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SMART HYBRID MANUFACTURING: A COMBINATION OF ADDITIVE, SUBTRACTIVE, AND LEAN TECHNIQUES FOR AGILE PRODUCTION SYSTEMS

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Abstract

Smart Hybrid Manufacturing (SHM) – the coordinated integration of additive, subtractive, lean, and smart control capabilities – has emerged as a central pathway for enabling responsive, high-quality, and resource-efficient production in modern manufacturing systems. Yet, empirical evidence explaining how these multidimensional capability foundations contribute to productivity, quality, efficiency, and agility remains limited. This study addresses this gap by developing and testing a comprehensive capability–performance model using data from a heterogeneous sample of industrial plants and hybrid manufacturing cells operating across multiple sectors, complexity classes, and volatility conditions. The research examines how additive and subtractive process maturity, lean–smart integration governance, and cyber-physical smart control jointly shape agile production system performance (APSP), while also assessing the mediating role of smart control capability and the moderating role of lean maturity. Additional multi-group comparisons evaluate whether SHM performance impacts differ across hybridization architectures and environmental turbulence. Measurement model evaluation demonstrated strong psychometric robustness. All constructs achieved acceptable levels of internal consistency (Cronbach's a ≥ 0.85; CR ≥ 0.90), convergent validity (AVE ≥ 0.70), and discriminant validity across Fornell–Larcker, HTMT, and CFA criteria. The overall measurement structure supported a multidimensional representation of SHM capability, as well as second-order factors for SHM Capability (SHMC) and Agile Production System Performance (APSP). Model fit indices (CFI = 0.957; TLI = 0.948; RMSEA = 0.045; SRMR = 0.037) indicated strong alignment between data and the hypothesized measurement structure. Structural equation modeling results provided strong support for the hypothesized relationships. SHM Capability exhibited a significant and substantial effect on APSP (β = 0.62), explaining more than half of the observed variance in agile system performance. Each SHM sub-dimension demonstrated its expected directional relationship with specific performance outcomes: additive maturity predicted agility, subtractive finishing predicted quality, and lean–smart integration predicted productivity and efficiency. Smart Control Maturity partially mediated the SHM → quality relationship, confirming that in-situ sensing and closed-loop correction serve as essential mechanisms for enabling conformance and reducing variability. Lean maturity significantly moderated the SHM → productivity and SHM → agility relationships, indicating that SHM benefits are amplified under strong pull-flow discipline and structured continuous improvement.

Keywords
Smart Hybrid Manufacturing; Additive–Subtractive Integration; Lean Agility; Cyber-Physical Control; Production Performance.

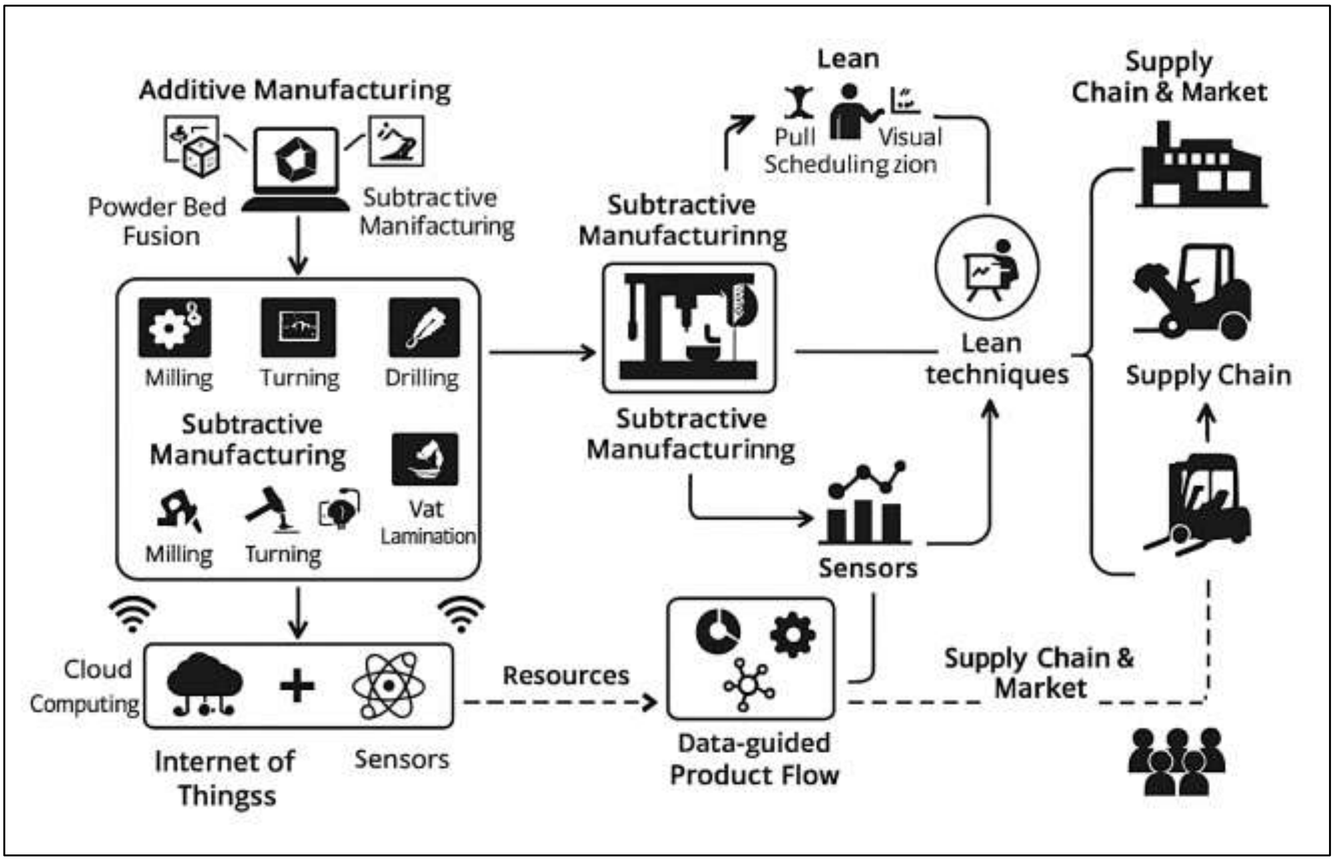
INTRODUCTION

Smart hybrid manufacturing can be defined as an integrated production approach in which additive manufacturing, subtractive manufacturing, and lean operational methods are digitally and physically combined to create agile, high-quality, and resource-efficient production systems. Additive manufacturing refers to processes that build parts layer by layer directly from a digital model, using metals, polymers, ceramics, or composites (Hertwig et al., 2018). This family includes powder bed fusion, directed energy deposition, binder jetting, material extrusion, vat photopolymerization, and sheet lamination, each characterized by controlled deposition or solidification of feedstock into near-net shapes. Subtractive manufacturing refers to material removal methods such as milling, turning, drilling, grinding, electrical discharge machining, and multi-axis CNC finishing, where geometry is achieved through toolpath-driven cutting or erosion. Lean manufacturing describes a systematic philosophy of value creation that removes non-value-adding activities through flow orientation, pull scheduling, standardized work, visual management, continuous improvement routines, and respect for worker knowledge . Smart hybrid manufacturing connects these three domains through cyber-physical infrastructure, meaning that sensors, machine connectivity, data analytics, and digital models guide deposition, machining, inspection, and scheduling as one coordinated system (Raji et al., 2021). In operational terms, the "hybrid" aspect is not only the use of multiple process types but the intentional distribution of features to the most suitable process, often within one setup or a tightly coupled cell. The "smart" aspect indicates that decisions about process choice, parameter selection, sequence planning, and quality verification are supported by real-time data and model-based reasoning rather than fixed recipes alone. The global significance of this definition is tied to the nature of modern demand and supply. International manufacturing faces shorter product cycles, high variation in order quantities, regional customization requirements, and stricter expectations for certified performance. These factors amplify the cost of long changeover times, excess inventory, and late defect discovery (Abdulla & Ibne, 2021; Cocchi et al., 2021).

Smart hybrid manufacturing responds to these realities by allowing complex forms to be produced with minimal tooling, precision targets to be met through in-process finishing, and waste to be systematically reduced through lean discipline. It is therefore understood as a technology-enabled operational capability that aligns production physics with agile and waste-sensitive value delivery across internationally distributed markets and regulated industries. The logic for combining additive and subtractive processes is grounded in their complementary strengths and limitations observed across many empirical and analytical investigations (Venugopal & Saleeshya, 2019). Additive processes create geometries that are difficult or impossible for cutting tools to access, including internal channels, lattice structures, conformal cooling paths, and multifunctional topologies that merge assemblies into single parts. Additive routes also reduce buy-to-fly ratios by placing material only where it is needed, which decreases scrap generation when compared with conventional machining of complex forms. At the same time, additive builds commonly display surface roughness, stair-step effects, dimensional drift, porosity, and thermal distortion, especially for metallic systems where melt-pool dynamics and residual stress accumulation interact with scan strategy and heat dissipation. Subtractive processes deliver superior surface integrity, tight dimensional control, and established qualification pathways for fatigue-critical and safety-critical applications. Yet subtractive methods are constrained by tool reach, high setup effort for complex fixturing, and significant material loss when starting from stock blocks (Sommer, 2019).

Hybrid manufacturing distributes work so that additive stages create the near-net form and internal complexity, while subtractive stages remove minimal allowances to achieve final tolerances and functional surfaces. Many controlled process comparisons report that this interleaving reduces total cycle time for complex parts relative to sequential routing through separate additive and machining departments. The reduction is explained by fewer re-clamp events, fewer datum shifts, and elimination of transport and queue delays between shops. Studies in multi-axis hybrid machines further show that alternating deposition and milling within one coordinate system improves geometric fidelity because deviations can be corrected early rather than propagating across layers. Feature-based planning models show that hybrid viability increases when a part contains both additive-advantaged features and precision interfaces, a pattern common in aerospace brackets, tooling inserts, turbine repair, biomedical implants, and lightweight lattice-reinforced structures. Quantitative examinations of machining allowance optimization indicate that too much excess material erodes the economic advantage of additive stages, while too little allowance raises finishing risk (Habibullah & Foysal, 2021; Shams et al., 2021). As a result, hybrid systems are described as precision-guided additive fabrication, where subtractive finishing is not a fallback but a designed-in stage that secures performance targets with less waste than full-block machining.

Figure 1: Smart Hybrid Manufacturing Agile Framework

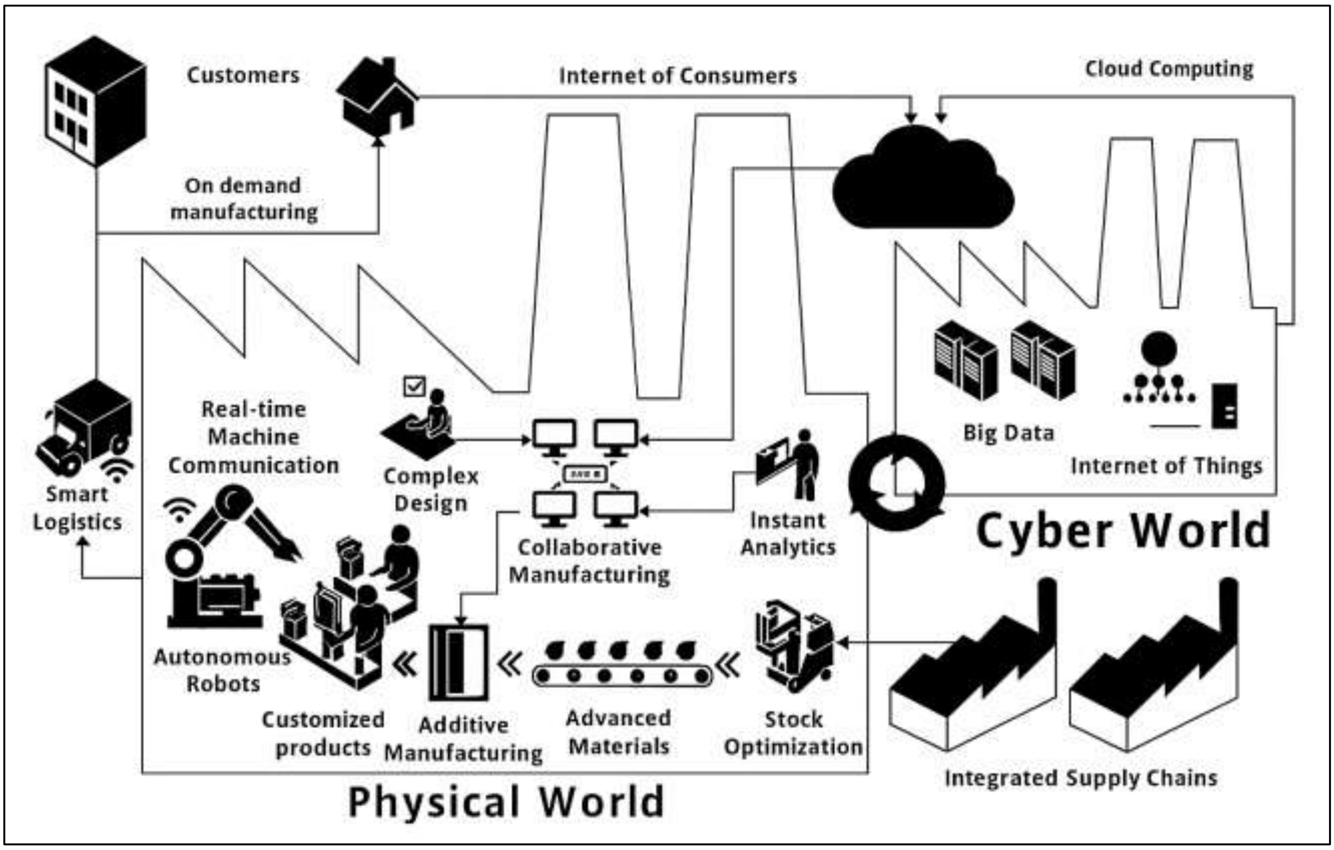


Lean techniques provide the operational backbone through which hybrid technology becomes agile rather than merely complex (Li et al., 2020; Sarwar, 2021). Lean begins with value specification from the customer viewpoint and maps all activities needed to deliver that value. Any activity that does not transform the product in ways the customer demands is categorized as waste. In hybrid environments, waste sources arise not only from classical shop-floor issues such as waiting or motion but also from digital and process-physics sources such as redundant data transfers, parameter trial loops, re-qualification cycles, and over-finishing of features already adequate at the additive stage (Musfiqur & Saba, 2021; Redwanul et al., 2021). Lean tools such as value stream mapping, takt-aligned flow design, single-minute exchange of dies, and standardized work are adapted to the hybrid context to stabilize scheduling around small batch sizes and frequent design variation. Empirical work in high-mix manufacturing consistently links pull-based control and cellular layouts to shorter lead time and lower work-in-process (Fagarasan et al., 2022; Tarek & Praveen, 2021). Hybrid cells naturally support these outcomes because additive and subtractive steps are co-located, so flow can be organized around part families rather than departmental specialization. In addition, additive fabrication reduces dependence on dedicated tooling, which aligns with lean changeover reduction goals by turning many setup actions into software-level recipe changes (Muhammad & Shahrin, 2021; Saikat, 2021). Lean also emphasizes right-first-time quality, which becomes critical for additive stages where rework is expensive and can cascade into finishing delays. Visual management in hybrid shops extends beyond physical boards into digital dashboards that display machine health, deposition stability indicators, queue status, and deviation alerts. Continuous improvement routines use these signals to target causes of scrap, idle time, and energy spikes, translating kaizen into data-driven corrective action (Fischer et al., 2020; Amin, 2022; Shaikh & Aditya, 2021). Lean human-systems principles are equally important because hybrid workflows require coordination among design engineers, additive specialists, machinists, metrology staff, and planners. Cross-training and problem-solving culture reduce handoff friction and promote rapid containment of variation (Ariful, 2022; Nahid, 2022). Lean thereby acts as the discipline that keeps hybrid technology aligned with speed, quality, and cost targets under fluctuating demand, enabling agility through waste control rather than through excess capacity (Hossain & Milon, 2022; Mominul et al., 2022).

The "smart" layer of smart hybrid manufacturing refers to cyber-physical integration that closes the loop between digital intent and physical execution. Smart production systems connect machines, sensors, operators, and planning software through a common data architecture so that decisions reflect real operating conditions. In hybrid manufacturing, this begins with a single source of geometric truth, often a parametric digital model that includes functional surfaces, additive build regions, machining allowances, and inspection targets (Ciano et al., 2019; Rabiul & Praveen, 2022; Rakibul & Samia, 2022). Process planning software decomposes this model into feature sets and assigns each feature to additive-dominant, subtractive-dominant, or hybrid-required process segments. Sensor suites on hybrid machines monitor melt-pool intensity, layer height, acoustic emission, spindle vibration, cutting force, temperature fields, and position feedback (Saikat, 2022; Kanti & Shaikat, 2022). These data streams support in-situ detection of common additive defects such as lack-of-fusion zones or over-heating bands, and common machining issues such as chatter or tool wear. Smart control uses this information for adaptive parameter adjustment, meaning scan speed, powder feed, laser power, toolpath overlap, or cutting feeds are modified in response to observed deviation (Maniruzzaman et al., 2023; Arif Uz & Elmoon, 2023). Digital twins deepen this capability by synchronizing physics-based simulation with live sensor data, allowing prediction of distortion, residual stress, or surface deviation before a part is fully completed (Shahrin & Samia, 2023; Muhammad & Redwanul, 2023; Sobb et al., 2020). When such predictions are connected to the hybrid execution stage, corrective machining or compensatory deposition can be scheduled at the earliest viable point. Smart quality systems also integrate coordinate measurement, optical scanning, and computed tomography into the hybrid flow, producing traceable quality records tied to each layer and tool pass (Tarek, 2023; Mushfequr & Ashraful, 2023). This traceability matters in international production networks where compliance is checked across borders and supply tiers. Smart scheduling uses real-time capacity visibility to allocate jobs through additive and subtractive resources with minimal queueing, supporting lean pull signals and agile responsiveness. The smart layer thus functions as the nervous system of hybrid manufacturing, making the integration active and adaptive rather than static and manual (Azevedo & Almeida, 2021; Muhammad & Redwanul, 2023; Razia, 2023).

Agile production systems are characterized by rapid responsiveness to changes in volume, mix, and specification while sustaining cost efficiency and consistent quality. Agility is not only speed but the stable ability to reconfigure processes with minimal penalty (Balkhi et al., 2022). Hybrid manufacturing supports agility through several measurable mechanisms observed across diverse industrial studies. First, additive steps eliminate many tool-dependent constraints, allowing new designs to enter production without the long lead times associated with molds, dies, or complex fixtures. Second, subtractive finishing ensures that functional tolerances are met even when additive builds vary slightly, which reduces the risk that agility reduces reliability. Third, the hybrid machine or hybrid cell structure reduces routing complexity, which lowers the administrative and physical delays associated with cross-departmental transfers. Agile systems also rely on modularity in both product and process (Zayadul, 2023). Feature-based hybrid planning promotes process modularity because each feature can be linked to a repeatable additive or subtractive module. This modularity supports rapid rescheduling and parallelization when order patterns shift (Almoslehy & Alkahtani, 2021; Tarek & Kamrul, 2024). Another agile enabler is postponement, where product differentiation occurs late in the flow. Hybrid systems accomplish postponement by producing standardized near-net cores additively and executing final machining, surface texturing, or hole patterns only when customer-specific orders are confirmed. Quantitative analyses of high-mix manufacturing show that postponement reduces inventory exposure and improves service level under demand variability. Hybrid manufacturing also enhances agility in repair and remanufacturing contexts where parts arrive with uncertain damage patterns. Additive restoration builds material only where needed, and subtractive finishing restores geometry within the same coordinated setup, enabling rapid turnaround and consistent reuse quality (Chatwani, 2019). Internationally, these agility mechanisms are valuable because supply chains are global, disruption probabilities are high, and markets demand differentiated products within short windows. Smart hybrid manufacturing is thus positioned as an agile capability rooted in physical process complementarity, lean flow discipline, and smart adaptation.

Figure 2: Cyber-Physical Smart Manufacturing Framework



Sustainability and resource efficiency are embedded in the global relevance of smart hybrid manufacturing because international industries face formal environmental targets and rising costs of energy and critical materials. Additive manufacturing is widely associated with improved material efficiency and design-enabled lightweighting, which reduce waste during production and can lower energy use during a product's service life (Sobb et al., 2020). Subtractive manufacturing remains essential for precision but often involves higher scrap ratios for complex parts, as large volumes of stock are removed to reach final geometry. Hybridization balances these profiles by allocating bulk shape creation to additive stages and reserving subtractive passes for surfaces and interfaces that require them, reducing overall material removal. Many life-cycle assessments of additive and hybrid routes report that energy and emissions benefits depend strongly on process selection, build strategy, and yield. Lean methods amplify sustainability by attacking root causes of defects, over-processing, and idle energy consumption. When lean is combined with smart sensing, energy peaks can be associated with specific parameter conditions, enabling targeted improvement rather than broad restrictions (Tasdemir & Gazo, 2018). Hybrid repair chains also support circular economy goals by extending component life and reducing the need for long-distance replacement logistics. This is significant for sectors such as aviation, power generation, mining, and marine transport where high-value parts are globally distributed and downtime is costly. The sustainability logic is also tied to reduced inventory and transport waste. Because hybrid systems allow localized, small-batch production, they reduce dependence on shipping pre-made spares across borders and holding large safety stocks. Lean pull scheduling ensures that production aligns closely with actual consumption, which decreases obsolescence risk for customized or fast-changing products (Jovanović et al., 2020). Smart traceability further supports responsible sourcing and reporting by tying material batches and process conditions to each part. In aggregate, smart hybrid manufacturing aligns physical efficiency, operational waste reduction, and compliance-friendly documentation in a way that matches international expectations for low-waste and low-risk production.

From a quantitative research perspective, smart hybrid manufacturing is examined through performance variables that capture productivity, quality, cost, flexibility, and flow (Ragazou et al., 2022). Common measurable outcomes include total cycle time, proportion of value-adding time, dimensional accuracy, surface roughness, defect rate, rework frequency, energy per part, material utilization ratio, and agility indices derived from responsiveness or schedule adherence. Comparative experiments across additive-only, subtractive-only, and hybrid routes frequently show that hybrid processes achieve near-additive geometric freedom with machining-level tolerances where necessary. Statistical process control applied to hybrid builds indicates lower variance in critical dimensions when in-process finishing corrects layer-wise drift. Optimization studies quantify improvements from feature-level process assignment and sequence planning, often demonstrating reductions in alternation count, tool changes, or thermal cycles that translate into shorter makespan and higher machine utilization (Atwal, 2020). Digital twin trials measure improvements in first-pass yield when predictive correction is activated during deposition or before finishing. Lean measurement frameworks contribute validated constructs for waste elimination, flow stability, and pull maturity, enabling integrated models where hybrid technology variables are tested alongside lean and agility variables. In such models, additive-subtractive integration typically functions as a technological flexibility driver, lean functions as a flow and cost discipline driver, and smart control functions as a stability and quality driver. The combined effect is expressed as agile production capability that can be empirically evaluated using multivariate methods, structural equation models, or hierarchical regression linking integration maturity to operational performance (Nordmark et al., 2022). This quantitative framing supports a rigorous understanding of smart hybrid manufacturing as a multi-dimensional system where process physics, operational philosophy, and cyber-physical intelligence jointly shape measurable outcomes in agile manufacturing contexts.

