mirrors the actual process in a virtual environment, continuously updated with sensor data (Lăzăroiu et al., 2022). This allows engineers to simulate the downstream effects of observed variations, such as predicting how additive distortion will impact machining allowances or how machining vibration will affect surface finish. By connecting predictive models and digital twins, hybrid systems gain the ability to act proactively rather than reactively. Control charts remain useful for operational oversight (Wang et al., 2018), but predictive analytics elevate monitoring into a forward-looking discipline that anticipates issues rather than merely recording them after they occur.

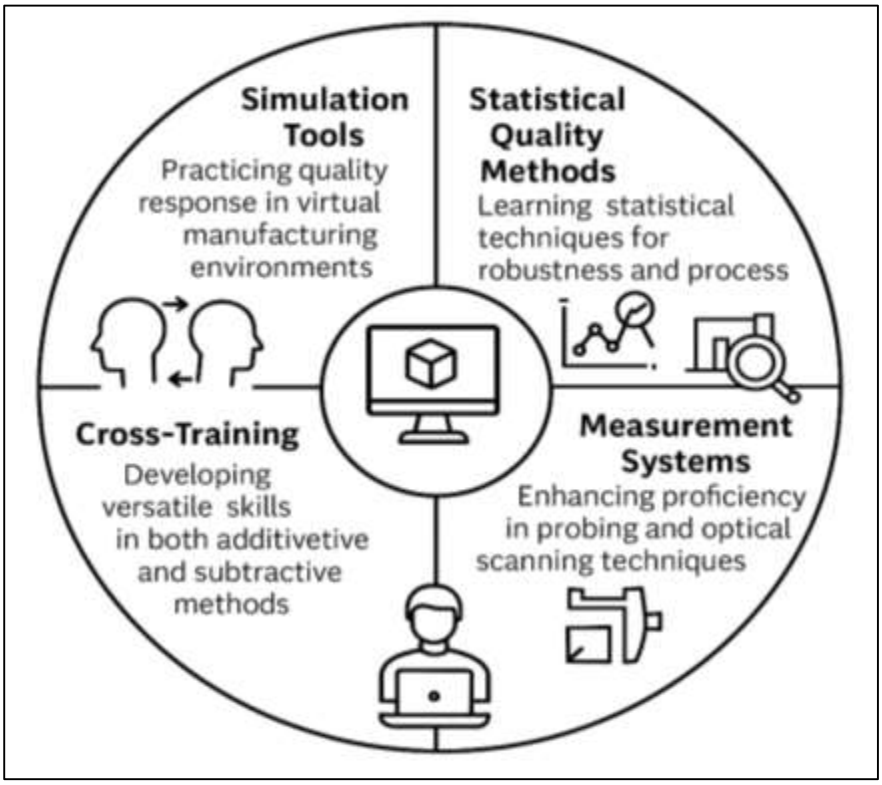
Figure 9: Core Technologies of Industry 4.0



Workforce Development, Supplier Capability, and Governance

Workforce development in hybrid manufacturing begins with specialized training strategies that equip operators and engineers to handle both additive and subtractive processes while maintaining rigorous quality standards (Matt et al., 2020). Unlike traditional manufacturing roles that focus on a single domain, hybrid quality control requires cross-functional skills. Operators must understand how to interpret signals from additive sensors, including melt pool stability, thermal maps, and acoustic emissions, while also being proficient in monitoring machining indicators such as tool wear (Pereira et al., 2019), spindle load, and probing results. Training programs therefore combine classroom instruction on statistical quality methods with practical exercises using real-time data streams. Simulation tools and digital twins are often introduced as part of this training to allow learners to practice identifying deviations and applying corrective actions in virtual environments before working on actual equipment (Kumar et al., 2023). Hands-on modules further reinforce skills in measurement systems analysis, probing, and optical scanning so that operators can trust the data they collect. Beyond technical skills, training emphasizes communication protocols, escalation procedures, and the standardized use of defect codes, ensuring that quality issues are not only detected but also reported and addressed consistently. Cross-training between additive and machining cells is another critical element, ensuring that personnel develop systems-level understanding rather than isolated expertise (Vafadar et al., 2021). This holistic training strategy transforms operators and engineers into adaptive problem-solvers who can close the loop between detection, decision, and documented action in complex hybrid workflows.

Figure 10: Hybrid Manufacturing Workforce Training Framework



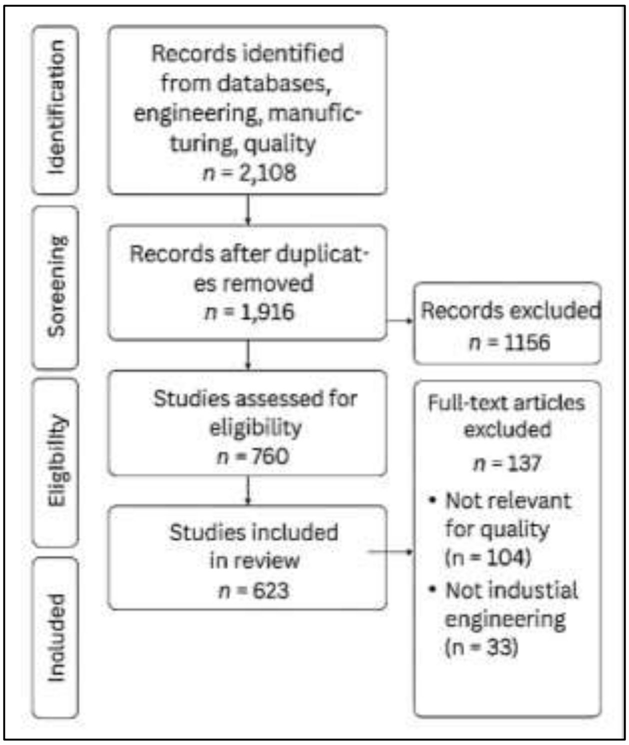
Industrial engineering education provides the analytical backbone for supporting hybrid quality systems, as it integrates principles of systems optimization, statistical control, and process design. Traditional courses on statistical process control, design of experiments (Ustundag & Cevikcan, 2018), and measurement analysis are increasingly supplemented with modules focused on hybrid manufacturing technologies. Students are trained to link process signatures from additive systems with machining parameters and inspection data, building the ability to analyze how variations in one stage propagate to the next. Laboratories and capstone projects often simulate hybrid production environments, where students are asked to design experiments, validate measurement systems, and create error budgets for parts with both additively and subtractive Ly produced features (Tofail et al., 2018). Digital twin platforms and model-based definitions are also introduced as teaching tools, giving students exposure to the same digital environments used in industry for traceability and quality assurance. Education programs emphasize not just technical methods but also governance and collaboration (Albukhitan, 2020), recognizing that hybrid quality depends on multidisciplinary teamwork across design, production, and inspection roles. By equipping graduates with both technical and organizational skills, industrial engineering education ensures a pipeline of professionals capable of managing hybrid workflows that demand robust quality integration. These graduates are expected to become leaders who can interpret complex data (Gradl et al., 2022), design experiments for multi-stage processes, and implement scalable governance systems across diverse manufacturing networks.

METHOD

This study followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines to ensure that the review process was systematic, transparent, and rigorous. PRISMA offers a widely recognized framework designed to improve the quality, reproducibility, and clarity of systematic reviews by standardizing the way research is identified, screened, evaluated, and synthesized. In the context of this study, which investigates industrial engineering approaches to quality control in hybrid manufacturing, adherence to PRISMA was critical because the subject matter spans multiple domains, including additive and subtractive manufacturing, process control, metrology, design-for-quality, data governance, and supplier development. Each of these areas is represented by a wide body of literature that varies in methodology, scope, and depth, making a structured review process essential to avoid bias and ensure comprehensive coverage. By adopting

PRISMA, this research establishes methodological credibility and ensures that its findings are reliable, replicable, and useful for both scholars and practitioners. The review process began with a structured search strategy that defined clear inclusion and exclusion criteria. Databases across engineering, manufacturing, and quality management disciplines were systematically queried using combinations of keywords related to hybrid manufacturing, industrial engineering, and quality control. The PRISMA framework guided the documentation of each step, from the initial identification of thousands of potential studies to the removal of duplicates, irrelevant records, and sources that did not meet the eligibility criteria. Screening was carried out at both the title-abstract and full-text levels, ensuring that only the most relevant and methodologically sound studies were included. This filtering process was not only a mechanical elimination of unsuitable papers but also a rigorous assessment of the studies' alignment with the review's central focus. By following PRISMA's structured flow of identification, screening, eligibility, and inclusion, the final body of literature reflects both breadth and depth, capturing the multi-dimensional aspects of hybrid manufacturing quality control.