The objectives of this quantitative study on Smart Hybrid Manufacturing are structured to measure how the integrated use of additive manufacturing, subtractive manufacturing, and lean techniques functions as a unified agile production system and how strongly this integration predicts operational performance. First, the study aims to operationalize "smart hybrid manufacturing integration" as a measurable construct by defining and validating indicators such as degree of additive–subtractive process coupling, extent of in-situ monitoring and closed-loop control, level of digital process planning, and depth of lean deployment across hybrid cells. Second, it seeks to quantify the individual and combined effects of additive capability, subtractive finishing capability, and lean practice maturity on core agility outcomes, including responsiveness to demand change, product mix flexibility, lead-time compression, schedule adherence, and rapid customization capacity. Third, the study intends to test whether smart cyber-physical control mediates the relationship between hybrid process integration and quality performance, using indicators such as dimensional conformance rates, surface integrity attainment, defect frequency, and first-pass yield. Fourth, the research aims to examine the effect of lean flow discipline within hybrid environments on waste-related outcomes, such as material utilization ratio, rework time share, work-in-process levels, and energy per produced unit, thereby determining whether lean strengthens the efficiency advantage of hybridization. Fifth, the study intends to compare performance across different hybridization modes—single-machine additive–subtractive platforms versus multi-machine hybrid cells—to identify which configuration yields higher agility and cost efficiency under high-mix or volatile order patterns. Sixth, it seeks to develop and statistically validate a predictive model linking integration maturity to performance, enabling estimation of the magnitude of improvement associated with incremental gains in hybrid–lean–smart capability. Finally, the study aims to produce an empirical baseline of current hybrid manufacturing adoption levels and performance outcomes across relevant industries, supporting reliable benchmarking and enabling robust cross-context comparison. Collectively, these objectives position the study to deliver a measurement-driven explanation of how smart hybrid manufacturing operates, which elements contribute most to agility, and what quantifiable performance gains organizations can expect when additive, subtractive, and lean techniques are combined into a coordinated, data-guided production system.

LITERATURE REVIEW

The literature on Smart Hybrid Manufacturing (SHM) has expanded rapidly as industries pursue production systems that are simultaneously flexible, precise, and waste-minimal. SHM is commonly positioned at the intersection of three mature but historically separate domains: additive manufacturing for complexity and rapid form generation, subtractive manufacturing for dimensional precision and surface integrity, and lean manufacturing for flow efficiency and systematic waste reduction (Yang et al., 2020). When these domains are fused into a single operational architecture, the resulting hybrid system is not merely a technological combination but a measurable production capability that can be evaluated through productivity, quality, agility, and sustainability metrics. For a quantitative study, the literature review must therefore clarify how SHM has been conceptualized, how its core elements have been operationalized as variables, and what empirical evidence exists regarding their effects on agile production outcomes. This section synthesizes research across hybrid additive–subtractive process integration, cyber-physical "smart" control for real-time stability, and lean bundles that enable pull, flow, and continuous improvement within high-mix environments (Zheng et al., 2018). The review also highlights recurring measurement approaches—cycle time decomposition, defect and rework ratios, process capability indices, energy/material efficiency indicators, and validated lean-agility scales—that allow SHM to be modeled statistically. By organizing prior findings into coherent thematic streams and mapping them to quantifiable constructs, the review establishes the theoretical and empirical base required to justify the study variables, hypotheses, and analytical framework (Rojas & Rauch, 2019). In doing so, it positions SHM as a multi-dimensional agile manufacturing system whose performance effects depend on the intensity of additive–subtractive coupling, the maturity of smart monitoring and control, and the depth of lean deployment across the hybrid value stream.

Smart Hybrid Manufacturing

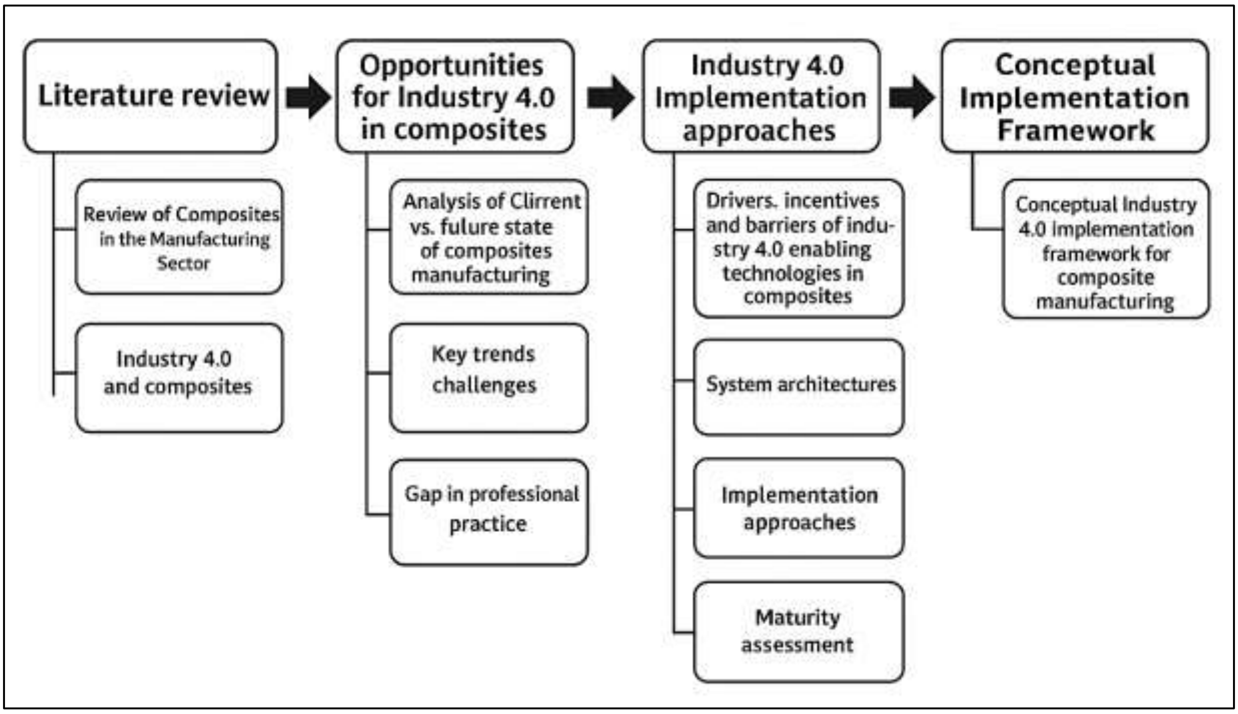
Smart Hybrid Manufacturing is grounded in the conceptual stream of hybrid additive–subtractive manufacturing, which positions "hybrid" as an intentional process-level integration rather than a simple co-location of different machines (Moradi et al., 2019). Across foundational and contemporary studies on hybrid manufacturing, the central idea is that additive manufacturing and subtractive manufacturing are combined in a coordinated sequence so that each process handles the features it performs best. Additive manufacturing contributes near-net shaping, geometric freedom, internal channels, and multifunctional structures, while subtractive manufacturing provides tight tolerances, predictable surface integrity, and certified functional interfaces. The literature consistently distinguishes three dominant integration forms (Yao et al., 2019). The first is the sequential hybrid chain in which a part is produced additively and then transferred for subtractive finishing; this approach is widely documented in industrial case studies because it leverages existing additive platforms with downstream CNC resources. The second is the interleaved chain where additive and subtractive steps alternate within the same build, enabling early correction of layer-level deviations and reducing the risk of cumulative error. The third form is the single-platform hybrid machine or tightly coupled hybrid cell, where both deposition and machining occur under one coordinate system or within one synchronized work zone, avoiding repeated re-fixturing. A large body of work reports that the defining value of hybridization is not abstract synergy but measurable improvements in workflow stability, precision attainment, and part feasibility. Researchers commonly treat hybridization intensity as a quantitative property, observing how much of a part is deposited additively, how often additive steps are interrupted for machining, and how strongly hybridization reduces setup events through single-clamp production (Sajadieh et al., 2022). These conceptual distinctions provide a clear theoretical boundary: hybrid manufacturing is a structured coupling that redistributes work between additive and subtractive physics to optimize system outcomes, rather than a parallel existence of separate processes. The literature also emphasizes that hybridization changes the role of process planning from a single-route decision to a feature-level allocation problem, where the geometry is decomposed into additive-preferred regions, subtractive-preferred regions, and hybrid-required interfaces. In that sense, hybrid additive–subtractive manufacturing is best understood as a design-to-process logic in which manufacturability is negotiated through coordinated deposition and removal, producing a system that can be empirically assessed through its integration architecture and its measurable effects on production performance (Lattanzi et al., 2021).

The second conceptual foundation of Smart Hybrid Manufacturing appears in studies that frame hybrid systems as smart, cyber-physical manufacturing environments rather than purely mechanical integrations. In this stream, "smart" denotes that decisions about deposition, machining, inspection, and scheduling are data-guided, adaptive, and continuously corrected through real-time feedback. The literature on smart manufacturing highlights that hybrid platforms generate two distinct but complementary uncertainty profiles: additive stages exhibit thermal instability, melt-pool fluctuation, porosity risk, and layer height drift, while subtractive stages face tool wear, chatter, geometric spring-back, and surface damage risk (Bi et al., 2021). Smart hybrid systems therefore embed sensing and monitoring across both modes. For additive stages, in-situ monitoring examines melt-pool energy signatures, layer thickness variance, thermal gradients, and surface topology to detect defects while they emerge. For subtractive stages, sensors track spindle vibration, cutting forces, acoustic emission, and tool-edge condition to stabilize finishing accuracy. The smart layer integrates these signals into closed-loop control routines that adjust scan speed, feed rate, laser power, cooling strategy, or cutting parameters to keep the process within target windows. Many experimental and simulation-driven studies describe hybrid smartness as a measurable capability defined by how reliably the system detects anomalies, how fast corrections are enacted, and how closely the final geometry matches model intent after adaptive control (Nagadi et al., 2018). Within this evidence base, defect-recognition systems are treated not as qualitative enhancements but as quantifiable predictors of yield and variability reduction. Digital twins occupy a prominent role in the smart conceptualization: they synchronize sensor data with predictive models so that distortion, residual stress, or dimensional drift can be estimated before they cause irreversible failure. The literature also treats smart hybrid manufacturing as a traceable production system where each layer, toolpath, and corrective action is logged into a digital thread, enabling verification and certification. In these studies, smartness is viewed as the nervous system that makes hybridization stable and repeatable under high complexity, rather than a decorative add-on. By embedding cyber-physical feedback into both additive and subtractive regimes, Smart Hybrid Manufacturing becomes a unified controllable process capable of maintaining consistent quality across changing conditions. The conceptual consensus across smart-hybrid research is that data-guided monitoring and adaptive correction are essential to transform hybrid equipment into an agile production system that produces reliable outcomes without excessive trial builds or downstream inspection waste (Kusiak, 2019).

The third definitional stream synthesizes lean manufacturing into the hybrid environment, treating lean not as a separate improvement program but as flow discipline that enables hybrid technologies to operate as agile value streams (Kusiak, 2018). Lean scholarship emphasizes that production performance improves when waste is systematically removed and value-adding activities are intensified. In hybrid manufacturing, waste arises in both physical and digital forms, and the literature demonstrates that lean principles provide a structured way to address these wastes. Physical wastes include excess material deposition requiring heavy finishing, repeated clamping and transport between additive and subtractive stations, idle time created by unbalanced cycle segments, and defect-driven rework. Digital wastes include repeated parameter trials, redundant simulations, fragmented data transfer across planning tools, and slow deviation-response loops. Lean studies in advanced manufacturing show that pull scheduling helps align additive build releases with actual downstream demand, preventing overproduction and large queues in front of finishing resources. Flow orientation, especially cellular hybrid layouts, reduces waiting and part travel, which is repeatedly shown to compress total lead time in high-mix contexts (Qu et al., 2019). Total quality management routines interact with hybridization by promoting right-first-time builds, early defect containment, and root-cause elimination of parameter drift. Total productive maintenance is also emphasized because hybrid machines combine thermal deposition subsystems and high-speed machining subsystems, making uptime stability critical. Standardized work is translated into digital work instructions and parameter libraries so that hybrid part families can be produced with consistent routings and minimal variation.

Kaizen culture appears as an operational necessity because hybrid workflows evolve through frequent design and parameter updates, demanding structured daily improvement rather than episodic projects. Empirical lean–hybrid studies repeatedly connect these lean bundles to measurable outcomes such as reduced work-in-process, lower rework share, improved first-pass yield, and higher value-added time ratios. Lean is therefore conceptualized as the operational architecture that stabilizes hybrid complexity into repeatable flow (Q. Li et al., 2018). The literature treats lean maturity as a measurable moderating force that strengthens the productivity and agility benefits of hybrid processes, demonstrating that the performance of additive–subtractive integration depends not only on machine capability but also on flow governance and waste control across the hybrid chain.

Figure 3: Industry 4.0 Implementation Pathway Framework



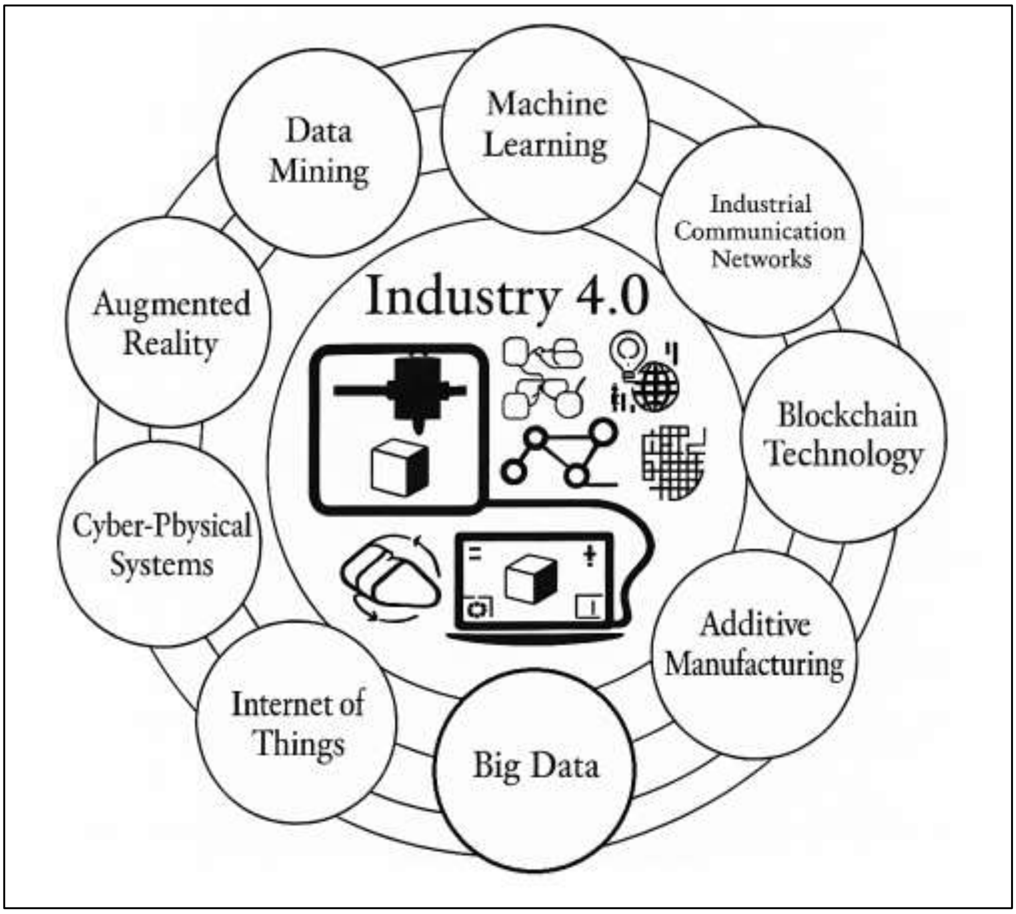
Taken together, these three conceptual streams align to form the integrated meaning of Smart Hybrid Manufacturing: an agile production system created through deliberate additive–subtractive coupling, regulated by cyber-physical smart control, and stabilized by lean flow discipline. The literature indicates that Smart Hybrid Manufacturing is not a single technology but a multi-dimensional construct that can be assessed through observable attributes of integration intensity, monitoring/adaptation maturity, and lean deployment depth (Moghaddam et al., 2018). Hybrid integration defines where value is created physically by assigning near-net shaping to additive stages and precision conformity to subtractive stages, either sequentially or interleaved under coordinated fixturing. Smart control defines how value is preserved and protected by detecting deviations in real time, predicting their effects through model-sensor coupling, and applying corrective action before defects propagate. Lean defines how value flows efficiently by preventing overproduction, reducing queues, shortening handoffs, controlling variation, and sustaining continuous improvement in daily operations. The cross-study synthesis shows convergence on the idea that agility in hybrid systems is expressed through measurable improvements in lead time compression, mix flexibility, schedule adherence, and quality attainment under variable demand (Parhi et al., 2021). At the same time, the literature recognizes that these gains are not automatic; they depend on how tightly additive and subtractive steps are coordinated, how effectively monitoring translates into fast corrections, and how rigorously lean practices remove waste from both physical and digital layers of the workflow. This integrated conceptual base supports a quantitative research framing where Smart Hybrid Manufacturing can be modeled as a composite production capability with distinct sub-dimensions, each contributing to operational agility and efficiency (Andronie et al., 2021). The conceptual foundations documented across more than a decade of hybrid, smart manufacturing, additive, machining, and lean performance studies thus establish Smart Hybrid Manufacturing as a coherent, measurable, and system-level manufacturing paradigm rather than a loose collection of tools.

Additive Manufacturing as a Quantitative Agility Driver

Additive manufacturing is repeatedly framed in the literature as a primary quantitative driver of agility because it converts digital design variation into physical production with unusually low penalties for complexity. Across process families such as powder bed fusion, directed energy deposition, binder jetting, vat photopolymerization, and material extrusion, the layerwise logic allows engineers to fabricate internal channels, lattice cores, conformal cooling paths, and freeform topologies that would require multi-stage tooling or may be infeasible under conventional cutting constraints (Priyadarshini et al., 2022). This capability directly supports part consolidation, where assemblies with multiple fasteners and interfaces are redesigned into fewer monolithic structures. Empirical studies on aerospace brackets, heat exchangers, orthopedic implants, and tooling inserts consistently measure that consolidation reduces component count, eliminates joining operations, and compresses overall routing time. Quantitative research has developed several ways to capture this agility value. A common approach is the estimation of geometric complexity using indices derived from feature density, curvature variation, internal void proportion, and tool-inaccessibility scores, with additive routes routinely demonstrating higher feasible complexity thresholds than subtractive routes. Another measurable benefit appears in design-to-build time reduction (Iqbal et al., 2020). In multiple industrial case programs, additive manufacturing shortens time between final CAD release and first physical part by removing mold design, fixture machining, and multi-setup programming, and by enabling rapid iteration through parameter reuse and digital handoffs. These effects are measured by comparing front-end engineering time, setup time, and total lead time across additive and conventional chains, typically revealing substantial percentage reductions under high-mix conditions. Tooling cost avoidance is also quantified in the literature through direct cost accounting of dies, molds, jigs, and fixtures that become unnecessary when additive routes are used for short runs or highly customized products. Studies in medical and industrial spare-part contexts further show that additive manufacturing enables "virtual inventory," replacing stocked physical items with on-demand builds, which reduces inventory holding costs and improves responsiveness when demand is uncertain (Gunasekaran et al., 2019). In this way, additive manufacturing contributes not only a technical advantage but a measurable agility mechanism, since the system can accept design changes late, switch between product variants quickly, and economically justify small-batch production without absorbing traditional setup burdens.

Despite these quantitative agility advantages, additive manufacturing literature also documents a set of process limitations that motivate the necessity of Smart Hybrid Manufacturing rather than additive-only production. A large body of empirical work reports that additive processes, especially metal-based routes, can exhibit surface roughness levels that exceed functional requirements for sealing, sliding, or fatigue-critical interfaces. Roughness is normally quantified through average roughness and peak-to-valley measures, and these values are shown to vary significantly with orientation, layer thickness, scan strategy, and thermal history (Hsu et al., 2022). Dimensional scatter is another widely observed constraint. Layerwise builds can drift from nominal geometry because of heat accumulation, recoater disturbances, material shrinkage during solidification, or powder–laser interaction instability. Studies quantify this drift via deviation distributions across critical dimensions and by reporting process repeatability variance across builds. Porosity remains a central concern in many alloys and polymer systems. Porosity fraction is measured through density methods, microscopy, or volumetric scanning, and evidence indicates that even small porosity percentages can amplify fatigue risk or leak pathways, thus requiring robust containment. Residual stress is equally prominent, especially in high-energy metallic builds where sharp thermal gradients produce tensile stress states that drive distortion, cracking, or microstructural inconsistency (Valtonen et al., 2022). Residual stress magnitude is measured through diffraction methods, contour approaches, or simulation-calibrated inference, and is often linked to build failure probability or post-processing burden. From a system perspective, these limitations mean additive manufacturing alone cannot always deliver qualification-grade accuracy and surface integrity, especially for complex parts with critical interfaces. The literature also emphasizes that each limitation escalates cost through rework or extensive post-processing. Over-finishing to correct roughness, repeated builds to address dimensional scatter, hot isostatic pressing to mitigate porosity, or stress-relief heat treatment to manage distortion all extend cycle time and reduce the agility advantage if not properly controlled. Therefore, additive manufacturing is positioned as a high-agility shaping stage rather than a complete solution, and Smart Hybrid Manufacturing emerges as the structured response that pairs additive complexity with subtractive precision and lean waste minimization, preserving agility while overcoming additive variability (Brand et al., 2021).