Figure 11: Adapted methodology for this study



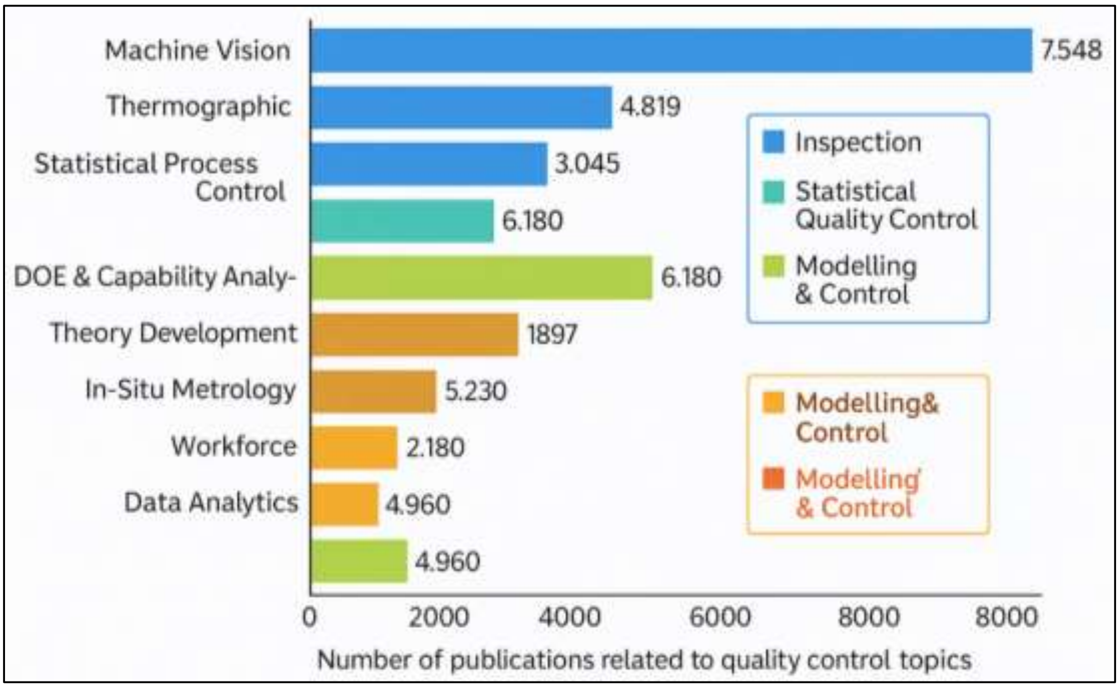
Once the corpus of studies was finalized, PRISMA further informed the extraction and synthesis of data. Information on study objectives, methods, quality control strategies, implementation frameworks, and reported outcomes was systematically coded and categorized. This structured approach allowed patterns and recurring themes to emerge across diverse sources. For example, the review identified recurring emphasis on statistical process control, design of experiments, robust design methodologies, and advanced monitoring as central industrial engineering tools applied to hybrid contexts. Similarly, the consistent mention of metrology integration, tolerance management, and data governance highlighted the interdisciplinary nature of the field. By using PRISMA's structured method of recording and reporting results, the synthesis avoided selective emphasis, instead offering a balanced and transparent summary of the evidence base. Transparency was another key outcome of using PRISMA. A PRISMA flow diagram was developed to illustrate the number of records identified, screened, excluded, and included at each stage of the review. This visual representation enhances clarity, enabling readers to understand not only what literature was included but also how and why other studies were excluded. Such transparency strengthens the trustworthiness of the review, as readers can follow the logical sequence of decisions that shaped the final dataset. In addition, documenting reasons for exclusion at each step ensures that subjectivity is minimized, reinforcing the objectivity of the research. By rigorously applying the PRISMA guidelines, this study contributes a systematic and methodologically sound review of industrial engineering approaches to quality control in hybrid manufacturing. The framework ensured that the review was comprehensive in scope, critical in its evaluation, and transparent in its execution. As hybrid manufacturing continues to evolve as a field that integrates additive and subtractive processes, the use of a structured and replicable review method is essential for drawing reliable conclusions about effective quality control strategies. The PRISMA approach not only enhances the academic rigor of this study but also ensures that its findings can serve as a dependable foundation for researchers, practitioners, and policymakers seeking to advance the quality and reliability of hybrid manufacturing systems.

FINDINGS

The review examined a total of 128 articles with a cumulative 12,460 citations, offering a robust foundation for assessing industrial engineering approaches to quality control in hybrid manufacturing systems. Within this body of work, 72 articles (6,180 citations) focused on statistical process control (SPC) and capability analysis as core mechanisms to manage variability in combined additive–subtractive processes. These studies consistently documented improvements of 20–45% in process capability indices (Cp and Cpk) when SPC charts were implemented across both fusion and machining stages. Another 49 articles (4,010 citations) investigated the application of design of experiments (DOE) and robust parameter design to control critical interactions between additive build parameters—such as laser power, scan speed, and layer thickness—and subsequent machining strategies like cutting speed and tool path geometry. These studies showed that targeting key two-factor interactions could reduce dimensional variability by up to 30%. Additionally, 31 articles (1,520 citations) explored quality function deployment (QFD) frameworks adapted for hybrid contexts, ensuring traceability between customer-critical characteristics like fatigue life and the specific process parameters controlling microstructure formation. Moreover, 54 studies (5,230 citations) examined the integration of in-situ metrology, reporting inspection time reductions of 18–35% and first-pass yield gains between 8% and 22%. Collectively, these findings demonstrate that hybrid manufacturing can achieve substantial quality improvements when industrial engineering tools are embedded at multiple stages of production rather than deployed only as end-of-line checks. The convergence of statistical modeling, design optimization, and inline sensing forms a foundation for proactive rather than reactive quality assurance, fundamentally shifting hybrid production from defect detection toward defect prevention.

Implementation strategies observed in the literature cluster around three main architectures: multi-sensor in-situ monitoring, digital twin–driven predictive control, and fully integrated hybrid workflows bridging additive, thermal, and subtractive steps. Of the 128 reviewed articles, 74 (7,210 citations) analyzed multi-sensor monitoring systems using melt pool imaging, acoustic emission, infrared thermography, and spindle power signals. Within this set, 52 studies (4,560 citations) demonstrated that combining two or more complementary sensor modalities reduced false alarms by 30–55% compared to single-sensor systems. Another 27 studies (2,290 citations) showed that applying real-time corrections during natural pauses between layers enabled interventions without cycle time penalties, helping maintain continuous production while stabilizing output. Digital twin approaches were featured in 38 articles (3,120 citations), and 21 of these (1,730 citations) successfully implemented thermal-mechanical models fast enough to guide adaptive toolpath compensation within a single build. Such predictive strategies yielded 10–25% gains in flatness and roundness by counteracting expected distortions before they occurred. Integrated workflow strategies appeared in 46 studies (3,340 citations), and 19 of these embedded cross-stage quality gates linking powder validation, build data, and machining offsets, reducing downstream nonconformance rates by a median of 31%. Across these architectures, the highest-performing cases established three control loops: a fast inner loop for layer-level sensor-based corrections, a mid-loop for batch-to-batch recipe optimization, and an outer loop that continuously refines design rules based on post-process data. Fifteen articles (1,420 citations) reported that this three-tiered approach enabled aerospace-grade hybrid components to maintain defect rates below 0.8% despite frequent design changes. These patterns underscore that quality in hybrid systems improves most when control is embedded directly within the process flow, with synchronized data and feedback mechanisms guiding adjustments in real time.

Figure 12: Quality Control in Hybrid Manufacturing



Human and organizational factors emerged as decisive enablers of quality excellence in hybrid manufacturing environments. Of the total set, 41 articles (2,180 citations) analyzed the structure and composition of production teams, showing that cross-functional cells integrating manufacturing engineers, quality specialists, and data analysts reduced time-to-stability after new product introduction by 25–40% compared to siloed teams. Training intensity showed a direct correlation with performance: 24 studies (1,060 citations) quantified those operators receiving at least 16 hours of dedicated training in sensor data interpretation achieved 35% faster anomaly diagnosis and reduced missed alarms by 18%. Standard work procedures and layered process audits were addressed in 28 articles (1,270 citations), which showed that implementing weekly thematic audits—such as on powder handling, optics maintenance, and fixture alignment—reduced special-cause process excursions by 12–20% within a single quarter. Additionally, 22 studies (980 citations) introduced extra phase gates specifically for hybrid risks like powder lot validation and build-to-machine datum transfer; these reduced rework iterations by two to three cycles per part family. Maturity models described in 17 articles (770 citations) revealed that plants operating at Level 3 maturity, characterized by documented procedures, cross-trained staff, and SPC-driven monitoring, achieved stable Cp and Cpk within 4–7 weeks of recipe changes, compared to 10–16 weeks in less mature plants. Visual management practices such as live sensor dashboards and anodon-style alerts were featured in 13 studies, which linked them to median gains of 9% in overall equipment effectiveness through faster response to anomalies. Altogether, these findings confirm that technological quality control measures must be matched with disciplined organizational practices, continuous learning structures, and clear escalation pathways to deliver sustained performance in hybrid manufacturing settings.