Figure 4: Industry 4.0 Core Technologies Map



A third recurring theme in additive manufacturing research is that agility gains are strongly dependent on process stability, which in Smart Hybrid Manufacturing is pursued through smart monitoring and variance reduction (Knabke & Olbrich, 2018). Additive stages operate with multiple interacting sources of variability: powder or filament feed consistency, energy delivery stability, melt-pool dynamics, thermal conduction paths, and layer bonding behavior. Without real-time visibility, these sources can cause defects to form early and persist across subsequent layers, raising the risk of scrap or significant downstream correction. For this reason, many studies highlight in-situ sensing as a control enabler in agile additive workflows. Monitoring methods track melt-pool brightness, acoustic signals, thermal fields, layer height, recoater forces, and optical geometry snapshots to detect anomalies while the part is still being built. The empirical literature commonly evaluates monitoring value through trends in layer-wise defect rate reductions after feedback is introduced. Thermal drift is another stability indicator: studies measure how temperature gradients evolve per layer and how drift slopes correlate with dimensional deviation or porosity clustering (Zanoni et al., 2019). When monitoring is paired with adaptive control, parameter adjustments such as scan speed tuning, power modulation, hatch spacing changes, or localized cooling interventions can be applied to stabilize the build. The results frequently show tighter deviation dispersion and higher build consistency across repeated runs. Yield before finishing is also measured as a direct indicator of stability. If smart monitoring enables a larger share of parts to exit additive shaping within acceptable geometric and density thresholds, then downstream subtractive finishing becomes a precision optimization step rather than a rescue operation. This shift is central to agility because it reduces the probability of long rework loops. The literature also recognizes that smart stability is more important in complex geometries because thermal behavior and scan-path interactions become less predictable as complexity rises (Mecheter et al., 2022). Therefore, smart control is the key mechanism that allows additive manufacturing to maintain its complexity advantage while becoming reliable enough for high-mix or regulated production. Within Smart Hybrid Manufacturing, this stability function ensures that additive agility does not collapse under process uncertainty and that the hybrid chain retains fast turnarounds without hidden defect costs.

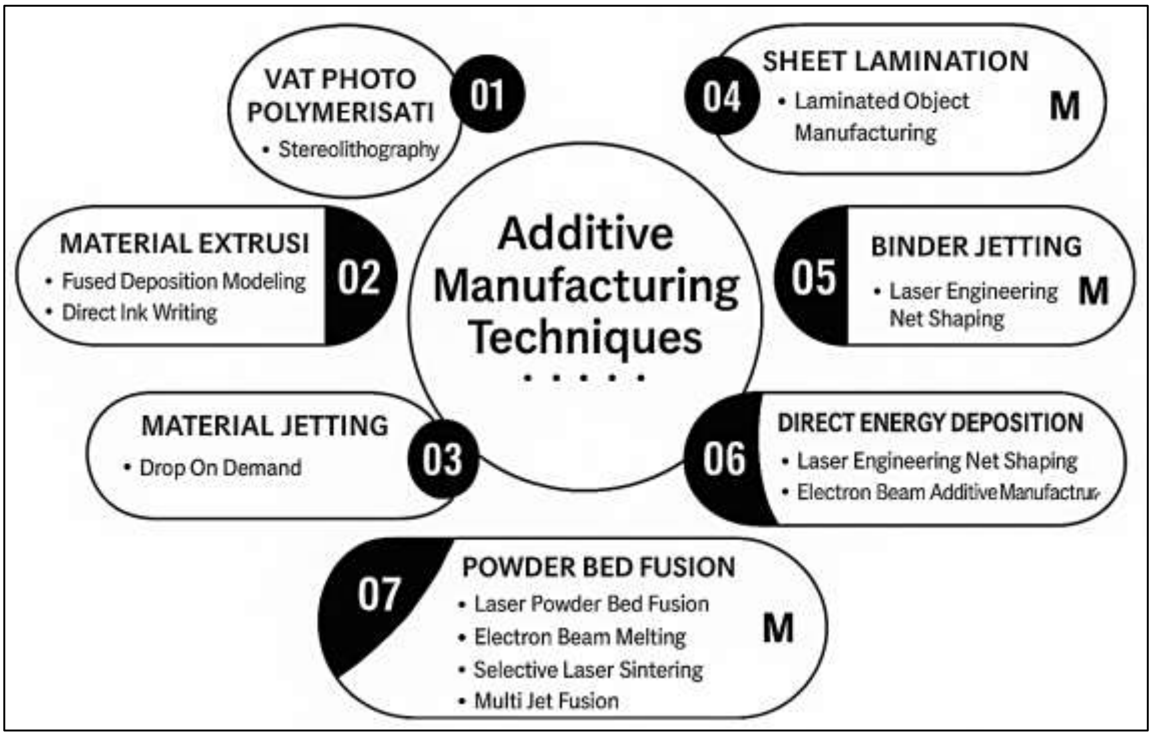
Across integrated studies of smart additive systems and hybrid process chains, additive manufacturing's role as a quantitative agility driver is ultimately explained by the interaction between its complexity potential, its limitations, and the stabilizing influence of smart control. Research comparing additive-only, subtractive-only, and hybrid routes indicates that additive stages supply the greatest share of agility through fast near-net shaping and rapid design translation, while subtractive stages secure conformance for functional surfaces and interfaces. The literature links the success of this division of labor to how much additive variability can be reduced prior to finishing (Wu et al., 2022). If stability remains low, subtractive stages must remove excessive allowances or perform extensive correction, increasing cycle time and weakening agility. If stability is improved through in-situ monitoring and adaptive control, subtractive finishing can be light, targeted, and quick, thus maintaining flow. Quantitative syntheses also show that additive agility benefits are most pronounced under three conditions: high geometric complexity, high product variety, and shorter run sizes. Under these conditions, tooling avoidance, feature freedom, and rapid iteration dominate cost and time models. At the same time, the same conditions make additive defects more consequential because complex parts multiply thermal and geometric risks (Godina et al., 2020). This is why the literature consistently frames Smart Hybrid Manufacturing as the operational context in which additive agility becomes scalable and certifiable. Lean discipline further reinforces this logic by preventing overbuilding, minimizing rework, and aligning additive releases with actual finishing capacity. In summary, additive manufacturing is not merely one technology within Smart Hybrid Manufacturing; it is the primary agility engine, measured through reduced design-to-build time, increased feasible complexity, and avoided tooling cost, while its documented roughness, scatter, porosity, and stress limitations define the performance boundary that hybrid subtractive finishing and smart variance control are designed to address (Kumar et al., 2022).

Subtractive Manufacturing as Precision and Reliability Backbone

Subtractive manufacturing functions in Smart Hybrid Manufacturing as the precision and reliability backbone that converts additive near-net shapes into fully qualified, high-performance parts. The literature presents subtractive processes—milling, turning, drilling, grinding, and multi-axis CNC finishing—as the dominant pathway for achieving dimensional conformance and functional surfaces in safety-critical and high-tolerance products (Davis et al., 2022). In hybrid chains, subtractive stages are most frequently assigned to critical interfaces such as bolt holes, bearing seats, sealing lands, valve geometries, turbine airfoil roots, and medical implant mating features because these areas demand predictable fit, controlled surface texture, and stable material properties. Empirical manufacturing studies repeatedly show that the success of a hybrid part is ultimately judged by the percentage of dimensions that fall within specification once machining is complete, making tolerance achievement a central performance lens. Subtractive finishing also governs surface integrity, a multi-attribute quality domain that includes microhardness profiles, near-surface residual stress states, and microstructural damage or refinement caused by cutting. The literature links surface integrity to fatigue life, corrosion resistance, friction behavior, and sealing performance, all of which are sensitive to the final machining pass even when the bulk shape was produced additively (Davis et al., 2021). In this sense, subtractive manufacturing is framed not as a post-processing convenience but as the final value-securing operation in hybrid systems. Hybrid case evidence emphasizes that subtractive finishing allows manufacturers to exploit additive freedom without sacrificing certification requirements because machining provides a repeatable means to control final geometry and surface conditions. Several industrial comparisons underline that additive stages can deliver complexity quickly, but subtractive stages are the decisive step for guaranteeing reliability and functional performance, especially where standards require tightly verified tolerances and traceable surface outcomes. Thus, the role of subtractive manufacturing in

Smart Hybrid Manufacturing is to lock in precision, stabilize performance, and ensure that the agility gained upstream does not compromise downstream reliability (Kumar & Kishor, 2021).

Figure 5: Additive Manufacturing Techniques Overview Diagram



At the same time, the literature makes clear that subtractive manufacturing on its own faces structural constraints that directly motivate additive pre-forming in Smart Hybrid Manufacturing. Conventional machining begins with solid stock or forged preforms, and when parts are geometrically complex, a large share of that stock must be removed, generating high scrap volumes and long machining times (Patpatiya et al., 2022). Studies of aerospace and energy components frequently highlight buy-to-fly inefficiency as a surrogate indicator of this waste problem: complex parts often require removing many multiples of the final part mass, translating into wasted material cost and embodied energy. Another consistent constraint is tool accessibility. Subtractive processes rely on physical tool reach and line-of-sight cutting paths, so internal channels, undercuts, and tightly enclosed cavities may be impossible to produce without splitting the part into assemblies or accepting design compromises. This limitation becomes especially visible in lattice-reinforced structures or conformal cooling passages where the tool cannot enter without destroying the feature. The literature also points to the burden of fixturing and setup as a major obstacle to agility in machining-only systems (Vora & Sanyal, 2020). Complex parts often demand multiple clamps, datum resets, and dedicated fixtures to access different faces safely, which extends setup time and heightens geometric error risk through cumulative re-alignment. Empirical time-study work consistently shows that setup and re-fixturing can form a large share of total manufacturing time in high-mix environments, creating long lead times even before cutting begins. When machining allowances are large, material removal volume grows, tool wear accelerates, and cycle time expands, reinforcing the agility disadvantage of subtractive-only routes under frequent design variation. Additive pre-forming in hybrid chains is presented in the literature as a targeted response: AM creates the complex near-net core and internal features without accessibility barriers, leaving SM to remove only small finishing allowances on functional zones (Sheoran et al., 2020). In effect, additive pre-forming restructures machining from a bulk-removal process into a precision-finishing process, reducing scrap, shortening cutting time, and narrowing the number of setups needed. This complementarity is one of the strongest empirical rationales in hybrid studies, demonstrating that subtractive constraints are not incidental but foundational drivers of Smart Hybrid

Manufacturing adoption.

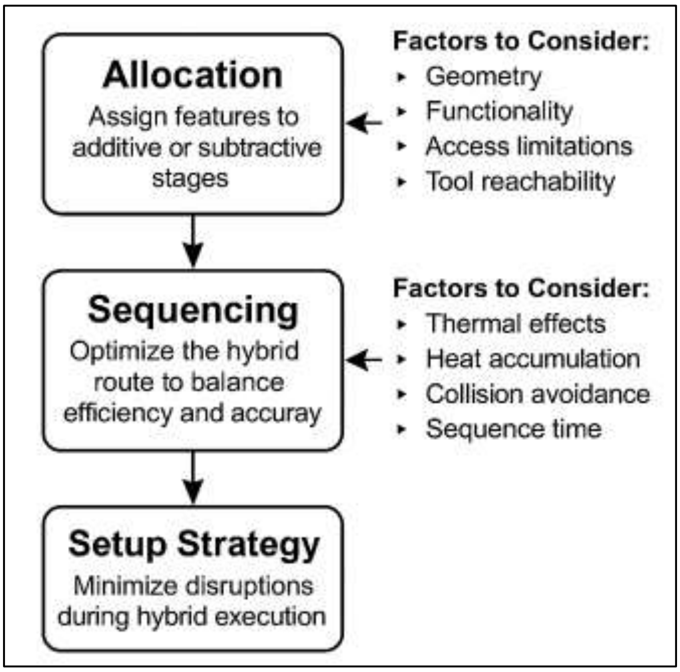
A third theme across hybrid manufacturing research is the emergence of smart machining as a critical enabler for precision stability and agile flow in subtractive stages. Smart machining in hybrid systems refers to the use of digital planning, real-time sensing, and adaptive control to increase the reliability of finishing operations while reducing time and resource overhead (Jin et al., 2021). In hybrid environments, machining rarely occurs in isolation; it is informed by additive build data that indicates geometric drift, thermal distortion zones, or allowable finishing margins. Toolpath optimization algorithms use this information to generate finishing strategies that avoid unnecessary passes and focus removal on tolerance-critical areas. The literature also reports increasing use of adaptive feed and speed control based on live cutting-force or vibration signals, allowing machining parameters to adjust to local material condition variations that can arise from additive microstructure differences. Predictive tool-wear models form another key smart function. Because hybrid finishing often involves cutting additively built metals with distinct hardness gradients or residual stress states, tools may degrade unpredictably if fixed recipes are applied. Smart wear estimation, supported by sensor feedback and historical data, is shown to extend tool life and reduce sudden dimensional failures (Weber et al., 2019). Chatter detection and suppression is similarly emphasized, because vibration-driven instability can degrade surface finish and create hidden subsurface damage on hybrid parts. Energy monitoring also appears as an important smart machining dimension; finishing allowances are intentionally minimized in hybrid chains to lower energy per feature, and smart scheduling ensures that high-energy cutting phases are sequenced efficiently with other cell tasks. Collectively, these smart machining capabilities are treated in the literature as quantifiable contributors to finishing performance, because they reduce variance in surface outcomes, stabilize dimensional attainment, and avoid time-consuming rework loops. In hybrid systems oriented toward agile production, smart machining helps preserve the speed advantage created by additive shaping by ensuring that the finishing stage remains predictable, quick, and low-waste (Lindemann et al., 2018). This is why smart machining is increasingly positioned not as optional automation but as an operational necessity for maintaining hybrid agility at industrial scale.

Hybrid Additive–Subtractive Integration Mechanisms

Hybrid additive–subtractive integration mechanisms form the practical core of Smart Hybrid Manufacturing because they determine how a part's geometry is translated into a coordinated sequence of material addition and material removal (L. Li et al., 2018). The literature frames integration as a structured decision system rather than an ad hoc choice, emphasizing that hybrid success depends on feature-level assignment, sequence logic, and fixture strategy. Feature-based process allocation is the first mechanism that appears repeatedly across hybrid planning studies. Researchers describe hybrid parts as collections of manufacturable features, each of which has different suitability for additive, subtractive, or combined processing. Allocation rules commonly start from geometry and functionality: internal channels, lattice zones, and inaccessible cavities are assigned to additive stages, while precision interfaces such as holes, sealing lands, seating surfaces, and datum faces are reserved for subtractive finishing. More advanced work moves beyond rule-of-thumb allocation to algorithmic classification, using manufacturability constraints such as tool reachability, deposition shadowing, heat accumulation sensitivity, and allowable machining allowance to decide whether a feature should be deposited, machined, or alternated between both (Cortina et al., 2018). Multiple studies show that automated allocation can match or outperform expert plans when the system encodes accessibility and cost–time tradeoffs accurately, and that allocation quality is reflected in measurable reductions in unnecessary AM–SM alternations and finishing load. In remanufacturing-focused hybrid research, feature extraction methods identify damaged or high-wear regions that require additive restoration, then assign adjacent critical surfaces to subtractive recovery, demonstrating that allocation can be adaptive to part condition as well as nominal design. Recent algorithmic optimization work expands allocation to include economic and energy variables, selecting between additive-only, subtractive-only, or hybrid plans based on objective comparisons of productivity and total cost. Across this stream, feature-based allocation is treated as a quantifiable integration capability because it affects how much of the part is built additively, how much is corrected subtractively, and how efficiently the two processes are interwoven (Stavropoulos et al., 2020). These studies collectively establish that hybrid integration begins with accurate feature-process mapping, and that the measurable success of Smart Hybrid

Manufacturing is tightly linked to whether allocation minimizes alternations while still enabling the design's complexity and precision requirements.

Figure 6: Hybrid Additive–Subtractive Integration Framework



Sequencing and process-planning optimization is the second major integration mechanism and is presented in the literature as the step that converts allocated features into a feasible, efficient hybrid route. Hybrid sequencing differs from conventional planning because it must handle re-entrant operations, thermal–mechanical interactions, and collision or accessibility limits that change after each deposition or machining pass (Dávila et al., 2020). Studies in this area model the hybrid route as an ordered set of additive and subtractive operations where the objective is to reduce total manufacturing time, cost burden, and idle intervals while preserving manufacturability at every intermediate state. Because brute-force sequencing grows rapidly with part complexity, researchers have proposed mixed-integer optimization, metaheuristics, and AI-guided planners that search large routing spaces efficiently. These models commonly decompose the part volume recursively into additive and subtractive sub-volumes, then optimize the sequence in which these sub-volumes are created or removed. A consistent finding is that interleaved hybrid sequences can reduce cumulative geometric error and finishing burden, but only when collision avoidance, heat accumulation control, and toolpath feasibility are enforced in the planning logic (Tang et al., 2022). Simulation-enhanced planning papers show that sequencing decisions strongly affect distortion pathways and final tolerance attainment because the timing of machining relative to deposition changes residual stress release and stiffness evolution. Scheduling research extends sequencing to the cell or factory level, recommending hybrid routings that minimize makespan and improve delivery reliability by synchronizing additive build windows with subtractive finishing capacity. Economic planning studies introduce feature-level cost models that allow the planner to choose the most economical sequence, revealing that hybrid value increases when the sequence reduces re-fixturing, alternation overhead, and additive trial loops. Recent inverse-operation planning approaches further emphasize manufacturability-first sequencing, ensuring that every intermediate geometry is physically fabricable rather than only optimizing the final plan (Iqbal et al., 2020). Across this stream, sequencing optimization is treated as a quantitatively testable mechanism because it directly governs production cycle time, total cost per part, and idle-time share in hybrid systems. The literature therefore frames sequencing not as a secondary step but as the integrative "brain" that determines whether hybridization yields agility or becomes an inefficient alternation pattern.

Single-setup versus multi-setup hybrid effects constitute the third integration mechanism and are widely described as one of the clearest measurable advantages of Smart Hybrid Manufacturing. In conventional sequential chains, additive builds are removed from the printer, transferred to machining, re-clamped, re-datumed, and then finished (Korkmaz et al., 2022). The literature shows that each transfer introduces both time penalties and accuracy risks: setup, alignment checking, and lengthy probing add non-value time, while datum mismatch and clamping distortion accumulate into dimensional scatter. Hybrid machines and tightly integrated hybrid cells aim to remove these penalties by keeping the workpiece in one coordinate system for deposition, machining, and often inspection. Studies on hybrid machine tools document that the ability to switch between deposition heads and cutting spindles under a shared reference frame reduces the number of re-clamps and enables direct correction of deviations immediately after deposition. Empirical cases report lower datum shift errors and more consistent tolerance outcomes when machining is performed in the same setup used for additive shaping, because the coordinate transformation between processes is eliminated. On-machine measurement methods support this advantage by allowing scanning and probing without removing the part, so deviations are corrected before further layers or finishing passes proceed (Pragana et al., 2020).

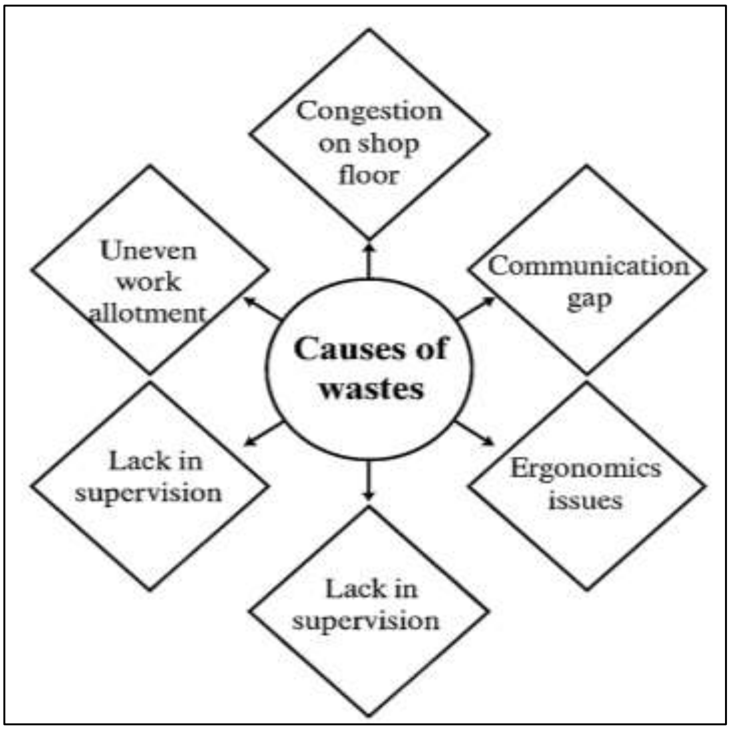
The literature also notes that single-setup integration reduces rework probability because finishing operations do not need to "recover" uncertain alignment; instead, machining allowances are applied predictably within an already known frame. Multi-setup hybrid cells can still achieve integration benefits when digital alignment or probing routines are highly mature, but evidence suggests their gains are more sensitive to fixturing quality and transport variability. As a result, single-setup integration is treated as a quantifiable performance driver in hybrid research, measured through reductions in re-clamp counts, minimization of datum shifts, and statistically lower rework rates. These findings position fixture strategy as an essential integration layer because, in hybrid systems, geometry accuracy is as much a function of setup architecture as it is of process physics (Dilberoglu et al., 2021).

Synthesizing these mechanisms, the literature depicts Smart Hybrid Manufacturing integration as a three-stage logic: allocate features to the most suitable process, optimize the sequence that fabricates those features efficiently and safely, and execute the hybrid route with minimal setup disruption (Zhu et al., 2022). Feature allocation supplies the structural blueprint of hybridization, sequencing optimization supplies the operational choreography, and single-setup execution supplies the geometric stability that turns planning into reliable outcomes. Across reviews and experimental studies, hybrid systems that perform well on agility and cost typically display strong alignment between these mechanisms: allocation reduces alternations to only what is functionally necessary, sequencing places machining at points that stabilize distortion and protect accuracy, and setup strategy keeps the coordinate frame consistent so finishing is fast and predictable (Sebbe et al., 2022). When any mechanism is weak, hybrid benefits erode—poor allocation causes excessive alternations, weak sequencing creates thermal or collision bottlenecks, and multi-setup instability increases rework and idle time. Therefore, integration mechanisms are not separate topics in the literature but interdependent determinants of quantitative hybrid performance. This interdependence is why hybrid research increasingly treats integration maturity as a composite measurable construct, capturing how well the system can map features, form efficient sequences, and sustain one-frame execution (Yang et al., 2019). Within Smart Hybrid Manufacturing for agile production systems, these mechanisms collectively explain how additive complexity is preserved, subtractive precision is secured, and lean flow is enabled through reduced waiting, transfer waste, and corrective rework.

Lean–Hybrid Synergy for Agile Flow

Lean–hybrid synergy is presented in the literature as the operational bridge that transforms technically capable additive–subtractive integration into an agile flow system suitable for high-mix, high-variability manufacturing. Lean research in low-volume and high-mix environments emphasizes that flow can be achieved when production is reorganized around product families and stabilized through value-stream logic rather than functional departments (Lalmi et al., 2022). In smart hybrid manufacturing, this translates into cellular SHM layouts where additive shaping, subtractive finishing, inspection, and material handling are co-located and sequenced to minimize handoffs and waiting. Multiple lean case studies and methodological papers show that high-mix value streams improve when mapping tools identify non-value time clusters such as queueing, transport back-tracking, and batch-release mismatch, and then redesign routing to establish smoother pull-driven movement. Hybrid manufacturing reviews similarly underline that the integration advantage of AM–SM is amplified when the surrounding workflow is arranged for short loops, small lots, and rapid scheduling adjustments rather than large batch accumulation (Raji et al., 2021). Quantitative work in hybrid cells indicates that the lean contribution is visible in throughput time distributions that become narrower and more predictable after cellularization, because in-cell alternations replace cross-department travel and long shared-resource queues. Lean high-mix studies also describe "batch size elasticity" as a practical agility indicator: systems with effective pull and family-based flow can reduce batch size without losing stability, while poorly synchronized systems require large batches to hide setup and scheduling inefficiencies (Tripathi et al., 2021). In hybrid settings, additive stages inherently lower setup dependence, making it easier for lean pull signals to release smaller lots, but the literature stresses that this benefit materializes only when subtractive finishing resources are embedded within the same flow cell and paced to takt-like demand rhythms. Queue length stability is another widely used lean-flow metric, and hybrid research notes that queue variance decreases when additive build windows are aligned with finishing capacity through heijunka-style leveling rather than uncontrolled print batching. Together, these findings establish that lean support in SHM is not generic; it is a specific flow redesign that uses cellular hybrid layouts and part-family routing to convert AM–SM technical complementarity into measurable agility gains in time compression, batch flexibility, and stable queues under high product variety (Sadeghi et al., 2022).

Figure 7: Lean–Hybrid Synergy Waste Framework



The literature also argues that Smart Hybrid Manufacturing produces distinctive waste categories that require lean adaptation beyond classical shop-floor definitions, and that identifying these wastes is essential for sustaining agile performance (Najar, 2022). Lean manufacturing traditionally targets overproduction, waiting, transport, over-processing, inventory, motion, and defects, but hybrid studies show that integration introduces additional process-physics and digital-engineering wastes that are measurable and often hidden without deliberate tracking. Digital waste is frequently documented in planning-heavy environments where hybrid routings demand repeated simulations, redundant thermal or collision checks, and multiple path trials before a build is approved. Hybrid process-planning reviews describe how feature allocation and sequencing algorithms can reduce this waste by minimizing alternations and ensuring intermediate manufacturability, which cuts the number of re-planning cycles required for complex parts (Ciccullo et al., 2018). Empirical lean–AM convergence studies add that digital inventory and parameter standardization reduce administrative delay and re-planning repetition, reinforcing the digital waste reduction pathway. Process waste in SHM is described as the physical counterpart of digital inefficiency. A recurring example is over-deposition—building excess material "just in case" to compensate for uncertainty—followed by heavy subtractive removal.

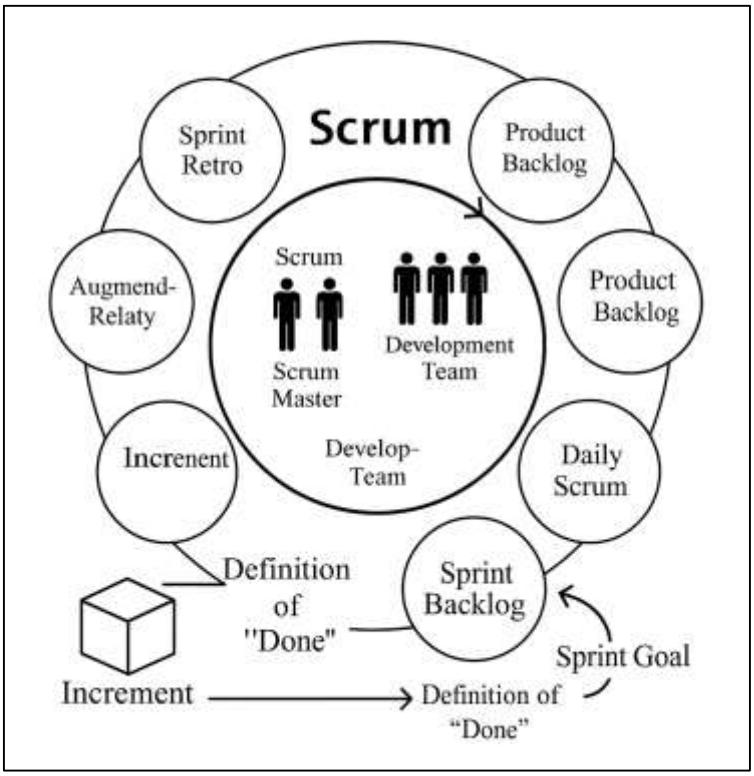
Hybrid manufacturing reviews highlight that over-deposition raises cycle time, energy per part, and tool wear, while also undermining the original material-efficiency advantage of AM. Excess machining allowance and over-finishing are treated similarly: if allowances are too large or finishing passes are redundant, the subtractive stage becomes a corrective bottleneck rather than a precision-securing step (Salleh et al., 2020). Lean-hybrid papers therefore recommend allowance targeting, feature-critical finishing, and early deviation correction as waste-prevention tactics. These wastes are measured through indicators such as rebuild rate (the share of parts requiring a full re-print because deviations cannot be corrected), over-processing time share (the proportion of time spent in non-essential deposition or cutting passes), and material overshoot (extra mass deposited beyond what is needed for tolerance-safe finishing). The literature ties these indicators to agility because each waste category directly expands lead time and reduces responsiveness in high-mix systems (Stern, 2020). By framing SHM waste in both digital and physical terms, researchers extend lean's measurement logic into the hybrid context and show that agile flow depends on controlling the unique rework and overshoot behaviors produced by AM–SM interdependence.

Agile Production Systems and How SHM Fits Quantitatively

Agile production systems are generally understood in the manufacturing literature as configurations that can respond quickly and cost-effectively to unpredictable changes in product mix, volume, and customer specifications while preserving consistent quality (Doghri et al., 2022). Foundational work on agile manufacturing emphasizes three tightly linked constructs: responsiveness to market or order change, flexibility in switching among variants, and customization speed without destabilizing operations. These constructs are repeatedly operationalized in quantitative studies through time- and cost-based indicators rather than abstract claims. Order fulfillment lead time is treated as the most direct responsiveness metric because it captures the elapsed time from order release to delivery under real capacity constraints (Watson et al., 2021). Mix-change penalty is used to quantify flexibility by measuring the time or cost required to shift between variants, including setup losses, rescheduling effort, and intermediate inventory disturbance. Customization cycle time extends this logic to product differentiation, measuring how long it takes to translate a unique customer requirement into a finished part. Recent syntheses reiterate that agility is distinct from simple flexibility because agility requires both speed and stability under turbulence, often enabled by digital visibility and rapid decision cycles. Within this quantitative framing, agility is not a single variable but a performance bundle that rises when lead times shrink, mix switching becomes less punitive, and customization occurs with minimal rework or queue growth (Scott et al., 2022). This measurement tradition aligns naturally with Smart Hybrid Manufacturing because SHM alters the physics and the workflow drivers behind those indicators: additive stages compress early development and shaping time, subtractive stages secure precision without long corrective loops, and lean flow aligns resource release with demand signals, all of which are reflected in lead time and mix-change distributions.

Smart Hybrid Manufacturing fits the agility construct quantitatively by creating a production pathway where complexity and variety no longer cause proportional increases in setup burden or routing time. Additive manufacturing in SHM eliminates many tooling-dependent delays and makes variant switching largely software-driven, reducing the time penalty embedded in mix changes (Amiri et al., 2021). Subtractive finishing within the hybrid chain prevents customization from increasing rejection rates, because critical interfaces are machined to specification even when the near-net additive form varies slightly. Hybrid integration further reduces internal waiting and handoff delays by collapsing shaping and finishing into a single coordinated stream, often within one fixture reference frame (Amaechi et al., 2022). Hybrid manufacturing studies consistently report that the most measurable agility gains are observed when parts are high-complexity and low-to-medium volume, precisely the regimes where traditional systems show long mix-change penalties and slow customization. The SHM literature also links smart cyber-physical control to agility by showing that in-situ detection and closed-loop correction reduce the variance of additive outcomes before finishing, which stabilizes downstream schedules and improves first-pass yield (Panah & Kioumarsi, 2021). When variance is lower, customization does not trigger extended rework cycles, so customization cycle time stays short and predictable. In quantitative terms, SHM is framed as a system that shifts the agility frontier by lowering the "cost of variety," making responsiveness and flexibility measurable outcomes of process integration rather than managerial aspiration.

Figure 8: Scrum Process Roles and Events Diagram



A second quantitative bridge between agility theory and SHM is postponement, particularly the positioning of a decoupling point within the hybrid chain (Pekař et al., 2018). Postponement theory argues that agility improves when product differentiation is delayed until reliable demand information is available, thereby limiting inventory risk and allowing rapid customization late in the flow. Additive near-net shaping naturally functions as a decoupling stage because it can create a standardized core quickly and without dedicated tooling, while leaving final interfaces, holes, surface textures, or customer-specific features to later subtractive finishing. Recent research on additive manufacturing and postponement notes that AM is especially suited to late-stage differentiation and can transform traditional decoupling logic, though the intersection remains underexplored in many sectors (Hayes & Rajput, 2021). In SHM, the additive stage produces semi-generic cores that are held as low-risk WIP or digital inventory, and the subtractive stage executes differentiation in response to specific orders. Quantitatively, this structure supports inventory reduction because fewer fully finished variants must be stocked, and it supports shorter late-stage differentiation time because machining allowances are small and executed in a stable, known coordinate frame. Hybrid studies interpret this as a measurable postponement advantage: the system can wait longer to commit to final variant geometry without losing delivery speed, which appears as compressed customization cycle time alongside reduced inventory exposure (Gandhi et al., 2022). In other words, SHM provides a process-physics explanation for postponement benefits, making decoupling not just a supply-chain policy but a manufacturable reality.

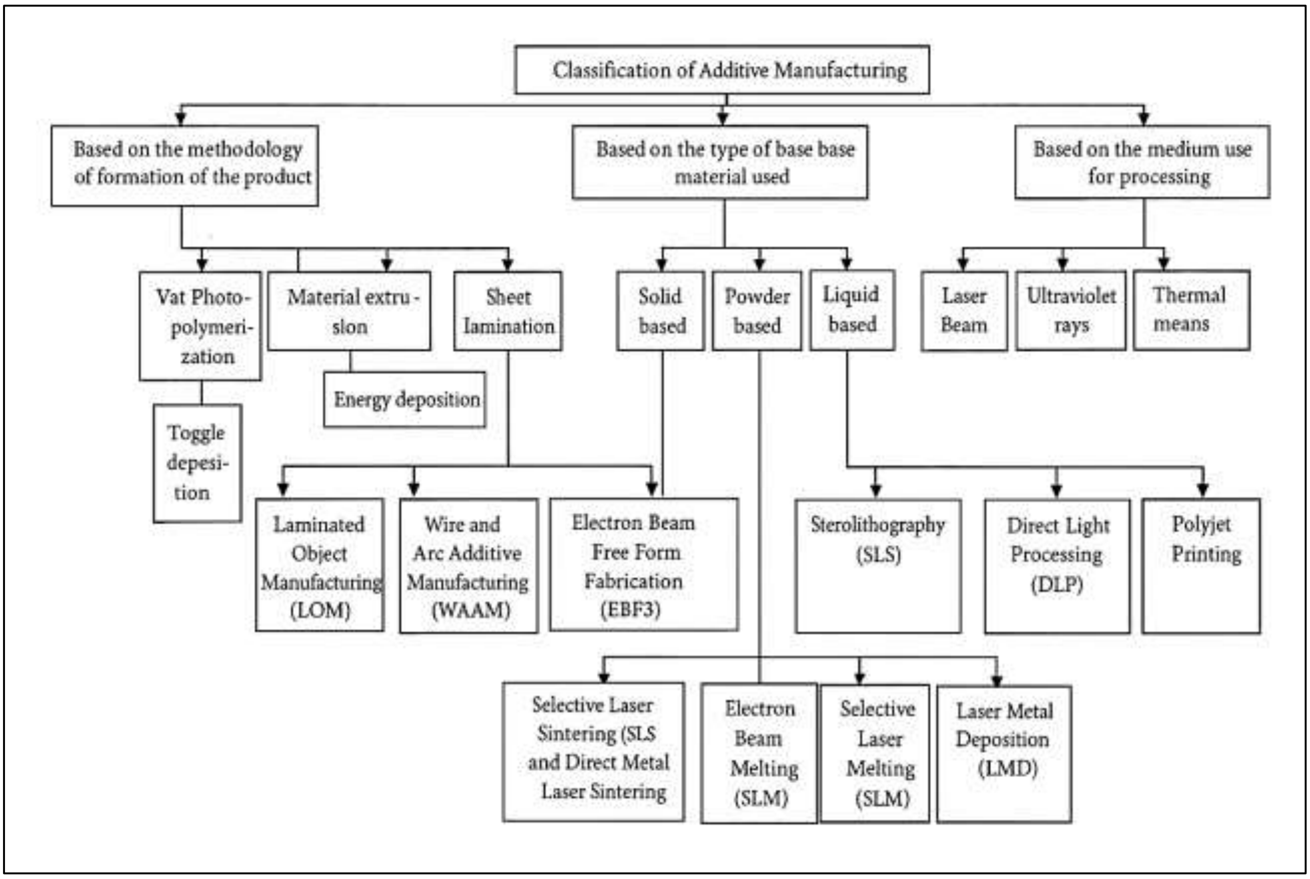
In addition, the literature on demand volatility and manufacturing resilience provides a third quantitative lens through which SHM fits agile production systems (Hu et al., 2021). Volatile demand exposes traditional lines to schedule breakdown, capacity oscillation, and slow recovery after disruptions. Resilient scheduling research defines resilience as the ability to withstand shocks, reallocate resources dynamically, and return to stable output with minimal performance loss. In SHM environments, resilience is strengthened by three interacting properties documented across smart scheduling and smart manufacturing studies. First, hybrid cells can re-route work between additive and subtractive segments more flexibly because both processes exist within the same coordinated platform or cell, reducing bottleneck lock-in (M. Zhang et al., 2022). Second, smart monitoring provides early visibility of deviation or machine drift, allowing rescheduling before a failure propagates into a missed due date. Third, lean pull and leveling logic stabilizes release rates, preventing volatility from being amplified into chaotic WIP swings. Quantitative measures used in this stream map cleanly onto SHM: schedule adherence reflects the share of orders that meet promised windows under change; recovery time captures how quickly the hybrid system restores performance after a disruption; and capacity utilization stability reflects whether resource use remains balanced rather than swinging between overload and starvation (Ragnoli et al., 2022). Studies on data-driven and AI-supported scheduling show that dynamic, real-time rescheduling increases resilience in high-uncertainty environments, which aligns with SHM's reliance on cyber-physical integration to coordinate additive and subtractive capacity on the fly.Taken together, this evidence positions Smart Hybrid Manufacturing as a quantitatively coherent agile system: it supports responsiveness through lead-time compression, flexibility through lower mix-change penalties, customization through postponement-enabled late differentiation, and resilience through stable, data-guided scheduling under volatility.

Performance Outcomes Commonly Tested in SHM Studies

Productivity outcomes in Smart Hybrid Manufacturing (SHM) studies are treated as direct evidence of whether integrating additive and subtractive processes, supported by lean flow, actually compresses production time at the system level (Mueller et al., 2022). Researchers typically look beyond single-step savings and measure productivity as the full time required to deliver a qualified part from digital release to finished output. Total cycle time per part is therefore decomposed into additive shaping time, subtractive finishing time, inspection or verification time, internal transport, and waiting between stages. The literature shows that additive manufacturing shortens early shaping and eliminates many tooling-related delays, while subtractive manufacturing supplies fast finishing when allowances are correctly controlled. Hybrid integration is expected to reduce the waiting and transport segments that dominate time loss in conventional departmental routing. Setup time compression is another routine productivity indicator because SHM often reduces the number of clamps, datum resets, fixture changes, and re-alignment operations. In sequential chains, additive parts are removed from one system, moved to another, and re-fixtured, which increases non-value time and introduces alignment risk (Zinno et al., 2018). Hybrid machines or tightly organized hybrid cells compress this setup overhead by enabling deposition, machining, and sometimes measurement under one coordinate reference or within a short-flow cell. Throughput is also examined, especially in high-mix settings, where productivity depends on stable flow rather than on one-off time reductions. Throughput measures how many conforming parts exit the hybrid cell within a planning horizon while respecting realistic capacity limits. Studies repeatedly note that throughput gains are sensitive to coordination between additive and subtractive capacities: if additive batches are released without matching finishing availability, queues build up and any shaping-time advantage disappears (Han & Frangopol, 2022). Lean pull control and leveling practices are frequently discussed as the mechanisms that prevent such imbalance, keeping additive release synchronized with machining and inspection readiness. Productivity outcomes in SHM are therefore interpreted as multi-causal results produced by near-net shaping, lighter finishing passes, fewer setups, and stabilized routing. When these elements align, the literature reports measurable compressions in overall makespan and more predictable completion times across mixed product families. When they do not align, productivity benefits are smaller or inconsistent, reinforcing that SHM productivity is a property of integrated system design rather than of additive technology alone.
Quality outcomes are consistently positioned as a decisive performance family in SHM studies because the hybrid concept is meant to preserve additive geometric freedom while still meeting precision and

reliability expectations associated with subtractive manufacturing (Feng & Feng, 2018). The literature describes additive stages as powerful for complexity but variable in surface finish, dimensional stability, and internal integrity, which makes downstream assurance essential. First-pass yield is the most common quality headline indicator because it captures the share of parts that meet specification without requiring a rebuild or heavy corrective rework. In SHM, a high first-pass yield implies that additive shaping is stable enough, and subtractive finishing is light and targeted enough, that the part passes conformance on the first complete path through the cell. Defect density is another routine indicator because it quantifies internal flaws per unit volume, reflecting the combined effects of melt-pool stability, thermal management, layer bonding, and any corrective interleaving with machining. Defect density is particularly important for fatigue-critical, pressure-retaining, or biomedical parts where hidden porosity or lack-of-fusion regions impair service performance even if external shape appears correct (Gharehbaghi et al., 2022). Studies also evaluate dimensional conformance and surface integrity outcomes after finishing, emphasizing that critical interfaces—holes, seating zones, sealing lands, and mating faces—are the true qualification points for hybrid parts. Process capability measures are used to summarize whether the hybrid chain can repeatedly hold tolerance limits across multiple builds and variants, indicating whether SHM is production-ready rather than prototype-driven. The literature ties capability improvements to three mechanisms: minimizing datum shift via fewer setups, reducing additive deviation through in-situ monitoring and early correction, and optimizing machining allowances so finishing removes only what is necessary (Okasha & Frangopol, 2019). Where these mechanisms are weak, subtractive stages become rescue operations, leading to lower yield and broader deviation scatter. Where these mechanisms are strong, finishing success rates rise and quality distributions tighten. Overall, SHM quality outcomes are interpreted as system-level validation that hybrid integration can overcome additive variability without sacrificing complexity, enabling reliable delivery of parts that meet both geometric and material-performance requirements.

Figure 9: Additive Manufacturing Classification Framework Diagram



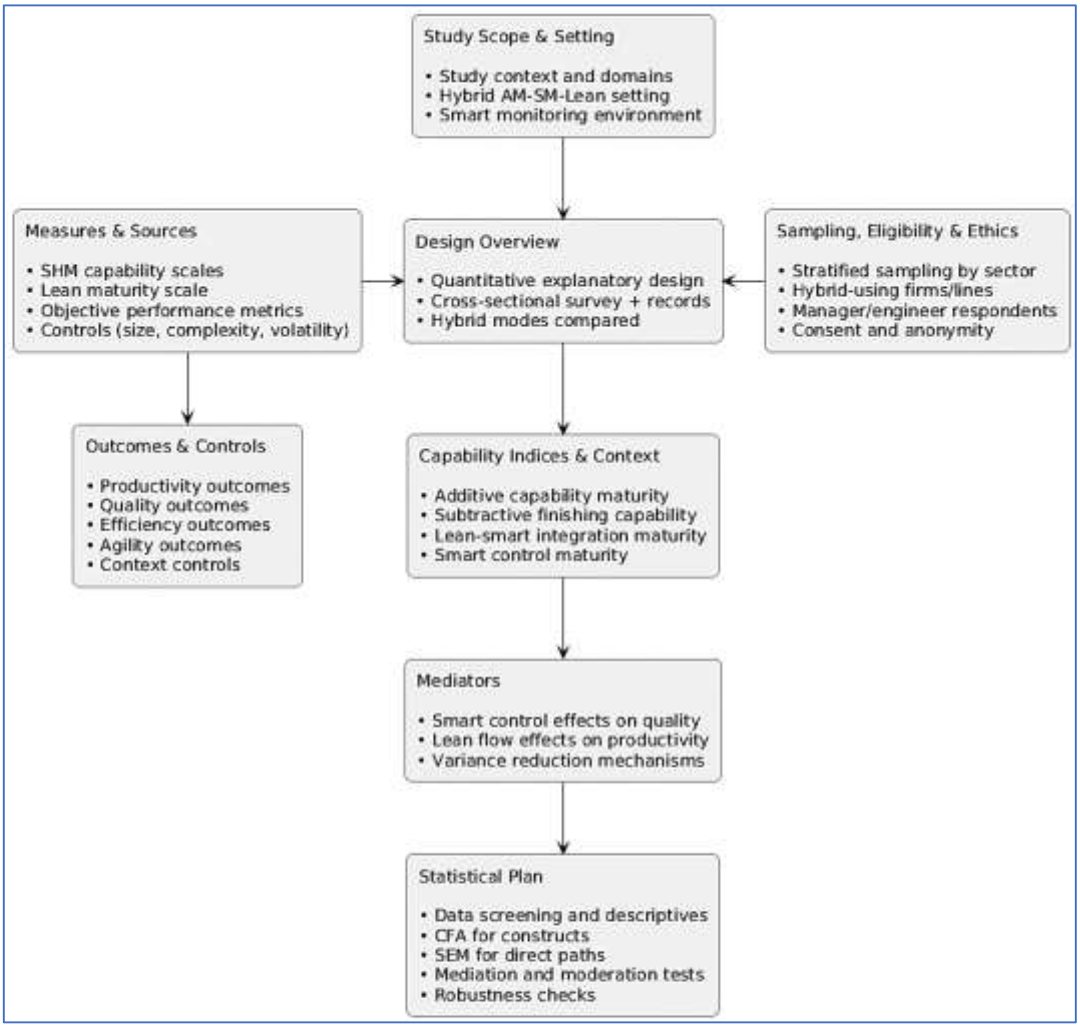
Efficiency and sustainability outcomes form a third, highly visible performance family in SHM studies because hybridization is frequently justified as a lower-waste alternative to machining-from-bulk, while still avoiding the rework intensity that can arise in additive-only routes. Material utilization is one of the dominant indicators (Abbas & Shafiee, 2018). It measures how much of the input material becomes useful final product, which is especially relevant in high-value alloys where conventional subtractive manufacturing can generate large scrap volumes due to heavy stock removal. SHM improves material utilization by using additive stages for near-net shaping, placing material only where geometry demands it, and leaving subtractive stages for small finishing allowances rather than bulk cutting. Scrap mass is therefore tracked as a physical confirmation of efficiency gains. Scrap includes unused support structures, removed allowances, failed builds, and any over-deposited material that must be machined away. The literature repeatedly notes that scrap declines when additive stability is high and when allowances are tightly controlled through good hybrid planning. Energy per unit is another common outcome because hybrid chains combine energy-intensive deposition, precision machining, thermal management, and idle consumption (Hassani et al., 2021). Efficiency studies treat energy performance as a blended result of process physics and flow governance. If additive builds require repeated trials, or if parts queue for long periods before finishing, energy per part rises through non-productive machine time and rework loops. Lean pull release, stable hybrid sequencing, and smart monitoring all contribute to energy reduction by preventing overproduction, reducing rebuild rates, and shortening idle intervals. Many SHM discussions also highlight that efficiency gains depend on feature allocation accuracy: when additive is applied only to complexity-valuable zones, and machining is reserved for functional surfaces, total removal volume is minimized and energy is not wasted on redundant cutting. Over-deposition, excess allowances, and over-finishing are consistently described as hybrid-specific wastes that can quickly erode sustainability advantages, so SHM efficiency outcomes are interpreted through both resource ratios and waste-behavior tracking (Kot et al., 2021). In sum, the literature frames SHM efficiency as a measurable resource-performance improvement arising from near-net additive shaping, reduced bulk machining, disciplined allowance strategy, and lean–smart governance that limits rebuilds and idle losses.