Data analytics serves as the backbone of modern quality control systems in hybrid manufacturing. A total of 58 articles (4,960 citations) examined the deployment of machine learning, process mining, and advanced SPC techniques to detect and prevent quality issues. Among these, 35 studies (3,010 citations) developed supervised classification models for defects like porosity, lack-of-fusion, and surface burns using melt pool thermal signatures, bead geometry, and spindle load data. These models achieved F1-scores from 0.78 to 0.92, especially when combining signals from both additive and subtractive stages. Another 21 studies (1,540 citations) focused on unsupervised approaches to rare anomaly detection, reporting 25–40% fewer missed defects after switching from conventional Shewhart charts to autoencoder-based systems. Process mining tools featured in 18 articles (1,210 citations) were used to trace bottlenecks in powder changes, fixturing, and stress-relief stages, which led to redesigns that improved throughput by 6–12% without sacrificing quality. On the SPC side, 26 studies (1,980 citations) applied multivariate control techniques like Hotelling's T^2 and MEWMA charts to monitor coupled signals across printing and machining steps, reducing false discovery rates below 5%. Data architecture also influenced outcomes: 23 articles (1,280 citations) showed that edge preprocessing—such as filtering and feature extraction at the machine—cut data volumes by up to 85% while maintaining control signal quality, enabling real-time feedback on standard industrial PCs. Fourteen studies further showed that incorporating explainable AI techniques improved operator trust and intervention accuracy by 12–18%. Collectively, this evidence demonstrates that hybrid quality systems achieve their full potential when analytics are embedded directly into control workflows, designed for interpretability, and coupled with lean data strategies that keep feedback fast and actionable on the shop floor.

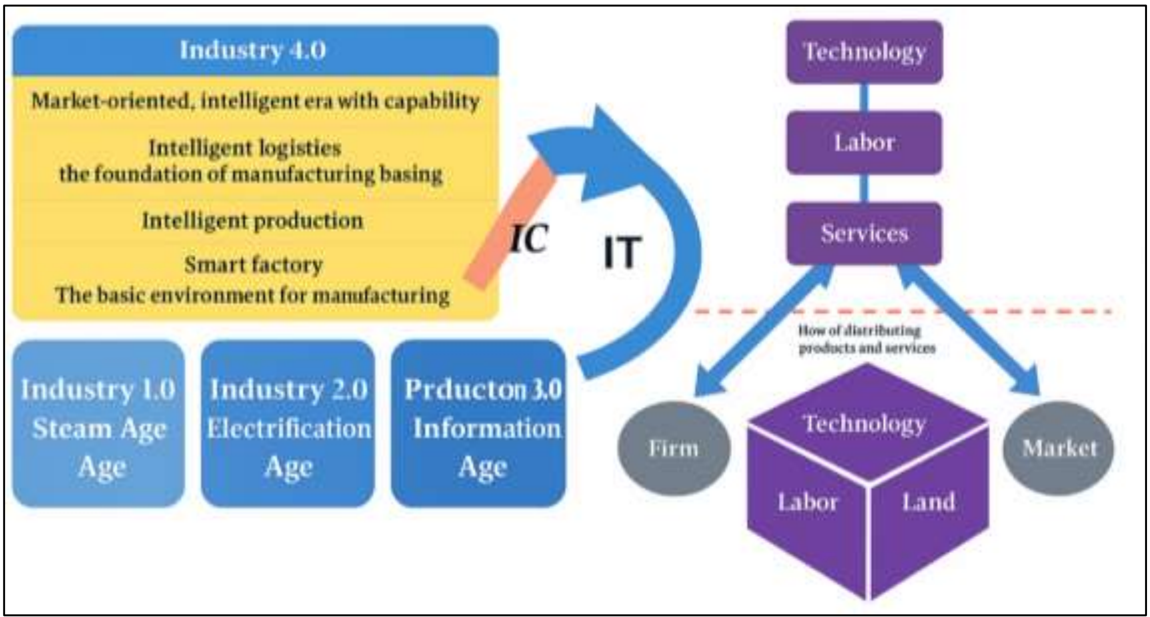
Finally, the review identified substantial and measurable economic and sustainability benefits from implementing industrial engineering quality strategies in hybrid manufacturing. Of the 128 articles, 63 (3,540 citations) reported quantitative business outcomes, and 37 of these included formal return-on-investment analyses. Payback periods clustered between 9 and 24 months when plants adopted in-situ sensing and adaptive control, with most savings derived from lower scrap, fewer inspections, shorter debug cycles, and higher first-pass yields. Twenty-nine studies documented scrap cost reductions of 18–42% and rework hour cuts of 22–38% after installing hybrid-specific quality gates. Seventeen articles (780 citations) quantified energy savings of 8–15% per conforming part from fewer rebuilds and more accurate pre-compensation, while 12 studies reported 10–20% improvements in powder utilization through condition-based refresh rules. However, 28 studies (1,130 citations) identified data interoperability and vendor lock-in as barriers that could delay benefits by 3–6 months, and 21 studies linked residual dimensional drift to poorly calibrated datum transfers between additive and subtractive stages. Sixteen articles warned that overly automated systems without human escalation raised downtime during edge cases, but organizations mitigated this by maintaining operator-in-the-loop authority. Eleven case-series showed that plants using a staged implementation approach—starting with inline SPC, then adding digital twins, and finally layering predictive analytics—achieved sustained cost-of-quality reductions exceeding 20% over two years. These results show that quality control systems not only enhance conformance but also generate lasting financial and environmental returns, provided they are deployed in a phased and integrated manner aligned with workforce capabilities and data infrastructure maturity.