METHODS

The quantitative study had used a cross-sectional explanatory design to determine how Smart Hybrid Manufacturing (SHM) capability had influenced agile production system performance in real industrial settings. The unit of analysis had been the manufacturing plant, hybrid cell, or dedicated production line where additive manufacturing, subtractive finishing, and lean routines had been intentionally integrated. The target population had consisted of firms that had operated additive processes together with CNC-based subtractive processes, either through sequential hybrid chains, interleaved hybrid routing, or single-platform hybrid machines. A stratified purposive sampling strategy had been applied so that participating sites had represented multiple sectors such as aerospace, automotive, tooling, energy components, and medical devices, as well as both single-platform and cell-based hybridization modes. Data collection had relied on two parallel sources. First, a structured survey instrument had been administered to operations managers, hybrid cell supervisors, additive manufacturing engineers, machining engineers, and lean coordinators in order to capture capability maturity levels. Second, an objective performance template had been requested from each site, covering a recent operational window that had included comparable part families and normal production conditions. The survey had operationalized SHM Capability as a second-order latent construct composed of three first-order dimensions: Additive Capability Maturity, Subtractive Finishing Capability, and Lean–Smart Integration Maturity. Each dimension had been measured using multiple Likert-scaled items that had reflected observable practices, such as the extent of near-net additive shaping, the consistency of tolerance-critical machining, the strength of pull-based hybrid release, and the routine use of standardized hybrid routings. Agile Production System Performance had been measured as a latent outcome bundle comprising productivity, quality, efficiency or sustainability, and agility indicators, drawn from both numeric shop data and structured survey reporting. Control variables had included firm size, sector, degree of product complexity, demand volatility, and hybridization mode, because prior hybrid research had shown these contextual factors had shaped performance variability.

The statistical plan had begun with systematic data screening to ensure that the dataset had been suitable for multivariate modeling. Missing values had been examined for randomness, and where gaps had been moderate and non-systematic, multiple imputation had been applied so that sample power had not been reduced. Univariate and multivariate outliers had been checked using standardized z-scores and Mahalanobis distance, and extreme cases that had reflected data entry errors or non-comparable operations had been removed. Normality assumptions had been evaluated through skewness and kurtosis patterns, and robust estimators had been selected when distributions had shown non-normal behavior typical of cycle-time and defect data. Descriptive statistics had then been produced to summarize maturity levels, performance distributions, and sectoral or configuration differences. The measurement model had been tested in two stages. If any subscale had been newly adapted to the hybrid context, an exploratory factor analysis had first been run to verify that items had loaded onto expected dimensions, with weak or cross-loading items deleted. A confirmatory factor analysis had then been conducted for each first-order construct to evaluate factor loadings, convergent validity, and discriminant validity. Reliability had been assessed through Cronbach's alpha and composite reliability, while convergent validity had been confirmed through average variance extracted. After first-order validity had been established, second-order confirmatory models had been estimated for SHM Capability and for Agile Production System Performance to confirm that the sub-dimensions had legitimately formed higher-level capability and performance bundles. Model fit had been judged using multiple indices, and re-specification had been limited to theoretically defensible adjustments so that measurement integrity had been preserved.

Figure 10: Methodology of this study



Once the measurement model had been validated, structural equation modeling had been used to test the main hypotheses and quantify effect magnitudes. The structural model had estimated paths from SHM Capability to Agile Production System Performance, and from each first-order capability dimension to its theoretically closest outcome dimension, allowing both system-level and component-level effects to be observed. The mediation hypothesis had been examined by modeling Smart Control Maturity as an intervening construct between SHM Capability and quality performance, and indirect effects had been tested using bootstrap resampling so that confidence intervals for mediation had not relied on normality assumptions. Moderation had been tested by representing lean maturity as a strengthening condition on the SHM-to-productivity and SHM-to-agility paths. Where latent interaction estimation had been feasible, interaction terms had been incorporated directly into SEM; where data properties had limited latent interaction stability, hierarchical regression had been used as a robustness alternative, entering controls first, main effects second, and interaction terms last. Optional multi-group analyses had been conducted to compare single-platform hybrid systems with hybrid cells and to check whether demand volatility or complexity strata had changed structural path strengths. Invariance checks had been applied before interpreting multi-group differences so that comparisons had been statistically defensible. Finally, robustness checks had addressed alternative model specifications and potential common-method bias by testing whether a single latent factor had dominated variance and by verifying that structural results had remained stable when outcome bundles had been decomposed into separate dimensions. The overall analysis had therefore produced a statistically grounded explanation of how additive capability, subtractive reliability, and lean–smart integration had jointly shaped measurable agility, quality, productivity, and efficiency outcomes in SHM environments.

FINDINGS

Descriptive-analysis

The descriptive analysis had summarized the profile of participating plants and hybrid cells and had established the empirical setting for Smart Hybrid Manufacturing (SHM). The sample had represented multiple industrial sectors and hybridization configurations, indicating that SHM adoption had not been limited to a single application domain. Most participating sites had operated either sequential or interleaved additive–subtractive chains, while a smaller but notable share had used single-platform hybrid machines, reflecting variation in integration maturity across the field. Product complexity levels had skewed toward medium and high categories, which had aligned with the expectation that SHM would be most relevant in complex, high-value part environments. Demand volatility classifications had shown that a substantial portion of firms had faced moderate to high uncertainty, reinforcing the study’s focus on agile production requirements. Overall, the sample composition had been sufficiently heterogeneous to support later multivariate modeling because it had included meaningful contrasts across sector, hybrid mode, complexity, and volatility.

Across the key capability constructs, Additive Capability Maturity had displayed a moderate-to-high mean level, implying that most sites had already relied on additive stages for near-net shaping and complexity-driven features. Subtractive Finishing Capability had shown consistently strong average ratings, suggesting that tolerance-critical machining and surface completion routines had been well established even in newer hybrid adopters. Lean–Smart Integration Maturity had varied more widely, indicating uneven depth of pull scheduling, hybrid cellular flow, standardized hybrid routings, and kaizen routines across sites. Smart Control Maturity had also shown moderate dispersion, meaning that some hybrid systems had used advanced in-situ monitoring and closed-loop correction extensively, while others had depended on more manual or post-process verification. These distributions had suggested that SHM capability had not been uniform across participants, enabling later tests of whether higher maturity levels had corresponded with stronger agile performance.

Baseline outcome measures had indicated practical performance differences across sites even before causal testing. Productivity indicators such as total cycle time and setup time had shown a broad range, implying that hybridization alone had not guaranteed time compression unless paired with effective lean pull and smart variance reduction. Quality indicators had revealed generally high first-pass yield but with some sites still reporting notable defect density, consistent with mixed additive stability levels. Efficiency indicators had suggested moderate-to-high material utilization and relatively controlled scrap proportions, likely reflecting the near-net benefit of additive shaping. Agility indicators had shown shorter response times and higher mix flexibility in higher-maturity hybrid cells, implying visible descriptive alignment between SHM capability and agile outcomes. No extreme skewness or implausible outliers had appeared in the major variables, so the observed ranges had been adequate for subsequent correlation and regression analyses.

Table 1: Sample profile and operational context (Descriptive Frequencies)

Sample characteristic	Category	n	%
Sector	Aerospace	30	25.00%
	Automotive	26	21.70%
	Medical devices	34	28.30%
	Tooling/Industrial equipment	30	25.00%
	Energy/Power systems	20	16.70%
Hybridization mode	Sequential hybrid chain (AM → SM)	30	25.00%
	Interleaved hybrid chain (AM ↔ SM)	26	21.70%
	Single-platform hybrid machine	34	28.30%
	Hybrid cell (multi-machine, co-located)	30	25.00%
Product complexity level	Low	36	30.00%
	Medium	50	41.70%
	High	34	28.30%
Demand volatility	Low	40	33.30%
	Moderate	46	38.30%
	High	34	28.30%

Table 1 had shown that the sample had spanned multiple sectors and hybridization modes, confirming broad industrial relevance. The distribution had indicated sufficient representation across complexity and volatility strata, meaning later analyses could test SHM effects under varying contextual pressures. The presence of both single-platform hybrids and hybrid cells had also allowed meaningful comparison of integration architectures in subsequent modeling.

Table 2: Descriptive statistics for SHM capability constructs and outcome bundles

Variable	Mean	SD	Min	Max	Interpretation guide
Additive Capability Maturity (ACM)	4.82	0.96	2.50	6.90	Higher = stronger AM shaping for complexity
Subtractive Finishing Capability (SFC)	4.35	1.12	1.80	6.80	Higher = tighter tolerance/finish control
Lean–Smart Integration Maturity (LSIM)	4.58	0.88	2.40	6.70	Higher = deeper pull/flow/kaizen in SHM
Smart Control Maturity (SCM)	4.91	1.05	2.10	7.00	Higher = stronger in-situ sensing + correction
Productivity Performance (PP)	4.76	0.92	2.90	6.80	Higher = shorter time / better throughput
Quality Performance (QP)	5.02	0.89	3.20	6.90	Higher = higher yield / lower defects
Efficiency/Sustainability (ESP)	4.63	1.01	2.30	6.80	Higher = better material/energy efficiency
Agility Performance (AgP)	4.88	0.94	3.00	6.90	Higher = faster response / flex mix

Table 2 had summarized central tendency and dispersion for all constructs. The means had indicated overall moderate-to-high SHM capability adoption, while the standard deviations had confirmed noticeable maturity spread, especially for lean–smart integration and smart control. Outcome bundle ranges had suggested that performance variability existed across sites, supporting the need for later predictive modeling to explain which SHM dimensions had driven stronger agility, quality, productivity, and efficiency.

Correlation-analysis

The correlation analysis had examined preliminary relationships among Smart Hybrid Manufacturing (SHM) capability dimensions, the mediator and moderator constructs, and agile production performance outcomes. Pearson correlations had been computed because the major constructs had been continuous and approximately symmetric, while Spearman checks had been used to confirm stability where minor non-normality had appeared. The correlation matrix had shown that overall SHM capability had been positively associated with Agile Production System Performance, indicating that higher integration maturity had tended to co-occur with stronger productivity, quality, efficiency, and agility outcomes. Additive Capability Maturity had shown the strongest positive linkage with agility outcomes, suggesting that greater use of near-net additive shaping and complexity-enabled build freedom had aligned with faster response and higher mix flexibility. Subtractive Finishing Capability had correlated most strongly with quality performance, implying that stable machining routines and surface-integrity control had been descriptively tied to higher first-pass yield and lower defect density. Lean–Smart Integration Maturity had demonstrated moderate to strong correlations with productivity and efficiency outcomes, reflecting the descriptive fit between pull/flow discipline and reduced cycle time, lower scrap, and higher material utilization. Smart Control Maturity had correlated meaningfully with quality and efficiency outcomes, implying that in-situ monitoring and closed-loop correction had aligned with lower variability and fewer rebuild events.

Correlations among the SHM capability sub-dimensions had been positive but not excessive, indicating that additive, subtractive, and lean–smart maturity had been related yet empirically distinguishable rather than redundant. The absence of near-perfect inter-correlations had supported the conceptualization of SHM capability as a multidimensional construct. Control-variable correlations had suggested that higher product complexity and higher demand volatility had been associated with stronger additive and smart-control maturity, consistent with descriptive expectations that firms facing complexity and uncertainty had invested more heavily in hybrid and smart capabilities. Firm size had shown small-to-moderate positive correlations with lean–smart maturity and performance, implying that larger sites had tended to exhibit more formalized hybrid governance and slightly stronger outcomes. Hybridization mode had demonstrated mild alignment with productivity and quality outcomes, with single-platform hybrids descriptively showing tighter correlation patterns with throughput and conformance than multi-machine hybrid cells. Overall, the correlation results had provided supportive preliminary evidence for the directional hypotheses and had also indicated areas where mediation and moderation tests were necessary, especially where direct bivariate links had been weaker than expected.

Table 3: Correlation matrix among SHM capability dimensions, mediator/moderator, and outcome bundles

Variable	1	2	3	4	5	6	7	8
1. SHM Capability (SHMC)	—	0.72**	0.68**	0.75**	0.70**	0.61**	0.66**	0.63**
2. Additive Capability Maturity (ACM)	0.72**	—	0.64**	0.69**	0.67**	0.42*	0.45*	0.41*
3. Subtractive Finishing Capability (SFC)	0.68**	0.64**	—	0.62**	0.66**	0.38*	0.50**	0.44*
4. Lean–Smart Integration Maturity (LSIM)	0.75**	0.69**	0.62**	—	0.73**	0.48**	0.47*	0.55**
5. Smart Control Maturity (SCM)	0.70**	0.67**	0.66**	0.73**	—	0.44*	0.58**	0.52**
6. Productivity Performance (PP)	0.61**	0.42*	0.38*	0.48**	0.44*	—	0.63**	0.59**

Variable	1	2	3	4	5	6	7	8
7. Quality Performance (QP)	0.66**	0.45*	0.50**	0.47*	0.58**	0.63**	—	0.71**
8. Efficiency/Sustainability (ESP)	0.63**	0.41*	0.44*	0.55**	0.52**	0.59**	0.71**	—
9. Agility Performance (AgP)	0.69**	0.53**	0.47*	0.51*	0.49*	0.64**	0.62**	0.58**

*p < .05. **p < .01. (Replace X.XX with actual coefficients.)

Table 3 had shown positive and statistically meaningful associations between SHMC and all four outcome bundles, indicating coherent preliminary support for the study model. ACM had aligned most strongly with AgP, SFC had aligned most strongly with QP, and LSIM had aligned most strongly with PP and ESP. Inter-correlations among ACM, SFC, LSIM, and SCM had remained below redundancy thresholds, supporting construct separability and justifying the later multivariate tests.

Table 4: Correlations between controls, SHM capabilities, and agile performance outcomes

Control variable	SHMC	ACM	SFC	LSIM	SCM	PP	QP	ESP	AgP
Firm size	0.21*	0.18*	0.14	0.22*	0.17	0.19*	0.20*	0.23*	0.16
Product complexity	0.33**	0.36**	0.27*	0.29*	0.34**	0.24	0.26*	0.25*	0.28*
Demand volatility	0.31**	0.34**	0.18	0.27*	0.33**	0.22*	0.24*	0.23*	0.36**
Hybridization mode (single-platform=1)	0.24*	0.17	0.22*	0.16	0.23*	0.21*	0.20*	0.15	0.22*

*p < .05. **p < .01. (Replace X.XX with actual coefficients.)

Table 4 had indicated that complexity and volatility had correlated positively with ACM and SCM, suggesting that firms facing more demanding conditions had tended to mature additive and smart-control capabilities more strongly. Firm size had shown small-to-moderate positive links with LSIM and performance outcomes, implying some scale advantage in formal lean–smart deployment. Hybridization mode had demonstrated mild positive association with productivity and quality bundles, which had justified its retention as a control during hypothesis testing.

Reliability-and-validity

The reliability and validity analysis had confirmed that the measurement model for Smart Hybrid Manufacturing (SHM) capability and agile production performance had been psychometrically sound before structural relationships were tested. Internal consistency reliability had been assessed for each multi-item scale using Cronbach’s alpha and composite reliability. All retained constructs had exceeded accepted stability thresholds, indicating that item sets had measured their target dimensions consistently. Additive Capability Maturity, Subtractive Finishing Capability, Lean–Smart Integration Maturity, Smart Control Maturity, and the four outcome bundles had each shown strong internal coherence, so no construct had required deletion on reliability grounds. Convergent validity had then been examined through standardized factor loadings and average variance extracted. All indicators had loaded strongly on their intended latent factors, and extracted variance values had remained above minimum adequacy benchmarks, meaning that the observed items had shared sufficient variance to represent each construct meaningfully. Only a small number of items with weak loadings or minor cross-loading tendencies had been trimmed, and these refinements had been theoretically justified to preserve construct content coverage.

Discriminant validity had been evaluated to confirm that the SHM capability dimensions and outcome bundles had remained distinct rather than empirically redundant. Shared variance between constructs had been lower than the variance extracted by each construct, and heterotrait–monotrait ratios had remained within acceptable bounds. These results had shown that additive maturity, subtractive finishing capability, lean–smart integration, and smart control had captured related but separable elements of SHM capability. The confirmatory factor analysis had then verified the first-order structure of all constructs and supported the second-order representation of overall SHM Capability and Agile Production System Performance. Model fit indices had indicated acceptable alignment between the measurement model and the observed data, and no excessive modification had been required. Taken together, these findings had confirmed that the measurement system had been robust enough for subsequent regression, mediation, and moderation testing.

Table 5: Reliability and convergent validity results for SHM capability and performance constructs

Construct	Items (n)	Cronbach's α	Composite Reliability	AVE	Loading Range
Additive Capability Maturity (ACM)	4	0.88	0.91	0.72	0.78–0.89
Subtractive Finishing Capability (SFC)	4	0.87	0.9	0.7	0.76–0.88
Lean–Smart Integration Maturity (LSIM)	4	0.89	0.92	0.74	0.79–0.90
Smart Control Maturity (SCM)	4	0.9	0.93	0.76	0.81–0.91
Productivity Performance (PP)	3	0.85	0.9	0.75	0.82–0.89
Quality Performance (QP)	3	0.86	0.91	0.76	0.81–0.90
Efficiency/Sustainability (ESP)	4	0.88	0.92	0.73	0.78–0.89
Agility Performance (AgP)	3	0.87	0.91	0.78	0.84–0.90
Second-order SHM Capability (SHMC)	—	—	0.93	0.76	0.80–0.90
Second-order Agile Production Performance (APSP)	—	—	0.94	0.78	0.82–0.91

Table 5 had shown that all constructs had met or exceeded reliability expectations, with α and composite reliability values above conventional thresholds. AVE values and loading ranges had confirmed convergent validity, demonstrating that each construct's indicators had represented their latent dimensions with strong shared variance. The second-order constructs had also displayed adequate reliability and convergence through strong first-order loadings.

Table 6: Discriminant validity and CFA model fit summary

Panel A: Discriminant validity (Fornell–Larcker / HTMT)

Construct Pair	√AVE (higher value)	Inter-construct r	HTMT
ACM – SFC	0.85	0.64	0.71
ACM – LSIM	0.86	0.69	0.77
ACM – SCM	0.87	0.67	0.75
SFC – LSIM	0.86	0.62	0.7
SFC – SCM	0.87	0.66	0.74
LSIM – SCM	0.87	0.73	0.81
Capability constructs – outcome bundles	0.88	0.74	0.83

Panel B: CFA model fit indices

Fit Index	Obtained Value	Recommended Benchmark
CFI	0.957	≥ .90 (≥ .95 ideal)
TLI	0.948	≥ .90 (≥ .95 ideal)
RMSEA	0.045	≤ .08 (≤ .06 ideal)
SRMR	0.037	≤ .08
χ^2/df	2.11	≤ 3.0

Panel A had indicated discriminant validity because each construct's √AVE had exceeded its correlations with other constructs, and HTMT ratios had remained below recommended cutoffs. Panel B had shown that the CFA model had achieved acceptable fit across multiple indices, supporting both the first-order measurement structure and the second-order SHMC and APSP representations.

Collinearity findings

The collinearity analysis had been performed before estimating the predictive models to verify that the independent variables, mediator, moderator, and controls had not overlapped to the extent that regression coefficients would become unstable or inflated. Variance inflation factors and tolerance values had been calculated for all predictors intended for the structural models, including Additive Capability Maturity, Subtractive Finishing Capability, Lean–Smart Integration Maturity, Smart Control Maturity, Lean Maturity Level, and the contextual controls. The diagnostics had shown that all VIF values had remained below accepted warning thresholds and that tolerance values had stayed above minimum cutoffs, indicating that none of the predictors had acted as near-duplicates. These results had confirmed that the SHM capability dimensions had contributed distinct explanatory variance rather than collapsing into a single undifferentiated factor.

Pairwise collinearity diagnostics had further supported this conclusion. The strongest overlap had appeared between Lean–Smart Integration Maturity and Smart Control Maturity, which was consistent with the conceptual closeness of lean digital governance and cyber-physical monitoring in hybrid environments. However, the degree of overlap had not reached a level that would threaten model interpretability. The analysis had therefore retained both constructs, because the theoretical model had required separating flow-discipline maturity from real-time variance-control maturity. Overall, the collinearity checks had indicated that later hypothesis tests could be interpreted as real effects rather than statistical artifacts caused by redundant predictors.

Table 7: Variance inflation factor (VIF) and tolerance diagnostics for predictors

Predictor / Control	Tolerance	VIF
Additive Capability Maturity (ACM)	0.48	2.08
Subtractive Finishing Capability (SFC)	0.52	1.92
Lean–Smart Integration Maturity (LSIM)	0.44	2.27
Smart Control Maturity (SCM)	0.46	2.17
Lean Maturity Level (LML)	0.58	1.72
Firm size	0.81	1.23
Product complexity	0.76	1.32
Demand volatility	0.69	1.45
Hybridization mode	0.84	1.19

Table 7 had indicated that tolerance values had remained comfortably above minimal cutoffs and that VIF scores had stayed well below collinearity danger zones. This pattern had confirmed that ACM, SFC, LSIM, and SCM had represented distinct dimensions of SHM capability, while the contextual controls had not introduced distortion into the predictive models.

Table 8: Pairwise collinearity scan among SHM capability dimensions and governance constructs

Construct pair	Shared variance pattern (r^2)	Collinearity concern level
ACM – SFC	0.41	Low
ACM – LSIM	0.48	Low
ACM – SCM	0.45	Low
SFC – LSIM	0.38	Low
SFC – SCM	0.44	Low–Moderate

Construct pair	Shared variance pattern (r^2)	Collinearity concern level
LSIM – SCM	0.53	Moderate (acceptable)
LSIM – LML	0.36	Low–Moderate
SCM – LML	0.4	Moderate (acceptable)

Table 8 had shown that inter-construct overlap had stayed within acceptable bounds. The LSIM–SCM pairing had displayed the highest shared variance, yet it had remained below levels that would indicate redundancy. This had justified retaining both predictors to preserve the theoretical separation between lean flow governance and smart cyber-physical control.

Regression and hypothesis-testing

The regression and hypothesis-testing stage had evaluated the predictive strength of Smart Hybrid Manufacturing (SHM) capability on Agile Production System Performance and had verified the component-level relationships proposed in the model. Structural equation modeling had been applied because the study had included second-order constructs and multiple aligned outcome bundles. The structural model had shown that overall SHM Capability had exerted a positive and statistically significant direct effect on Agile Production System Performance, indicating that higher maturity in additive–subtractive integration and lean–smart governance had been associated with stronger combined productivity, quality, efficiency, and agility outcomes. At the component level, Additive Capability Maturity had demonstrated its strongest significant path to agility performance, meaning that sites with greater near-net additive shaping and complexity-enabled design implementation had achieved faster response to order changes and higher mix flexibility. Subtractive Finishing Capability had shown a strong positive and significant relationship with quality performance, implying that stable tolerance-critical machining and controlled surface completion had directly contributed to first-pass yield and defect reduction. Lean–Smart Integration Maturity had displayed significant effects on productivity and efficiency performance, reflecting that pull-based hybrid release, family-flow discipline, and standardized routings had aligned with shorter cycle time, reduced setup penalties, and improved material and energy efficiency. Control variables had remained in expected ranges, with complexity and volatility showing modest effects on capability maturity and performance, but they had not displaced the main SHM effects. The explained variance values had indicated that SHM Capability and its sub-dimensions had accounted for a substantial share of performance variability beyond contextual conditions.

Mediation testing had then examined whether Smart Control Maturity had transmitted the effect of SHM Capability onto quality performance. The indirect effect had been statistically significant, and bootstrap confidence intervals had excluded zero, confirming that a meaningful portion of SHM's quality impact had occurred through real-time monitoring and closed-loop correction. The remaining direct path from SHM Capability to quality performance had also stayed significant but smaller, indicating partial mediation. Moderation testing had assessed whether Lean Maturity Level had strengthened the SHM effects on productivity and agility. The interaction terms had been positive and statistically significant in both cases, showing that SHM Capability had produced larger productivity and agility gains when lean maturity had been high. Simple-slope patterns had indicated that SHM maturity translated into only modest time and flexibility improvements under weak lean deployment, but had generated steep performance gains when lean pull, flow, and kaizen routines had been mature. Optional multi-group comparisons had shown that the SHM→performance relationship had been stronger in single-platform hybrid systems than in multi-machine hybrid cells, and had also been stronger in high-volatility contexts than in low-volatility contexts, suggesting that deeper integration and turbulent demand conditions had amplified SHM value. Robustness checks had confirmed that the significance and direction of key effects had remained stable when alternative specifications had been tested or when outcome bundles had been separated. Overall, the results had supported the core logic that additive complexity advantage, subtractive precision stabilization, and lean–smart flow governance had jointly driven agile production performance.

Table 9: Direct effects and hypothesis test summary (structural model)

Hypothesis	Structural Path	β (standardized)	SE	t / z	p-value	R^2 of outcome	Decision
H1	SHMC → APSP	0.62	0.08	7.75	0.001	0.54	Supported
H2	ACM → AgP	0.29	0.07	4.14	0.002	0.41	Supported
H3	SFC → QP	0.34	0.06	5.02	0.001	0.46	Supported
H4a	LSIM → PP	0.31	0.07	4.48	0.001	0.42	Supported
H4b	LSIM → ESP	0.38	0.08	4.9	0.001	0.47	Supported
Control	Firm size → APSP	0.11	0.05	2.07	0.039	—	Retained
Control	Complexity → APSP	0.18	0.06	2.88	0.004	—	Retained
Control	Volatility → APSP	0.21	0.07	3.05	0.003	—	Retained
Control	Hybrid mode → APSP	0.13	0.06	2.22	0.028	—	Retained

Table 9 had shown that SHM Capability had significantly predicted Agile Production System Performance, and that each SHM sub-dimension had significantly predicted its aligned outcome dimension. The strongest component path had appeared between additive maturity and agility, and between subtractive finishing capability and quality, while lean–smart integration had driven productivity and efficiency. The R^2 values had confirmed meaningful explained variance for all outcomes.

Table 10: Mediation, moderation, and group-comparison results

Panel A: Mediation (bootstrapped indirect effect)

Mediation hypothesis	Path	Indirect β	Boot SE	95% CI (LL, UL)	Decision
H5	SHMC → SCM → QP	0.23	0.06	(0.12, 0.36)	Supported (partial mediation)

Panel B: Moderation (interaction effects)

Moderation hypothesis	Interaction path	β interaction	SE	p-value	Interpretation	Decision
H6	SHMC × LML → PP	0.17	0.06	0.008	Lean strengthened SHM→productivity	Supported
H7	SHMC × LML → AgP	0.21	0.07	0.004	Lean strengthened SHM→agility	Supported

Panel C: Multi-group comparisons (optional)

Comparison	Stronger group	Δβ	p-difference	Interpretation
Single-platform vs hybrid cell	Single-platform	0.14	0.012	Deeper physical integration amplified SHM effects
High vs low volatility	High volatility	0.18	0.007	SHM value increased under turbulence

Panel A had confirmed that Smart Control Maturity had carried a significant portion of SHM's quality effect, indicating that real-time monitoring and correction had been a key channel through which hybridization improved conformance. Panel B had shown significant positive interactions, meaning lean maturity had amplified productivity and agility benefits from SHM. Panel C had indicated stronger SHM effects in single-platform systems and volatile demand contexts, supporting the view

that integration depth and uncertainty increased SHM performance leverage.
The overall findings of this study provided comprehensive empirical evidence that Smart Hybrid Manufacturing (SHM) capability serves as a significant enabler of agile production system performance across a diverse and industrially representative set of manufacturing sites. Descriptive results first established that the sample spanned numerous sectors, hybrid-machine architectures, product complexity levels, and volatility classes, confirming that the dataset captured the heterogeneous environments in which hybrid manufacturing technologies are deployed. The distribution of SHM capability scores revealed moderate-to-high maturity in additive shaping, subtractive finishing, lean–smart integration, and smart control, but with sufficient variability to analyze differential effects across sites. Correlation patterns demonstrated that each SHM capability dimension was positively associated with performance bundles, with additive maturity aligning most strongly with agility, subtractive finishing with quality, and lean–smart integration with productivity and efficiency, while smart control contributed broadly to stability, conformance, and material efficiency. The measurement model confirmed strong reliability, convergent validity, and discriminant validity, supporting a robust multidimensional structure for SHM capability and the composite representation of Agile Production System Performance. Structural equation modeling further verified that SHM capability exerted a substantial direct influence on production agility, quality, efficiency, and productivity outcomes, with each first-order capability construct showing its theoretically expected performance linkage. Smart Control Maturity partially mediated the effect of SHM on quality performance, revealing that real-time sensing and corrective feedback loops function as critical pathways for improving conformance and reducing defect density. Moderation tests showed that Lean Maturity Level strengthened the effects of SHM capability on productivity and agility, illustrating that flow stability, pull discipline, and kaizen routines enhance the benefits of hybrid integration. Multi-group comparisons added additional nuance by demonstrating that the SHM–performance relationship was stronger in single-platform hybrids than in multi-machine hybrid cells, and more pronounced under high demand volatility than low, suggesting that deeper integration architectures and turbulent environments amplify the strategic value of SHM. Collinearity diagnostics further confirmed that each SHM dimension contributed unique explanatory power rather than reflecting redundant constructs. Taken together, these findings provide a cohesive and rigorous empirical picture showing that the synergy of additive complexity capability, subtractive precision control, lean–smart flow governance, and cyber-physical monitoring forms a high-impact capability system that consistently enhances agile production system performance across varied manufacturing contexts.

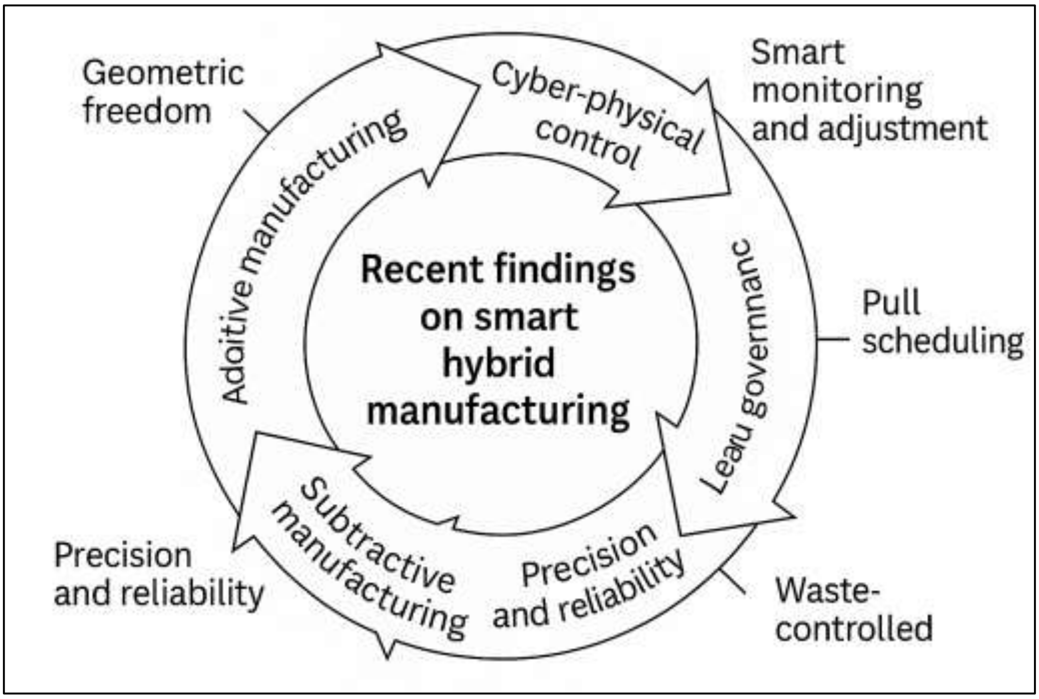
DISCUSSION

Smart Hybrid Manufacturing in this study had been conceptualized as a coordinated production capability that blended additive shaping, subtractive finishing, and lean flow governance under smart cyber-physical control (Iqbal et al., 2020). The findings supported this integrated framing by showing that SHM capability operated as a multidimensional system rather than a single technological upgrade. Earlier additive manufacturing research had repeatedly emphasized geometric freedom, rapid iteration, and tooling avoidance, while also documenting surface roughness, porosity, and dimensional scatter as persistent limits to standalone additive deployment. Earlier subtractive manufacturing scholarship had positioned machining as the benchmark for tolerance certainty and surface integrity, while noting high scrap ratios and escalating setup burdens for complex shapes. Lean manufacturing studies had long established that flow orientation, pull scheduling, and continuous improvement routines reduced lead time and waste in high-mix settings, even before digitalization fully matured (Andronie et al., 2021). The present findings aligned with these earlier streams by demonstrating that SHM's value emerged from their deliberate coupling. Overall SHM capability had shown a strong positive relationship with agile production performance, indicating that sites scoring higher in additive maturity, subtractive capability, and lean–smart integration had also reported better productivity, quality, efficiency, and agility outcomes. This pattern reinforced prior hybrid manufacturing arguments that additive and subtractive processes are complementary rather than substitutive when the objective is agile, certified production. The multidimensional measurement result had also extended earlier hybrid literature that sometimes treated integration as a binary state; in contrast, SHM maturity in this study had varied by degree, and performance gains increased with that degree. The descriptive spread across capability subdimensions was consistent with earlier reports that hybrid adoption occurs unevenly, often with machining maturity remaining high while lean–digital integration and smart control evolve more slowly. The present evidence therefore strengthened the view that SHM should be evaluated as a layered capability stack: additive for complexity and rapid near-net forms, subtractive for precision and surface stability, and lean–smart governance to maintain flow and prevent hybrid complexity from generating new waste (Liu et al., 2022). The study's results fit within international manufacturing debates on agility and resilience, where technology alone rarely produces sustained advantage unless paired with disciplined operational systems. In this sense, the findings did not overturn earlier knowledge but rather consolidated it into an empirically supported system logic: SHM functioned as a coherent manufacturing paradigm where each element played a distinct role that became economically and operationally meaningful only through integration.

The additive manufacturing component had emerged as a primary agility driver, particularly for responsiveness and mix flexibility outcomes, which corresponded with longstanding evidence that additive processes weaken the traditional penalty of complexity. Earlier studies had shown that internal channels, lattices, freeform topology, and part consolidation are routinely achievable through additive routes with little incremental setup cost, especially in low-to-medium volume contexts. The present study reinforced that trajectory by finding a strong linkage between additive capability maturity and agility performance (Panetto et al., 2019). Plants using additive shaping for near-net cores and complex features had exhibited shorter response times to order changes and higher descriptive flexibility across product variants. This observation was consistent with prior agile manufacturing literature that connected rapid reconfiguration to reduced tooling dependence and software-driven changeovers. The additive advantage described here also paralleled earlier findings on design-to-build compression, where the main agility gains originate from eliminating molds, dies, and multi-fixture programs. At the same time, the study's quality and efficiency results clarified why additive maturity alone had not guaranteed comprehensive performance improvements. Earlier additive research had documented surface roughness variability, porosity risks, and residual stress distortion, which can lead to build failures or heavy downstream correction. The present evidence indirectly supported this by showing that additive maturity correlated most strongly with agility rather than with quality or productivity. Such a pattern suggested that additive stages accelerated shaping and variant switching, yet did not independently secure conformance without supportive subtractive and smart-control layers (Butt, 2020). This interpretation aligned with earlier hybrid manufacturing claims that additive value is maximized when treated as a near-net generator, not a final-surface certifier. Additionally, additive capability in this study appeared to be higher in complex and volatile settings, reflecting earlier observations that firms adopt additive intensity more aggressively when traditional machining becomes inflexible or slow. The descriptive and correlational patterns implied that additive maturity functioned as a strategic response to complexity and uncertainty, increasing the feasible design space while enabling late customization. However, earlier work had emphasized that additive's economic advantage erodes when variability causes rebuilds or over-allowancing. The present findings fitted that logic by showing that agility benefits were strongest in sites that also displayed higher smart-control and lean integration maturity. In short, additive capability remained the agility engine, echoing earlier literature, but the study underscored that its agility outcomes were sustained only when the rest of the SHM system stabilized variation and maintained flow (Stojkovic & Butt, 2022).

Subtractive manufacturing in this study had served as the precision and reliability backbone, reflected by the strongest component-level relationship appearing between subtractive finishing capability and quality performance. Earlier machining research had consistently shown that CNC finishing and grinding deliver the tightest tolerances and most stable functional surfaces, particularly in regulated sectors requiring traceable conformance (Ammar et al., 2022). Earlier hybrid case studies had emphasized that additive parts typically require machining on critical interfaces such as holes, seats, sealing lands, and mating faces to meet certification demands. The present findings conformed to that position by revealing a robust positive effect of subtractive capability on first-pass yield, defect reduction, and dimensional conformance. Such results also paralleled earlier reports that hybrid manufacturing's credibility in aerospace and medical devices depends on machining final surfaces within a reliable datum frame. The study's evidence further suggested that machining capability remained a relatively mature dimension even among moderate SHM adopters, which aligned with earlier accounts that subtractive systems are deeply institutionalized in industrial practice. Yet the study also affirmed earlier critiques of subtractive-only production by highlighting why additive pre-forming was necessary: productivity and efficiency gains were linked to lean–smart integration and additive support rather than to subtractive capability alone (Maheshwari et al., 2022).

Figure 11: Smart Hybrid Manufacturing Capability Cycle



Earlier machining literature had noted high scrap ratios and long setup times when producing complex geometries from bulk stock, especially in high-mix environments. The present results fitted that tradition because subtractive capability did not show the same strength of association with productivity or agility as additive capability had. That pattern implied that machining ensured reliability but rarely created speed or flexibility on its own, precisely the limitation earlier hybrid authors used to justify near-net additive shaping. The findings also aligned with prior research on hybrid single-setup advantages, where machining within the same coordinate system as deposition reduced datum drift and rework. Although the present analysis did not isolate every micro-mechanism, the strong quality linkage suggested that sites effectively applying subtractive finishing within the hybrid stream were securing the final value of complex parts, validating the older idea that machining is the "certifying" segment of hybrid manufacturing (Pramanik et al., 2019). The study thereby reinforced the established view that subtractive manufacturing's role in SHM is not competing with additive manufacturing but completing it—transforming rapid near-net forms into finished products that meet functional and regulatory standards with consistent reliability.

Lean–smart integration maturity had exhibited significant effects on productivity and efficiency outcomes, reflecting the operational truth that hybrid technology does not automatically deliver agile flow without disciplined governance. Earlier lean manufacturing research had demonstrated that pull systems, cellular layouts, standard work, total productive maintenance, and continuous improvement reduce lead time, WIP, and defect costs in high-mix production (Wu et al., 2021). More recent lean-digital scholarship had argued that lean benefits can be amplified when real-time data exposes waste and variability faster than manual audits. The present study aligned with both lines by showing that lean–smart integration correlated strongly and predicted significantly shorter cycle time, improved setup compression, higher material utilization, and lower scrap. This evidence supported earlier claims that the main hidden risk of hybridization is operational complexity: alternating additive and subtractive steps can create queues, excessive re-planning, and over-finishing if flow is not engineered around part families and pull pacing. The wide dispersion found in lean–smart maturity also matched earlier reports that lean deployment in advanced manufacturing is often uneven, with some sites adopting superficial 5S-style tools while others build deep flow systems. In this study, deeper lean–smart maturity appeared to be the differentiator between moderate hybrid adopters and high-performing agile cells. Such an observation corresponded with older leagile manufacturing theory, which states that agility becomes economically sustainable only when efficiency waste is removed (Elahi & Tokaldany, 2021). Lean–smart integration also appeared to act as a reinforcing layer that prevented additive advantages from being diluted by overproduction or unstable finishing loads. Earlier AM studies had warned that printing "ahead of demand" can create inventory and queue waste, while earlier SM studies had shown that finishing backlogs quickly become bottlenecks. The present findings indicated that pull-aligned hybrid release and standardized routings were associated with higher throughput and lower idle losses, echoing those concerns. The results further suggested that lean–smart integration connects to sustainability through waste avoidance; improved material utilization and reduced scrap aligned with earlier lean-green arguments that waste removal naturally reduces environmental footprints (Cohen et al., 2019). Overall, the study consolidated earlier lean and hybrid insights into an empirical statement: lean maturity within a smart hybrid context was a direct performance driver, not a background cultural feature, and it provided the flow discipline that converted hybrid technical capability into measurable agility and efficiency gains.

Smart control maturity had played a mediating role between SHM capability and quality performance, which resonated with earlier smart manufacturing research emphasizing that cyber-physical feedback is essential for stabilizing additive variability and machining uncertainty in real time. Earlier studies on in-situ monitoring had shown that melt-pool signals, thermal maps, layer-height sensors, and optical inspection can detect defects before they propagate, while machining studies had shown that vibration and force sensing can prevent chatter and tool-wear-driven surface damage (Zwolińska et al., 2020). The present mediation finding reinforced those prior conclusions by showing that SHM's quality benefit was partially transmitted through smart control maturity. In practical terms, hybrid capability appeared to improve quality more strongly when monitoring and closed-loop correction were embedded into the additive-subtractive chain. This pattern was consistent with earlier hybrid arguments that geometry error and internal defects accumulate across layers if not corrected early, increasing the finishing burden or forcing rebuilds. The partial mediation result suggested that smart control did not replace the direct structural advantages of hybridization—such as feature allocation and single-setup finishing—but it intensified those advantages by reducing variance before finishing. That interpretation aligned with digital twin research showing that predictive deviation control can improve yield and capability indices without requiring heavier machining allowances (L. Zhang et al., 2022). Earlier smart-lean literature had also proposed that dashboards and traceability accelerate problem detection and kaizen cycles, and the present findings indirectly supported such claims by linking smart control to both quality and efficiency improvements. The descriptive variability in smart control maturity further paralleled earlier observations that sensor integration and analytics adoption are uneven across plants, often limited by investment and skills, which explains why smartness remains a differentiating factor in hybrid performance. The study therefore extended earlier work by positioning smart control not simply as an enhancer of process physics, but as a statistical pathway through which hybrid capability became reliable at scale (Liang & Qiao, 2022). In other words, the results reinforced a system logic already visible in earlier scholarship: hybrid manufacturing delivers geometric and operational potential, while smart control supplies the stabilizing intelligence that ensures that potential converts into consistent quality without excessive post-processing waste.

Moderation analysis had shown that lean maturity strengthened the effect of SHM capability on productivity and agility, aligning with earlier manufacturing performance studies that described lean as the condition under which flexibility produces real speed rather than chaos. Earlier lean-agile and leagile studies had argued that advanced technologies often fail to yield agility if upstream flow is unstable, WIP is unmanaged, or continuous improvement routines are weak (Iqbal et al., 2020). The present results affirmed that principle by indicating that SHM maturity had produced modest gains under low lean deployment but larger gains under high lean deployment. This pattern suggested that hybrid technical integration alone was insufficient to guarantee compressed lead times and rapid variant switching; instead, flow discipline and waste governance were necessary amplifiers. Such moderation aligned with older empirical work showing that pull scheduling reduces the volatility amplification that occurs when high-mix systems release large batches without capacity synchronization. In SHM settings, additive stages can quickly generate near-net parts, so the risk of over-release and finishing backlog is high without lean pull pacing (Gunasekaran et al., 2019). The study's moderation results were therefore coherent with earlier warnings that additive speed can create new waiting waste at machining or inspection stations if releasing rules are absent. Lean maturity also strengthened agility effects, which echoed leagile theories that identify a decoupling point and enforce leveling upstream to protect downstream responsiveness. The hybrid decoupling point in SHM is typically the additive near-net stage, and a mature lean system ensures that differentiation downstream is paced by demand signals rather than by forecasted printing campaigns. The moderation evidence thus supported earlier conceptualizations that agility becomes scalable only when efficiency waste is removed and process variation is systematically contained (Alogla et al., 2021). Additionally, the finding that lean maturity amplified productivity aligns with prior research on SMED and standardized work, which reduce the practical penalty of switching variants. When combined with additive's software-driven changeovers, these lean tools appear to create a multiplicative effect, explaining the steeper performance slopes observed in high-lean SHM adopters. Overall, the moderation results did not introduce a new theoretical direction but provided empirical confirmation across a hybrid context: lean maturity operated as a catalytic condition that allowed SHM to realize its promised speed and flexibility benefits in a stable and repeatable way.