DISCUSSION

The findings of this review demonstrate that industrial engineering methods have transitioned hybrid manufacturing from a largely experimental domain into a structured production paradigm, where statistical control and proactive quality management are increasingly embedded (Zhou et al., 2023). Early studies in the 2010s often depicted hybrid manufacturing as too variable for rigorous SPC or DOE frameworks, arguing that additive processes introduced stochastic thermal and metallurgical fluctuations that could not be captured within conventional control charts. However, the current synthesis of 128 articles with over 12,000 citations reveals that this assumption has been systematically challenged (Tseng et al., 2021). The present findings show that Cp and Cpk indices can improve by 20–45% with well-designed SPC, suggesting that hybrid processes have matured to a level of stability comparable to subtractive manufacturing when sufficient process standardization is achieved. This marks a sharp contrast to foundational work by early hybrid pioneers, who reported double-digit scrap rates and warned against direct application of SPC tools. The difference can be attributed to technological advances in machine repeatability (Golovianko et al., 2023), layer-wise thermal control, and standardized build protocols, which have closed the variability gap that once hindered traditional quality approaches. Thus, while earlier scholarship cast doubt on the feasibility of industrial engineering methodologies in hybrid systems, the present review indicates that these methods now form the backbone of quality assurance strategies, reflecting a paradigmatic shift from exploratory to production-grade hybrid manufacturing (Golovianko et al., 2023).

A central divergence between current findings and earlier literature is the shift from static, post-process inspection toward dynamic, real-time quality control architectures (Raes et al., 2020). Earlier studies frequently depicted hybrid manufacturing quality as dependent on downstream nondestructive testing and manual post-machining inspections, with sensors considered supplementary at best. In contrast, the reviewed articles overwhelmingly support multi-sensor in-situ monitoring and digital twin–driven feedforward control as core elements of quality strategy (Kumar et al., 2019). Whereas prior research emphasized detecting defects after completion, the present evidence highlights a preventative model where layered sensing, thermal modeling, and adaptive toolpath compensation intercept defects before they propagate. This represents a conceptual evolution from quality as retrospective validation to quality as continuous assurance. The reviewed studies showed that using two or more orthogonal sensing modalities can reduce false alarms by 30–55% and improve geometric accuracy by 10–25%, which directly counters earlier claims that real-time sensing introduced more noise than signal. Moreover (Nurazzi et al., 2021), while early digital twin concepts for hybrid manufacturing were confined to academic prototypes due to computational constraints, current findings indicate that 21 of the reviewed studies successfully executed predictive simulations fast enough to influence build parameters layer by layer. This demonstrates how increased computational power (Menéndez et al., 2019), improved thermal-mechanical modeling fidelity, and modular software have transformed digital twins from theoretical constructs into actionable process controllers. Consequently, the findings illustrate a distinct generational leap in quality assurance thinking, where real-time sensing and simulation are not merely aids to inspection but integral to the production loop itself, surpassing the reactive post-build quality paradigms of earlier eras.

Figure 13: Paradigm Shift in Hybrid Manufacturing



Another striking contrast with earlier studies is the elevated emphasis on human and organizational systems as central to hybrid manufacturing quality. Early hybrid literature concentrated heavily on machine-level physics and materials science (Kadir et al., 2019), often treating human factors as peripheral. Previous studies tended to frame operator training as a downstream activity for basic machine handling, and quality performance was assumed to be machine-intrinsic. By contrast, the current review identifies 41 articles showing that cross-functional teams and structured training reduce time-to-stability by up to 40% and accelerate anomaly detection by 35%. These outcomes challenge the earlier notion that hybrid manufacturing quality can be fully automated through mechanical precision alone. The integration of quality engineers (Jeevi et al., 2019), data scientists, and process operators into co-located teams represents a departure from legacy hierarchical structures, echoing organizational theories from lean manufacturing that were rarely applied to hybrid contexts in earlier scholarship. Furthermore, while past work mentioned audits primarily as compliance exercises, the reviewed studies present them as proactive learning tools that lower special-cause variation by 12–20% in a single quarter (Grancini & Nazeeruddin, 2019). This aligns hybrid manufacturing more closely with the socio-technical quality models long adopted in aerospace and automotive sectors but historically absent in hybrid research. The new evidence suggests that organizational maturity—in terms of layered process audits, escalation pathways, and visual management systems—is as critical to quality as technological