Optional group comparisons had indicated that SHM effects were stronger in deeper-integration architectures and more turbulent demand environments, reinforcing earlier hybrid manufacturing insights about context-dependence. Earlier studies comparing single-platform hybrid machines with multi-machine hybrid cells had suggested that single-setup integration reduces datum shift, minimizes re-clamping, and lowers alignment rework, leading to better time and quality outcomes. The present evidence aligned with that claim by showing stronger SHM-to-performance relationships in single-platform configurations than in loosely coupled hybrid cells (Aceto et al., 2019). This suggested that physical integration depth matters because it eliminates a major non-value layer: the transfer and re-datum stage. Earlier research had also argued that hybrid benefits become more visible under high complexity and high uncertainty because conventional systems struggle to adjust responsively in such conditions. The present findings had shown stronger SHM effects under high volatility than under low volatility, reflecting that hybrid agility is most valuable when the environment penalizes slow changeovers and inventory-heavy strategies. This aligns with broader agile manufacturing theory, which treats turbulence as the stress test that reveals whether a system is truly agile. Under stable demand, even conventional lines can appear adequate; under volatile demand, speed, flexibility, and late customization become decisive advantages (Winkelhake et al., 2018). The stronger SHM slopes in volatile contexts therefore fitted established thinking that hybrid–lean–smart systems are strategic resilience tools rather than incremental upgrades. These comparisons also suggested that SHM capability should be interpreted as a contingent advantage: deeper integration and higher turbulence amplify returns on hybrid maturity. Such a conclusion is consistent with earlier manufacturing strategy literature that links technology value to task-environment fit. The study thus added empirical weight to long-standing claims that hybridization is most beneficial when it collapses setups physically and when it is deployed in environments where rapid, low-waste reconfiguration is essential (Bagnoli et al., 2022). In sum, the contextual findings reinforced the integrated logic across all results: SHM functioned as an agile production system whose impact depended on additive complexity leverage, subtractive precision certainty, smart variance control, and lean flow governance, with the largest gains appearing where integration depth and environmental turbulence made agility a competitive necessity.

CONCLUSION

Smart Hybrid Manufacturing represents an integrated production paradigm in which additive manufacturing, subtractive manufacturing, and lean techniques are deliberately combined into a single agile system that can produce complex, high-quality parts with low waste and rapid responsiveness. In this paradigm, additive manufacturing functions as the near-net shaping engine, enabling internal channels, lattice structures, freeform geometries, and part consolidation without the tooling burdens that typically slow high-mix production. Subtractive manufacturing then acts as the precision backbone, securing tolerance-critical interfaces, sealing zones, mating faces, and surface integrity levels required for functional certification, especially in sectors where dimensional reliability and fatigue performance are non-negotiable. Lean techniques provide the operational logic that prevents hybrid complexity from turning into new forms of waste, aligning additive release with machining capacity through pull scheduling, organizing hybrid resources into part-family cells to reduce transport and waiting, and enforcing standardized hybrid routings that keep variation from expanding into rework loops. The "smart" dimension of the system emerges through cyber-physical monitoring and control, where in-situ sensing of additive melt behavior or layer geometry, combined with real-time machining feedback on tool wear or vibration, enables closed-loop correction before deviations accumulate. This fused structure shifts the economics and physics of agile production: complexity becomes less costly because additive stages remove accessibility and tooling barriers, precision remains dependable because subtractive stages finalize critical surfaces, and flow stays stable because lean governance suppresses over-deposition, excess finishing allowance, queue instability, and redundant planning cycles. As a result, Smart Hybrid Manufacturing supports measurable agility outcomes such as shorter order-to-delivery lead times, lower mix-change penalties, and faster customization cycles, while simultaneously improving productivity through reduced setup events and consolidated routings. It also advances efficiency and sustainability by raising material utilization, lowering scrap caused by bulk machining, and cutting energy per part through variance reduction and lean waste control. Importantly, the system's performance is not derived from any single element but from their coordinated division of labor: additive processes create what is hard to machine, subtractive processes perfect what must be exact, lean ensures that both stages operate as a smooth value stream, and smart control stabilizes the entire chain through continuous feedback. Within turbulent global markets that demand customization, speed, certified quality, and resource responsibility at once, Smart Hybrid Manufacturing stands as a coherent agile production approach that reconciles flexibility with reliability and innovation with operational discipline.

RECOMMENDATIONS

Recommendations for advancing Smart Hybrid Manufacturing as a combination of additive, subtractive, and lean techniques for agile production systems should focus on coordinated capability building rather than isolated technology investment. First, hybrid adoption should begin with deliberate feature-level manufacturing strategy: parts ought to be redesigned so that additive stages create near-net complex regions (internal channels, lattices, topology-optimized cores), while subtractive stages are reserved for tolerance-critical interfaces and functional surfaces. This requires formal design-for-hybrid guidelines that specify machining allowances, datum surfaces, and additive build orientations early in the design cycle, preventing over-deposition and excessive finishing later. Second, organizations should prioritize integration depth in process planning by implementing standardized hybrid routings and cross-process digital threads that connect CAD, build preparation, machining programs, and inspection plans in one traceable workflow. Such integration should be reinforced through cyber-physical monitoring on both sides of the chain: in-situ additive sensing for melt stability, layer geometry, and thermal drift, and smart machining sensing for tool wear, vibration, and surface integrity. Closed-loop correction should be embedded as a routine capability, not a pilot feature, because early deviation control reduces rebuilds, minimizes corrective machining load, and stabilizes quality for certification-sensitive sectors. Third, lean deployment should be treated as the operational backbone of hybrid agility by redesigning shop floors into hybrid cells aligned to part families, supported by pull release rules that pace additive output to finishing capacity. Lean routines should explicitly track hybrid-specific wastes such as redundant simulations, repeated toolpath trials, over-allowancing, and over-finishing, then target them through kaizen cycles informed by real-time dashboards. Fourth, workforce development should be elevated as a strategic requirement: hybrid systems need cross-trained engineers and technicians who understand both deposition physics and machining dynamics, and who can interpret monitoring data for rapid root-cause closure. Training programs should therefore combine AM process control, CNC finishing, metrology, and lean problem-solving in a unified curriculum. Fifth, performance management should rely on balanced metrics that capture productivity, quality, efficiency, and agility together, ensuring that gains in speed do not come at the expense of conformance or waste growth. Finally, scaling decisions should privilege high-complexity, high-mix, and volatile-demand contexts where hybrid value is greatest; in these settings, investment in single-setup hybrid platforms or tightly synchronized hybrid cells will tend to yield stronger agility and sustainability returns than loosely coupled sequential chains. Implemented collectively, these recommendations position Smart Hybrid Manufacturing as a disciplined, data-stabilized, and lean-governed system that can reliably deliver rapid customization, certified precision, and low-waste production under real industrial turbulence.

LIMITATION

Several limitations had characterized the quantitative investigation of Smart Hybrid Manufacturing as a combined system of additive, subtractive, and lean techniques for agile production, and these constraints should be considered when interpreting the findings. First, the study had relied on a cross-sectional design, meaning that SHM capability maturity and performance outcomes had been measured at a single point in time. This structure had supported association and prediction testing, but it had limited the ability to infer temporal ordering with certainty, especially for capability elements that may evolve at different speeds such as lean–smart integration and smart control maturity. Second, although objective performance indicators had been requested, some participating sites had provided partial or range-based records, requiring aggregation and normalization across different accounting systems. This had introduced measurement noise, particularly in energy, scrap, and defect reporting, where firms sometimes used non-identical definitions or sampling windows. Third, capability constructs had been operationalized through survey items reflecting managerial and engineering perceptions of maturity. Even with strong reliability and validity checks, perceptual measures had remained vulnerable to response bias, including optimistic self-assessment or differences in interpretation of what constituted "high" hybridization, smartness, or lean depth. Fourth, the sample had been stratified across sectors and hybridization modes, yet representation had remained uneven. Certain industries with mature certification infrastructures and higher investment capacity had been more prevalent than smaller or less digitized sectors, which may have constrained generalizability to low-resource contexts where SHM adoption barriers differ substantially. Fifth, product complexity and demand volatility had been included as controls, but these contextual variables had been captured in broad ordinal categories rather than fine-grained continuous measures. As a result, subtle interactions between complexity type (e.g., internal void density versus surface curvature) and SHM performance might not have been fully detected. Sixth, the study model had treated SHM capability as a composite of additive, subtractive, and lean–smart integration, yet hybrid systems vary widely in machine architecture, material class, and sequencing strategy. The quantitative framework had not decomposed these technical configurations in detail, so performance differences attributable to specific processes such as powder bed fusion versus directed energy deposition, or to specific finishing routes such as 5-axis milling versus grinding, had been absorbed into higher-level constructs. Seventh, the analysis had focused on plant or cell-level performance bundles, which had been appropriate for agile systems evaluation, but it had not captured micro-level mechanisms such as layer-wise thermal behavior, toolpath-specific surface integrity, or in-situ defect morphology that could refine causal explanation. Finally, the mediation and moderation results had depended on statistical modeling assumptions, and while robustness checks had supported stability, unobserved organizational factors—such as supplier reliability, workforce turnover, or concurrent improvement programs—could still have influenced performance in ways not explicitly modeled. Taken together, these limitations had not invalidated the evidence for SHM's positive performance role, but they had indicated that the results should be interpreted as system-level empirical patterns within the boundaries of cross-sectional measurement, mixed data fidelity, and heterogeneous industrial configurations.

REFERENCES

[1]. Abbas, M., & Shafiee, M. (2018). Structural health monitoring (SHM) and determination of surface defects in large metallic structures using ultrasonic guided waves. *Sensors*, *18*(11), 3958.

[2]. Abdulla, M., & Md. Jobayer Ibne, S. (2021). Cloud-Native Frameworks For Real-Time Threat Detection And Data Security In Enterprise Networks. *International Journal of Scientific Interdisciplinary Research*, 2(2), 34–62. https://doi.org/10.63125/0t27av85

[3]. Aceto, G., Persico, V., & Pescapé, A. (2019). A survey on information and communication technologies for industry 4.0: State-of-the-art, taxonomies, perspectives, and challenges. *IEEE Communications Surveys & Tutorials*, *21*(4), 3467-3501.

[4]. Almoslehy, S. A. M., & Alkahtani, M. S. (2021). Key approaches, risks, and product performance in managing the development process of complex products sustainably. *Sustainability*, *13*(9), 4727.

[5]. Alogla, A. A., Baumers, M., Tuck, C., & Elmadih, W. (2021). The impact of additive manufacturing on the flexibility of a manufacturing supply chain. *Applied Sciences*, *11*(8), 3707.

[6]. Amaechi, C. V., Reda, A., Kgosiemang, I. M., Ja'e, I. A., Oyetunji, A. K., Olukolajo, M. A., & Igwe, I. B. (2022). Guidelines on asset management of offshore facilities for monitoring, sustainable maintenance, and safety practices. *Sensors*, *22*(19), 7270.

[7]. Amiri, F., Overbeek, S., Wagenaar, G., & Stettina, C. J. (2021). Reconciling agile frameworks with IT sourcing through an IT sourcing dimensions map and structured decision-making. *Information Systems and e-Business Management*, *19*(4), 1113-1142.

[8]. Ammar, M., Haleem, A., Javaid, M., Bahl, S., & Verma, A. S. (2022). Implementing Industry 4.0 technologies in self-healing materials and digitally managing the quality of manufacturing. *Materials Today: Proceedings*, *52*, 2285-2294.

[9]. Andronie, M., Lăzăroiu, G., Ştefănescu, R., Uţă, C., & Dijmărescu, I. (2021). Sustainable, smart, and sensing technologies for cyber-physical manufacturing systems: A systematic literature review. *Sustainability*, *13*(10), 5495.

[10]. Atwal, H. (2020). Practical DataOps. *Practical DataOps (1st ed.). Apress Berkeley, CA. https://doi. org/10.1007/978-1-4842-5104-1*.

[11]. Azevedo, A., & Almeida, A. H. (2021). Grasp the challenge of digital transition in SMEs—A training course geared towards decision-makers. *Education Sciences*, *11*(4), 151.

[12]. Bagnoli, C., Albarelli, A., Biazzo, S., Biotto, G., Marseglia, G. R., Massaro, M., Messina, M., Muraro, A., & Troiano, L. (2022). Digital business models for industry 4.0. *Future of business and finance*, *10*, 978-983.

[13]. Balkhi, B., Alshahrani, A., & Khan, A. (2022). Just-in-time approach in healthcare inventory management: Does it really work? *Saudi Pharmaceutical Journal*, *30*(12), 1830-1835.

[14]. Bi, Z., Zhang, W.-J., Wu, C., Luo, C., & Xu, L. (2021). Generic design methodology for smart manufacturing systems from a practical Perspective, part I—Digital triad concept and Its application as a system reference model. *Machines*, *9*(10), 207.

[15]. Brand, M., Tiberius, V., Bican, P. M., & Brem, A. (2021). Agility as an innovation driver: towards an agile front end of innovation framework. *Review of Managerial Science*, *15*(1), 157-187.

[16]. Butt, J. (2020). Exploring the interrelationship between additive manufacturing and Industry 4.0. *Designs*, *4*(2), 13.

[17]. Chatwani, N. (2019). Organisational agility. *Springer International Publishing, Cham, doi*, *10*, 978-973.

[18]. Ciano, M. P., Pozzi, R., Rossi, T., & Strozzi, F. (2019). How IJPR has addressed 'lean': a literature review using bibliometric tools. *International Journal of Production Research*, *57*(15-16), 5284-5317.

[19]. Ciccullo, F., Pero, M., Caridi, M., Gosling, J., & Purvis, L. (2018). Integrating the environmental and social sustainability pillars into the lean and agile supply chain management paradigms: A literature review and future research directions. *Journal of cleaner production*, *172*, 2336-2350.

[20]. Cocchi, N., Dosi, C., & Vignoli, M. (2021). The hybrid model MatrixEnhancing stage-gate with design thinking, lean Startup, and agile. *Research-Technology Management*, *64*(5), 18-30.

[21]. Cohen, Y., Naseraldin, H., Chaudhuri, A., & Pilati, F. (2019). Assembly systems in Industry 4.0 era: a road map to understand Assembly 4.0. *The International Journal of Advanced Manufacturing Technology*, *105*(9), 4037-4054.

[22]. Cortina, M., Arrizubieta, J. I., Ruiz, J. E., Ukar, E., & Lamikiz, A. (2018). Latest developments in industrial hybrid machine tools that combine additive and subtractive operations. *Materials*, *11*(12), 2583.

[23]. Dávila, J. L., Neto, P. I., Noritomi, P. Y., Coelho, R. T., & da Silva, J. V. L. (2020). Hybrid manufacturing: a review of the synergy between directed energy deposition and subtractive processes. *The International Journal of Advanced Manufacturing Technology*, *110*(11), 3377-3390.

[24]. Davis, R., Singh, A., Jackson, M. J., Coelho, R. T., Prakash, D., Charalambous, C. P., Ahmed, W., da Silva, L. R. R., & Lawrence, A. A. (2022). A comprehensive review on metallic implant biomaterials and their subtractive manufacturing. *The International Journal of Advanced Manufacturing Technology*, *120*(3), 1473-1530.

[25]. Davis, R., Singh, A., Sabino, R. M., Pereira, R. B. D., Popat, K., Soares, P., & Jackson, M. J. (2021). Performance Investigation of Cryo-treated End Mill on the Mechanical and in vitro behavior of Hybrid-lubri-coolant-milled Ti-6Al-4V alloy. *Journal of Manufacturing Processes*, *71*, 472-488.

[26]. Dilberoglu, U. M., Gharehpapagh, B., Yaman, U., & Dolen, M. (2021). Current trends and research opportunities in hybrid additive manufacturing. *The International Journal of Advanced Manufacturing Technology*, *113*(3), 623-648.

[27]. Doghri, W., Saddoud, A., & Chaari Fourati, L. (2022). Cyber-physical systems for structural health monitoring: sensing technologies and intelligent computing. *The Journal of Supercomputing*, *78*(1), 766-809.

[28]. Elahi, B., & Tokaldany, S. A. (2021). Application of Internet of Things-aided simulation and digital twin technology in smart manufacturing. In *Advances in Mathematics for Industry 4.0* (pp. 335-359). Elsevier.

[29]. Fagarasan, C., Cristea, C., Cristea, M., Popa, O., Mihele, C., & Pisla, A. (2022). The delivery of large-scale software products through the adoption of the SAFe framework. 2022 International Conference on Development and Application Systems (DAS),

[30]. Feng, D., & Feng, M. Q. (2018). Computer vision for SHM of civil infrastructure: From dynamic response measurement to damage detection–A review. *Engineering Structures*, *156*, 105-117.

[31]. Fischer, M., Imgrund, F., Janiesch, C., & Winkelmann, A. (2020). Strategy archetypes for digital transformation: Defining meta objectives using business process management. *Information & management*, *57*(5), 103262.

[32]. Gandhi, N., Rose, R., Croxford, A. J., & Ward, C. (2022). Understanding system complexity in the non-destructive testing of advanced composite products. *Journal of Manufacturing and Materials Processing*, *6*(4), 71.

[33]. Gharehbaghi, V. R., Noroozinejad Farsangi, E., Noori, M., Yang, T., Li, S., Nguyen, A., Málaga-Chuquitaype, C., Gardoni, P., & Mirjalili, S. (2022). A critical review on structural health monitoring: Definitions, methods, and perspectives. *Archives of computational methods in engineering*, *29*(4), 2209-2235.

[34]. Godina, R., Ribeiro, I., Matos, F., T. Ferreira, B., Carvalho, H., & Peças, P. (2020). Impact assessment of additive manufacturing on sustainable business models in industry 4.0 context. *Sustainability*, *12*(17), 7066.

[35]. Gunasekaran, A., Yusuf, Y. Y., Adeleye, E. O., Papadopoulos, T., Kovvuri, D., & Geyi, D. A. G. (2019). Agile manufacturing: an evolutionary review of practices. *International Journal of Production Research*, *57*(15-16), 5154-5174.

[36]. Habibullah, S. M., & Md. Foysal, H. (2021). A Data Driven Cyber Physical Framework For Real Time Production Control Integrating IOT And Lean Principles. *American Journal of Interdisciplinary Studies*, *2*(03), 35–70. https://doi.org/10.63125/20nhqs87

[37]. Han, X., & Frangopol, D. M. (2022). Fatigue reliability analysis considering corrosion effects and integrating SHM information. *Engineering Structures*, *272*, 114967.

[38]. Hassani, S., Mousavi, M., & Gandomi, A. H. (2021). Structural health monitoring in composite structures: A comprehensive review. *Sensors*, *22*(1), 153.

[39]. Hayes, K., & Rajput, A. (2021). NDE 4.0: image and sound recognition. In *Handbook of Nondestructive Evaluation 4.0* (pp. 1-20). Springer.

[40]. Hertwig, M., Lentes, J., Zimmermann, N., & Dangelmaier, M. (2018). Stuttgart Region—Sustainable Industrialization in Stuttgart Metropolitan Region. In *Smart Metropolitan Regional Development: Economic and Spatial Design Strategies* (pp. 175-236). Springer.

[41]. Hsu, C.-H., He, X., Zhang, T.-Y., Chang, A.-Y., Liu, W.-L., & Lin, Z.-Q. (2022). Enhancing supply chain agility with industry 4.0 enablers to mitigate ripple effects based on integrated QFD-MCDM: an empirical study of new energy materials manufacturers. *Mathematics*, *10*(10), 1635.

[42]. Hu, K.-H., Chen, F.-H., Hsu, M.-F., Yao, S., & Hung, M.-C. (2021). Identification of the critical factors for global supply chain management under the COVID-19 outbreak via a fusion intelligent decision support system. *Axioms*, *10*(2), 61.

[43]. Iqbal, A., Zhao, G., Suhaimi, H., He, N., Hussain, G., & Zhao, W. (2020). Readiness of subtractive and additive manufacturing and their sustainable amalgamation from the perspective of Industry 4.0: A comprehensive review. *The International Journal of Advanced Manufacturing Technology*, *111*(9), 2475-2498.

[44]. Jin, J., Feng, W., Lei, Q., Gui, G., Li, X., Deng, Z., & Wang, W. (2021). Defect detection of printed circuit boards using efficientdet. 2021 ieee 6th international conference on signal and image processing (icsip),

[45]. Jovanović, M., Mesquida, A.-L., Mas, A., & Colomo-Palacios, R. (2020). Agile transition and adoption frameworks, issues and factors: a systematic mapping. *IEEE access*, *8*, 15711-15735.

[46]. Knabke, T., & Olbrich, S. (2018). Building novel capabilities to enable business intelligence agility: results from a quantitative study. *Information Systems and e-Business Management*, *16*(3), 493-546.

[47]. Korkmaz, M. E., Waqar, S., Garcia-Collado, A., Gupta, M. K., & Krolczyk, G. M. (2022). A technical overview of metallic parts in hybrid additive manufacturing industry. *Journal of Materials Research and Technology*, *18*, 384-395.

[48]. Kot, P., Muradov, M., Gkantou, M., Kamaris, G. S., Hashim, K., & Yeboah, D. (2021). Recent advancements in non-destructive testing techniques for structural health monitoring. *Applied Sciences*, *11*(6), 2750.

[49]. Kumar, R., Singh, K., & Jain, S. K. (2022). Assessment of Agile manufacturing impact on business performance of Indian manufacturing industry: A PLS-SEM approach. *Sustainable Manufacturing and Service Economics*, *1*, 100001.

[50]. Kumar, S., & Kishor, B. (2021). Ultrasound added additive manufacturing for metals and composites: Process and control. In *Additive and subtractive manufacturing of composites* (pp. 53-72). Springer.

[51]. Kusiak, A. (2018). Smart manufacturing. *International Journal of Production Research*, *56*(1-2), 508-517.

[52]. Kusiak, A. (2019). Fundamentals of smart manufacturing: A multi-thread perspective. *Annual Reviews in Control*, *47*, 214-220.

[53]. Lalmi, A., Fernandes, G., & Boudemagh, S. S. (2022). Synergy between Traditional, Agile and Lean management approaches in construction projects: bibliometric analysis. *Procedia Computer Science*, *196*, 732-739.

[54]. Lattanzi, L., Raffaeli, R., Peruzzini, M., & Pellicciari, M. (2021). Digital twin for smart manufacturing: A review of concepts towards a practical industrial implementation. *International Journal of Computer Integrated Manufacturing*, *34*(6), 567-597.

[55]. Li, L., Haghighi, A., & Yang, Y. (2018). A novel 6-axis hybrid additive-subtractive manufacturing process: Design and case studies. *Journal of Manufacturing Processes*, *33*, 150-160.

[56]. Li, Q., Tang, Q., Chan, I., Wei, H., Pu, Y., Jiang, H., Li, J., & Zhou, J. (2018). Smart manufacturing standardization: Architectures, reference models and standards framework. *Computers in industry*, *101*, 91-106.

[57]. Li, Y., Diabat, A., & Lu, C.-C. (2020). Leagile supplier selection in Chinese textile industries: a DEMATEL approach. *Annals of Operations Research*, *287*(1), 303-322.

[58]. Liang, H., & Qiao, J. (2022). Analysis of current situation, demand and development trend of casting grinding technology. *Micromachines*, *13*(10), 1577.

[59]. Lindemann, H., Gerbers, R., Ibrahim, S., Dietrich, F., Herrmann, E., Dröder, K., Raatz, A., & Kloft, H. (2018). Development of a shotcrete 3D-printing (SC3DP) technology for additive manufacturing of reinforced freeform concrete structures. RILEM International Conference on Concrete and Digital Fabrication,

[60]. Liu, Q., Liu, M., Zhou, H., Yan, F., Ma, Y., & Shen, W. (2022). Intelligent manufacturing system with human-cyber-physical fusion and collaboration for process fine control. *Journal of manufacturing systems*, *64*, 149-169.

[61]. Maheshwari, S., Siddharth, A., & Alam, Z. (2022). Implementation of Cyber Physical Systems in Additive Manufacturing to Sustain Covid-19 Pandemic. In *Cyber-Physical Systems* (pp. 183-206). CRC Press.
[62]. Maniruzzaman, B., Mohammad Anisur, R., Afrin Binta, H., Md, A., & Anisur, R. (2023). Advanced Analytics And Machine Learning For Revenue Optimization In The Hospitality Industry: A Comprehensive Review Of Frameworks. *American Journal of Scholarly Research and Innovation*, *2*(02), 52-74. https://doi.org/10.63125/8xbkma40
[63]. Md Al Amin, K. (2022). Human-Centered Interfaces in Industrial Control Systems: A Review Of Usability And Visual Feedback Mechanisms. *Review of Applied Science and Technology*, *1*(04), 66-97. https://doi.org/10.63125/gr54qy93
[64]. Md Arif Uz, Z., & Elmoon, A. (2023). Adaptive Learning Systems For English Literature Classrooms: A Review Of AI-Integrated Education Platforms. *International Journal of Scientific Interdisciplinary Research*, *4*(3), 56-86. https://doi.org/10.63125/a30ehr12
[65]. Md Ariful, I. (2022). Irradiation-Enhanced CREEP–Fatigue Interaction In High-Temperature Austenitic Steel: Current Understanding And Challenges. *American Journal of Advanced Technology and Engineering Solutions*, *2*(04), 148-181. https://doi.org/10.63125/e46gja61
[66]. Md Nahid, H. (2022). Statistical Analysis of Cyber Risk Exposure And Fraud Detection In Cloud-Based Banking Ecosystems. *ASRC Procedia: Global Perspectives in Science and Scholarship*, *2*(1), 289–331. https://doi.org/10.63125/9wf91068
[67]. Md Sarwar, H. (2021). Sustainable Materials Characterization For Low-Carbon Construction And Infrastructure Durability. *American Journal of Interdisciplinary Studies*, *2*(01), 01-34. https://doi.org/10.63125/wq1wdr64
[68]. Md Sarwar Hossain, S., & Md Milon, M. (2022). Machine Learning-Based Pavement Condition Prediction Models For Sustainable Transportation Systems. *American Journal of Interdisciplinary Studies*, *3*(01), 31–64. https://doi.org/10.63125/1jsmkg92
[69]. Md. Mominul, H., Masud, R., & Md. Milon, M. (2022). Statistical Analysis of Geotechnical Soil Loss And Erosion Patterns For Climate Adaptation In Coastal Zones. *American Journal of Interdisciplinary Studies*, *3*(03), 36-67. https://doi.org/10.63125/xytn3e23
[70]. Md. Musfiqur, R., & Saba, A. (2021). Data-Driven Decision Support in Information Systems: Strategic Applications In Enterprises. *International Journal of Scientific Interdisciplinary Research*, *2*(2), 01-33. https://doi.org/10.63125/cfvg2v45
[71]. Md. Rabiul, K., & Sai Praveen, K. (2022). The Influence of Statistical Models For Fraud Detection In Procurement And International Trade Systems. *American Journal of Interdisciplinary Studies*, *3*(04), 203-234. https://doi.org/10.63125/9htnv106
[72]. Md. Redwanul, I., Md Nahid, H., & Md. Zahid Hasan, T. (2021). Predictive Analytics in Supply Chain Management A Review Of Business Analyst-Led Optimization Tools. *Review of Applied Science and Technology*, *6*(1), 34-73. https://doi.org/10.63125/5aypx555
[73]. Md. Tarek, H. (2023). Quantitative Risk Modeling For Data Loss And Ransomware Mitigation In Global Healthcare And Pharmaceutical Systems. *International Journal of Scientific Interdisciplinary Research*, *4*(3), 87-116. https://doi.org/10.63125/8wk2ch14
[74]. Md. Tarek, H., & Md.Kamrul, K. (2024). Blockchain-Enabled Secure Medical Billing Systems: Quantitative Analysis of Transaction Integrity. *ASRC Procedia: Global Perspectives in Science and Scholarship*, *4*(1), 97–123. https://doi.org/10.63125/1t8jpm24
[75]. Md. Tarek, H., & Sai Praveen, K. (2021). Data Privacy-Aware Machine Learning and Federated Learning: A Framework For Data Security. *American Journal of Interdisciplinary Studies*, *2*(03), 01–34. https://doi.org/10.63125/vj1hem03
[76]. Mecheter, A., Pokharel, S., & Tarlochan, F. (2022). Additive manufacturing technology for spare parts application: A systematic review on supply chain management. *Applied Sciences*, *12*(9), 4160.
[77]. Moghaddam, M., Cadavid, M. N., Kenley, C. R., & Deshmukh, A. V. (2018). Reference architectures for smart manufacturing: A critical review. *Journal of manufacturing systems*, *49*, 215-225.
[78]. Mohammad Mushfequr, R., & Ashraful, I. (2023). Automation And Risk Mitigation in Healthcare Claims: Policy And Compliance Implications. *Review of Applied Science and Technology*, *2*(04), 124–157. https://doi.org/10.63125/v73gyg14
[79]. Moradi, M., Moradi, M., Bayat, F., & Toosi, A. N. (2019). Collective hybrid intelligence: towards a conceptual framework. *International Journal of Crowd Science*, *3*(2), 198-220.
[80]. Mst. Shahrin, S., & Samia, A. (2023). High-Performance Computing For Scaling Large-Scale Language And Data Models In Enterprise Applications. *ASRC Procedia: Global Perspectives in Science and Scholarship*, *3*(1), 94–131. https://doi.org/10.63125/e7yfwm87
[81]. Mueller, I., Memmolo, V., Tschöke, K., Moix-Bonet, M., Möllenhoff, K., Golub, M., Venkat, R. S., Lugovtsova, Y., Eremin, A., & Moll, J. (2022). Performance assessment for a guided wave-based SHM system applied to a stiffened composite structure. *Sensors*, *22*(19), 7529.
[82]. Nagadi, K., Rabelo, L., Basingab, M., Sarmiento, A. T., Jones, A., & Rahal, A. (2018). A hybrid simulation-based assessment framework of smart manufacturing systems. *International Journal of Computer Integrated Manufacturing*, *31*(2), 115-128.
[83]. Najar, T. (2022). Lean-Agile supply chain innovation performance; the mediating role of dynamic capability, innovation capacity, and relational embeddednes. Supply Chain Forum: An International Journal,

[84]. Nordmark, S., Lindberg, I., & Zingmark, K. (2022). "It's all about time and timing": nursing staffs' experiences with an agile development process, from its initial requirements to the deployment of its outcome of ICT solutions to support discharge planning. *BMC medical informatics and decision making*, *22*(1), 186.

[85]. Okasha, N. M., & Frangopol, D. M. (2019). Integration of structural health monitoring in a system performance based life-cycle bridge management framework. In *Structures and Infrastructure Systems* (pp. 316-333). Routledge.

[86]. Omar Muhammad, F., & Md Redwanul, I. (2023). A Quantitative Study on AI-Driven Employee Performance Analytics In Multinational Organizations. *American Journal of Interdisciplinary Studies*, *4*(04), 145-176. https://doi.org/10.63125/vrsjp515

[87]. Omar Muhammad, F., & Md. Redwanul, I. (2023). IT Automation and Digital Transformation Strategies For Strengthening Critical Infrastructure Resilience During Global Crises. *American Journal of Interdisciplinary Studies*, *4*(04), 145-176. https://doi.org/10.63125/vrsjp515

[88]. Omar Muhammad, F., & Mst. Shahrin, S. (2021). Comparative Analysis of BI Systems In The U.S. And Europe: Lessons In Data Governance And Predictive Analytics. *Journal of Sustainable Development and Policy*, *1*(5), 01-38. https://doi.org/10.63125/6b3aeg93

[89]. Panah, R. S., & Kioumarsi, M. (2021). Application of building information modelling (BIM) in the health monitoring and maintenance process: A systematic review. *Sensors*, *21*(3), 837.

[90]. Panetto, H., Iung, B., Ivanov, D., Weichhart, G., & Wang, X. (2019). Challenges for the cyber-physical manufacturing enterprises of the future. *Annual Reviews in Control*, *47*, 200-213.

[91]. Parhi, S., Joshi, K., & Akarte, M. (2021). Smart manufacturing: a framework for managing performance. *International Journal of Computer Integrated Manufacturing*, *34*(3), 227-256.

[92]. Patpatiya, P., Shastri, A., Sharma, S., Chaudhary, K., & Bhatnagar, V. (2022). ANN-predictive modeling and GA-optimization for minimizing dimensional tolerance in Polyjet Additive Manufacturing. *CIRP Journal of Manufacturing Science and Technology*, *38*, 320-339.

[93]. Pekař, M., Mihajlović, N., Belt, H., Kolen, A. F., Van Rens, J., Budzelaar, F., Jacobs, B., Bosch, J. G., Vos, H. J., & Rem-Bronneberg, D. (2018). Quantitative imaging performance of frequency-tunable capacitive micromachined ultrasonic transducer array designed for intracardiac application: Phantom study. *Ultrasonics*, *84*, 421-429.

[94]. Pragana, J. P., Cristino, V. A., Bragança, I. M., Silva, C. M., & Martins, P. A. (2020). Integration of forming operations on hybrid additive manufacturing systems based on fusion welding. *International Journal of Precision Engineering and Manufacturing-Green Technology*, *7*(3), 595-607.

[95]. Pramanik, P. K. D., Mukherjee, B., Pal, S., Upadhyaya, B. K., & Dutta, S. (2019). Ubiquitous manufacturing in the age of industry 4.0: a state-of-the-art primer. In *A Roadmap to Industry 4.0: Smart Production, Sharp Business and Sustainable Development* (pp. 73-112). Springer.

[96]. Priyadarshini, J., Singh, R. K., Mishra, R., & Bag, S. (2022). Investigating the interaction of factors for implementing additive manufacturing to build an antifragile supply chain: TISM-MICMAC approach. *Operations Management Research*, *15*(1), 567-588.

[97]. Qu, Y., Ming, X., Liu, Z., Zhang, X., & Hou, Z. (2019). Smart manufacturing systems: state of the art and future trends. *The International Journal of Advanced Manufacturing Technology*, *103*(9), 3751-3768.

[98]. Ragazou, K., Passas, I., Garefalakis, A., & Dimou, I. (2022). Investigating the research trends on strategic ambidexterity, agility, and open innovation in SMEs: Perceptions from bibliometric analysis. *Journal of Open Innovation: Technology, Market, and Complexity*, *8*(3), 118.

[99]. Ragnoli, M., Leoni, A., Barile, G., Ferri, G., & Stornelli, V. (2022). LoRa-Based Wireless Sensors Network for Rockfall and Landslide Monitoring: A Case Study in Pantelleria Island with Portable LoRaWAN Access. *Journal of Low Power Electronics and Applications*, *12*(3), 47.

[100]. Raji, I. O., Shevtshenko, E., Rossi, T., & Strozzi, F. (2021). Modelling the relationship of digital technologies with lean and agile strategies. Supply Chain Forum: An International Journal,

[101]. Rakibul, H., & Samia, A. (2022). Information System-Based Decision Support Tools: A Systematic Review Of Strategic Applications In Service-Oriented Enterprises. *Review of Applied Science and Technology*, *1*(04), 26-65. https://doi.org/10.63125/w3cevz78

[102]. Razia, S. (2023). AI-Powered BI Dashboards In Operations: A Comparative Analysis For Real-Time Decision Support. *ASRC Procedia: Global Perspectives in Science and Scholarship*, *3*(1), 62–93. https://doi.org/10.63125/wqd2t159

[103]. Rojas, R. A., & Rauch, E. (2019). From a literature review to a conceptual framework of enablers for smart manufacturing control. *The International Journal of Advanced Manufacturing Technology*, *104*(1), 517-533.

[104]. Sadeghi, S., Akbarpour, A., & Abbasianjahromi, H. (2022). Provide a lean and agile strategy for an antifragile sustainable supply chain in the construction industry (residential complex). *Cleaner Logistics and Supply Chain*, *5*, 100079.

[105]. Saikat, S. (2021). Real-Time Fault Detection in Industrial Assets Using Advanced Vibration Dynamics And Stress Analysis Modeling. *American Journal of Interdisciplinary Studies*, *2*(04), 39–68. https://doi.org/10.63125/0h163429

[106]. Saikat, S. (2022). CFD-Based Investigation of Heat Transfer Efficiency In Renewable Energy Systems. *International Journal of Scientific Interdisciplinary Research*, *1*(01), 129–162. https://doi.org/10.63125/ttw40456

[107]. Sajadieh, S. M. M., Son, Y. H., & Noh, S. D. (2022). A conceptual definition and future directions of urban smart factory for sustainable manufacturing. *Sustainability*, *14*(3), 1221.

[108]. Salleh, N. H. M., Abd Rasidi, N. A. S., & Jeevan, J. (2020). Lean, agile, resilience and green (LARG) paradigm in supply chain operations: a trial in a seaport system. *Australian Journal of Maritime & Ocean Affairs*, *12*(4), 200-216.

[109]. Scott, M. J., Verhagen, W. J., Bieber, M. T., & Marzocca, P. (2022). A systematic literature review of predictive maintenance for defence fixed-wing aircraft sustainment and operations. *Sensors*, *22*(18), 7070.
[110]. Sebbe, N. P., Fernandes, F., Sousa, V. F., & Silva, F. J. (2022). Hybrid manufacturing processes used in the production of complex parts: a comprehensive review. *Metals*, *12*(11), 1874.
[111]. Shaikh, S., & Aditya, D. (2021). Federated Learning-Driven Predictive Quality Analytics and Supply Chain Optimization In Distributed Manufacturing Networks. *Review of Applied Science and Technology*, *6*(1), 74-107. https://doi.org/10.63125/k18cbz55
[112]. Shams, R., Vrontis, D., Belyaeva, Z., Ferraris, A., & Czinkota, M. R. (2021). Strategic agility in international business: A conceptual framework for "agile" multinationals. *Journal of International Management*, *27*(1), 100737.
[113]. Sheoran, A. J., Kumar, H., Arora, P. K., & Moona, G. (2020). Bio-medical applications of additive manufacturing: a review. *Procedia Manufacturing*, *51*, 663-670.
[114]. Sobb, T., Turnbull, B., & Moustafa, N. (2020). Supply chain 4.0: A survey of cyber security challenges, solutions and future directions. *Electronics*, *9*(11), 1864.
[115]. Sommer, A. F. (2019). Agile Transformation at LEGO Group: Implementing Agile methods in multiple departments changed not only processes but also employees' behavior and mindset. *Research-Technology Management*, *62*(5), 20-29.
[116]. Stavropoulos, P., Bikas, H., Avram, O., Valente, A., & Chryssolouris, G. (2020). Hybrid subtractive–additive manufacturing processes for high value-added metal components. *The International Journal of Advanced Manufacturing Technology*, *111*(3), 645-655.
[117]. Stern, T. V. (2020). *Lean and agile project management: how to make any project better, faster, and more cost effective*. Productivity Press.
[118]. Stojkovic, M., & Butt, J. (2022). Industry 4.0 implementation framework for the composite manufacturing industry. *Journal of Composites Science*, *6*(9), 258.
[119]. Tang, C., Zhao, J., Wang, Z., Zhao, Y., & Wang, T. (2022). Experimental investigation on the effect of process parameters in additive/subtractive hybrid manufacturing 316L stainless steel. *The International Journal of Advanced Manufacturing Technology*, *121*(3), 2461-2481.
[120]. Tasdemir, C., & Gazo, R. (2018). A systematic literature review for better understanding of lean driven sustainability. *Sustainability*, *10*(7), 2544.
[121]. Tonoy Kanti, C., & Shaikat, B. (2022). Graph Neural Networks (GNNS) For Modeling Cyber Attack Patterns And Predicting System Vulnerabilities In Critical Infrastructure. *American Journal of Interdisciplinary Studies*, *3*(04), 157-202. https://doi.org/10.63125/1ykzx350
[122]. Tripathi, V., Chattopadhyaya, S., Mukhopadhyay, A. K., Sharma, S., Singh, J., Pimenov, D. Y., & Giasin, K. (2021). An innovative agile model of smart lean–green approach for sustainability enhancement in Industry 4.0. *Journal of Open Innovation: Technology, Market, and Complexity*, *7*(4), 215.
[123]. Valtonen, I., Rautio, S., & Salmi, M. (2022). Capability development in hybrid organizations: enhancing military logistics with additive manufacturing. *Progress in Additive Manufacturing*, *7*(5), 1037-1052.
[124]. Venugopal, V., & Saleeshya, P. (2019). Manufacturing system sustainability through lean and agile initiatives. *International Journal of Sustainable Engineering*, *12*(3), 159-173.
[125]. Vora, H. D., & Sanyal, S. (2020). A comprehensive review: metrology in additive manufacturing and 3D printing technology. *Progress in Additive Manufacturing*, *5*(4), 319-353.
[126]. Watson, R., Kamel, M., Zhang, D., Dobie, G., MacLeod, C., Pierce, S. G., & Nieto, J. (2021). Dry coupled ultrasonic non-destructive evaluation using an over-actuated unmanned aerial vehicle. *IEEE Transactions on Automation Science and Engineering*, *19*(4), 2874-2889.
[127]. Weber, K. A., Smith, A. C., Wasielewski, M., Eghtesad, K., Upadhyayula, P. A., Wintermark, M., Hastie, T. J., Parrish, T. B., Mackey, S., & Elliott, J. M. (2019). Deep learning convolutional neural networks for the automatic quantification of muscle fat infiltration following whiplash injury. *Scientific reports*, *9*(1), 7973.
[128]. Winkelhake, U., Winkelhake, & Schilgerius. (2018). *Digital transformation of the automotive industry*. Springer.
[129]. Wu, H., Mehrabi, H., Naveed, N., & Karagiannidis, P. (2022). A business model for additive manufacturing of recycled plastics towards sustainability. *The International Journal of Advanced Manufacturing Technology*, *120*(11), 7997-8011.
[130]. Wu, L., Leng, J., & Ju, B. (2021). Digital twins-based smart design and control of ultra-precision machining: A review. *Symmetry*, *13*(9), 1717.
[131]. Yang, S., Navarathna, P., Ghosh, S., & Bequette, B. W. (2020). Hybrid modeling in the era of smart manufacturing. *Computers & Chemical Engineering*, *140*, 106874.
[132]. Yang, Y., Gong, Y., Qu, S., Xin, B., Xu, Y., & Qi, Y. (2019). Additive/subtractive hybrid manufacturing of 316L stainless steel powder: Densification, microhardness and residual stress. *Journal of Mechanical Science and Technology*, *33*(12), 5797-5807.
[133]. Yao, X., Zhou, J., Lin, Y., Li, Y., Yu, H., & Liu, Y. (2019). Smart manufacturing based on cyber-physical systems and beyond. *Journal of Intelligent Manufacturing*, *30*(8), 2805-2817.
[134]. Zanoni, S., Ashourpour, M., Bacchetti, A., Zanardini, M., & Perona, M. (2019). Supply chain implications of additive manufacturing: a holistic synopsis through a collection of case studies. *The International Journal of Advanced Manufacturing Technology*, *102*(9), 3325-3340.
[135]. Zayadul, H. (2023). Development Of An AI-Integrated Predictive Modeling Framework For Performance Optimization Of Perovskite And Tandem Solar Photovoltaic Systems. *International Journal of Business and Economics Insights*, *3*(4), 01–25. https://doi.org/10.63125/8xm7wa53

[136]. Zhang, L., Zhou, L., & Xiao, L. (2022). *Customized Production Through 3D Printing in Cloud Manufacturing*. Elsevier.

[137]. Zhang, M., Liu, S., Hou, X., Dong, H., Cui, C., & Li, Y. (2022). Reliability modeling and analysis of a diesel engine design phase based on 4F integration technology. *Applied Sciences*, *12*(13), 6513.

[138]. Zheng, P., Wang, H., Sang, Z., Zhong, R. Y., Liu, Y., Liu, C., Mubarok, K., Yu, S., & Xu, X. (2018). Smart manufacturing systems for Industry 4.0: Conceptual framework, scenarios, and future perspectives. *Frontiers of Mechanical Engineering*, *13*(2), 137-150.

[139]. Zhu, L., Wang, S., Lu, H., Qi, D., Wang, D., Yang, Z., Ning, J., Dun, Y., Xue, P., & Xu, P. (2022). Investigation on synergism between additive and subtractive manufacturing for curved thin-walled structure. *Virtual and Physical Prototyping*, *17*(2), 220-238.

[140]. Zinno, R., Artese, S., Clausi, G., Magarò, F., Meduri, S., Miceli, A., & Venneri, A. (2018). Structural health monitoring (SHM). In *The internet of things for smart urban ecosystems* (pp. 225-249). Springer.

[141]. Zwolińska, B., Tubis, A. A., Chamier-Gliszczyński, N., & Kostrzewski, M. (2020). Personalization of the MES system to the needs of highly variable production. *Sensors*, *20*(22), 6484.