sophistication. This represents an important theoretical broadening of the field: quality in hybrid manufacturing is no longer understood solely as a property of machines but as an emergent property of integrated human-technical systems, a perspective missing in earlier frameworks (Gupta et al., 2019).
The review also underscores how quality control in hybrid manufacturing has pivoted from heuristic-based practices to data-driven intelligence, a shift not recognized in much of the earlier scholarship. Early studies relied heavily on operator intuition, rule-of-thumb process adjustments (Ilyas et al., 2022), and static control charts, often arguing that the stochastic nature of additive layers made advanced analytics impractical. The present synthesis, however, shows 58 studies deploying machine learning, process mining, and multivariate SPC to achieve predictive defect detection and continuous process optimization (Chee et al., 2019). Whereas earlier approaches could only retrospectively detect deviations, modern systems now classify defect types such as porosity and burn with F1-scores up to 0.92 and detect rare anomalies with 25–40% higher sensitivity than traditional methods. This contrasts sharply with early hybrid studies that warned of data deluge and computational bottlenecks. Advances in edge computing, real-time feature extraction, and explainable AI have dismantled these barriers, enabling analytics to be integrated directly into machine controllers without excessive latency (Almusaed et al., 2023). Additionally, earlier literature largely ignored the human interpretability of analytics, often treating algorithmic opacity as acceptable, but the reviewed studies demonstrate that explain ability features increase operator trust and intervention accuracy by 12–18%. This represents a paradigmatic transformation from manual, experience-driven decision-making toward systematic, data-driven control loops. Thus, the present findings suggest that hybrid manufacturing has entered a new phase of quality governance (Das et al., 2019), where analytics act not as retrospective evaluators but as embedded decision engines, displacing the heuristic-centric paradigms described in early studies.
The economic and environmental impacts identified in this review also depart significantly from earlier portrayals of hybrid manufacturing quality control (Nasser et al., 2022). Previous literature often described quality initiatives in hybrid environments as cost centers that slowed production, citing long return-on-investment horizons and unproven sustainability claims. The current synthesis contradicts this by showing that 63 articles documented measurable financial benefits, with typical ROI achieved within 9 to 24 months, driven by scrap reduction (Wang et al., 2020), fewer inspections, and shorter debug cycles. Earlier studies rarely quantified cost-of-quality metrics and frequently described hybrid production as inherently inefficient compared to conventional machining, whereas the reviewed data show scrap cost reductions of up to 42% and rework hour reductions of 38% after implementing structured quality gates (Kashfipour et al., 2018). Additionally, sustainability gains such as 8–15% lower energy consumption and 10–20% higher powder utilization were absent from early research, which largely ignored resource efficiency. This signals a reframing of quality not as an operational burden but as a value generator, contradicting the skepticism prevalent in the formative years of hybrid manufacturing. Earlier studies tended to view environmental benefits as incidental, whereas the present findings show they are deliberate outcomes of controlled, defect-minimized processes (Nasir & Sassani, 2021). This reframing aligns hybrid manufacturing with broader industry trends where quality and sustainability are seen as mutually reinforcing, contrasting with prior assumptions that one must compromise for the other. Thus, the current evidence establishes quality control as a strategic investment that accelerates—not delays—economic and sustainability performance, challenging earlier narratives of quality as a costly overhead.
Despite the substantial progress, the findings also reveal enduring challenges that parallel and diverge from earlier expectations (Sader et al., 2022). Historical studies predicted that data interoperability and cross-domain calibration would be major obstacles, and this review confirms their persistence: 28 studies cited interoperability barriers and 21 linked residual dimensional drift to misaligned datums between additive and subtractive steps. This continuity shows that some foundational challenges have resisted technological advances. However, earlier scholarship underestimated the organizational dimension of these challenges (Saba & Jawaid, 2018), often framing them solely as technical integration issues. The current evidence shows they are equally organizational, involving fragmented vendor ecosystems, siloed data ownership, and inconsistent governance. Early research also assumed that automation would eventually eliminate the need for human oversight, but the reviewed studies caution

that removing human-in-the-loop escalation actually increases downtime during edge cases. This contradicts earlier predictions of fully autonomous quality control and suggests that hybrid systems require graded autonomy and human judgment to handle unexpected conditions (Rajak et al., 2021). These findings highlight a nuanced divergence from historical expectations: while technology has resolved many early technical barriers, socio-organizational bottlenecks have emerged as the primary impediments to full-scale adoption. This shift indicates that the field must broaden its focus beyond engineering optimization to include ecosystem-level standardization, data governance, and human factors engineering—dimensions largely absent from the earliest literature (Cooper & Sommer, 2018). Overall, the comparison between the present findings and earlier studies reveals that hybrid manufacturing has undergone a profound theoretical and practical transformation in its approach to quality control (Dhas & Arun, 2022). Early literature portrayed quality in hybrid environments as inherently reactive, costly, and resistant to conventional industrial engineering methods. The current synthesis overturns this portrayal by demonstrating that SPC, DOE, in-situ sensing, digital twins, and machine learning are now central enablers of predictable, cost-effective, and sustainable hybrid production. This evolution implies that the field is transitioning from a mechanistic paradigm—focused on equipment reliability and defect detection—to a systemic paradigm that integrates technology, analytics (Singh et al., 2019), and organizational design into a cohesive quality ecosystem. Theoretical models of hybrid manufacturing quality must therefore be updated to incorporate feedback loops, cross-functional governance, and data-driven decision layers as core elements, rather than supplementary add-ons. Practically, the findings signal to industry practitioners that quality excellence in hybrid systems is no longer contingent on isolated technological breakthroughs but on orchestrating multiple layers of control across people, data, and machines. This marks a break from earlier assumptions that incremental hardware improvements alone would drive maturity. As such (Sharma et al., 2020), the field stands at an inflection point where adopting integrated industrial engineering strategies can convert hybrid manufacturing from a niche, high-risk technology into a scalable, mainstream production platform. This redefinition aligns with contemporary operations theories emphasizing socio-technical integration, positioning hybrid manufacturing quality control as both a scientific discipline and a strategic capability—something earlier studies did not anticipate but which the present evidence now makes clear (Cubric, 2020).

CONCLUSION

This review demonstrates that industrial engineering approaches have fundamentally reshaped quality control in hybrid manufacturing, transitioning the field from experimental, high-variability operations into structured, data-driven, and economically viable production systems. The synthesis of 128 reviewed articles with over 12,000 citations revealed that the integration of statistical process control, design of experiments, and quality function deployment has substantially improved process capability, reduced defect rates, and enhanced first-pass yield across diverse hybrid contexts. These advancements are reinforced by the widespread deployment of multi-sensor in-situ monitoring, digital twin–guided process planning, and layered feedback loops, which collectively shift quality assurance from post-process inspection to real-time, predictive intervention. Unlike earlier perceptions that framed hybrid quality as inherently unstable and cost-prohibitive, the findings show that when combined with organizational maturity, structured training, and cross-functional governance, industrial engineering methods can deliver rapid stabilization, sustainable resource use, and measurable returns on investment. Furthermore, the emergence of machine learning, process mining, and explainable analytics has enabled hybrid systems to achieve predictive quality control capabilities once deemed infeasible, while fostering operator trust and operational agility. Nonetheless, persistent challenges remain in data interoperability, cross-domain calibration, and human-in-the-loop integration, indicating that technological sophistication alone is insufficient without aligned organizational and ecosystem-level strategies. Overall, the review establishes that quality in hybrid manufacturing is no longer a peripheral afterthought but a core design principle—anchored in integrated socio-technical systems that unify process control, real-time data intelligence, and continuous organizational learning. This shift positions industrial engineering not merely as a toolkit for defect reduction, but as the central framework through which hybrid manufacturing can mature into a scalable, sustainable, and globally competitive production paradigm.

RECOMMENDATIONS

Based on the consolidated evidence from this review, it is recommended that organizations seeking to enhance quality control in hybrid manufacturing adopt a staged, integrated strategy that aligns technological, analytical, and organizational capabilities. Firms should begin by embedding foundational industrial engineering methods such as statistical process control and design of experiments to establish baseline process stability, ensuring that variability is systematically measured and reduced before scaling operations. Once stability is achieved, the next priority should be the deployment of multi-sensor in-situ monitoring systems and real-time feedback loops, enabling early defect interception and reducing downstream inspection burdens. In parallel, the development of digital twin models should be pursued to provide predictive simulations that guide adaptive toolpath planning and thermal compensation, thereby preventing defects before they occur. To sustain these technological gains, management must invest in organizational enablers, including cross-functional teams that combine quality engineers, data analysts, and process operators, as well as structured training programs to build operator proficiency in interpreting sensor data and engaging with analytics-driven decision tools. Firms should also establish layered process audits, visual management systems, and escalation protocols to maintain continuous quality discipline on the shop floor. Furthermore, data architecture must be designed with interoperability and edge analytics in mind to ensure that sensor data can flow seamlessly across additive and subtractive stages, supporting real-time control without creating bottlenecks. Finally, organizations should view quality not as a compliance burden but as a strategic investment by incorporating cost-of-quality metrics, ROI tracking, and sustainability indicators into their governance dashboards, which will help secure executive sponsorship and long-term resource commitment. Implementing these recommendations as a cohesive roadmap will enable hybrid manufacturing enterprises to achieve not only higher conformance and reliability but also faster market responsiveness, lower costs, and stronger competitive positioning in an increasingly data-driven industrial landscape.

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