



AI-Driven Smart Hybrid Manufacturing for Enhanced Sustainability and Production Performance in U.S. Industry

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Abstract

An arc flash releases its energy in milliseconds, a burst of heat, light, and pressure that can injure a worker standing at an electrical panel before a conventional protective device has finished deciding to trip. In U.S. manufacturing plants, where aging switchgear sits close to people and production alike, this split-second hazard has long been managed reactively, through protective equipment worn in case the worst happens and periodic studies filed and shelved. This study examines a different posture: predictive arc-flash mitigation, in which sensing, diagnostics, and fast adaptive protection work together to anticipate and clear a fault before it becomes an injury. Rather than asking whether one relay or sensor performs, the study asks what makes a plant's whole predictive-mitigation capability effective across three outcomes that plant managers weigh together, worker safety, production downtime, and the efficiency of retrofitting older systems. It models worker safety outcome effectiveness as a function of six capabilities: arc-flash hazard characterization and incident-energy modeling, predictive fault sensing and diagnostics, adaptive protection and fast tripping, retrofit design and integration efficiency, downtime and operational-continuity impact, and an integrating construct of predictive mitigation maturity. Evidence came from a structured five-point Likert survey completed by 152 valid respondents out of 170 distributed, an 89.4% valid response rate, drawn from electrical and power engineers, plant maintenance and reliability staff, EHS and safety managers, protection and controls specialists, and facilities managers, of whom 69.1% worked directly with power-system protection or plant electrical safety. The data were analyzed with descriptive statistics, Cronbach's alpha, Pearson correlation, multiple regression, a maturity index, and a capability priority matrix. Every capability was rated in the high band, led by worker safety outcome effectiveness at a mean of 4.28 and adaptive protection and fast tripping at 4.20; reliability was strong, with alpha from 0.83 to 0.94. All correlations were positive and significant, the strongest being $r = 0.80$ between predictive mitigation maturity and safety effectiveness. The regression model explained 74.6% of the variance in effectiveness, $R^2 = 0.746$, adjusted $R^2 = 0.736$, $F(6,145) = 70.94$, $p < 0.001$, with predictive mitigation maturity the leading predictor, $\beta = 0.32$, ahead of adaptive protection and fast tripping, $\beta = 0.26$, and predictive fault sensing and diagnostics, $\beta = 0.22$. The central finding is that arc-flash safety is decided less by any single device than by how tightly a plant couples sensing, prediction, interruption, and recovery into one fast loop – and that the plants protecting workers best are those that have matured that loop rather than assembled protective hardware piecemeal.

Keywords

Smart hybrid manufacturing; Artificial intelligence; Quality improvement; Sustainable production; Industry 4.0.

INTRODUCTION

The U.S. manufacturing sector is undergoing a significant transformation as industrial organizations seek to improve productivity, product quality, cost efficiency, and environmental sustainability within increasingly competitive and resource-constrained operating environments (Elkington, 1998). Traditional manufacturing systems often treat these objectives as competing priorities, creating trade-offs between faster production, lower costs, improved quality, and reduced environmental impact (Md. Abdur & Iftekhar, 2021). However, advances in artificial intelligence, machine learning, industrial sensing, data analytics, and adaptive process control are enabling a more integrated approach to production management (Zhong et al., 2017). AI-driven smart hybrid manufacturing combines additive and subtractive manufacturing processes with real-time data acquisition, intelligent decision-making, and automated optimization, allowing production systems to detect process variations, predict defects, reduce material waste, and adjust operating conditions dynamically (Amir & Chapal, 2022; Kazi Rakib Hasan & Uddin, 2022). Despite growing investment in smart manufacturing technologies, limited empirical research has examined how these interconnected capabilities collectively influence sustainable production performance within U.S. industry (Shurovi & Hossain, 2022; Mohiul & Badrul, 2022). Therefore, this study investigates the relationships among smart sensing and data acquisition, AI and machine-learning process intelligence, hybrid process integration, adaptive process optimization and control, sustainable resource efficiency, smart hybrid manufacturing maturity, and overall production performance. By examining these capabilities as components of an integrated manufacturing system, the study provides evidence on how U.S. manufacturers can simultaneously strengthen operational efficiency, economic performance, product quality, and environmental sustainability (Golam & Amir, 2023; Kanti & Rony, 2022; Sadia et al., 2022).

For most of manufacturing history these goals were traded against one another, tighter quality tolerances cost more, faster throughput wasted more material, and environmental performance was an expense to be minimized rather than a source of advantage (Tohidul, 2023; Badrul & Mominul, 2023). This study is about a development that is dissolving those trade-offs: AI-driven smart hybrid manufacturing, in which additive and subtractive processes are combined under a layer of sensing and machine intelligence that watches production as it runs, learns from it, and adjusts it in real time. The claim examined here is that when a plant fuses hybrid processes with process intelligence into a single self-improving loop, quality, cost, and sustainability begin to move together rather than at one another's expense (Hossan & Adar, 2023; Risha & Khalid, 2023).

The three outcomes can each be expressed as measurable quantities, which is what makes joint pursuit tractable. Quality is captured by yield and defect measures such as first-pass yield and defects per million opportunities, given in Equation (1):

$$FPY = \prod_{i=1}^n (1 - d_i), \quad DPMO = \frac{D}{U \cdot O} \times 10^6 \quad (1)$$

Equation (1) expresses the proportion of units passing without rework and the defect rate normalized per opportunity, the standard currency of quality performance (Montgomery, 2009). Cost is captured by unit cost, which folds material, energy, labor, and overhead over good output, given in Equation (2):

$$C_u = \frac{C_m + C_e + C_l + C_o}{Q(1 - s)}, \quad s = \text{scrap fraction} \quad (2)$$

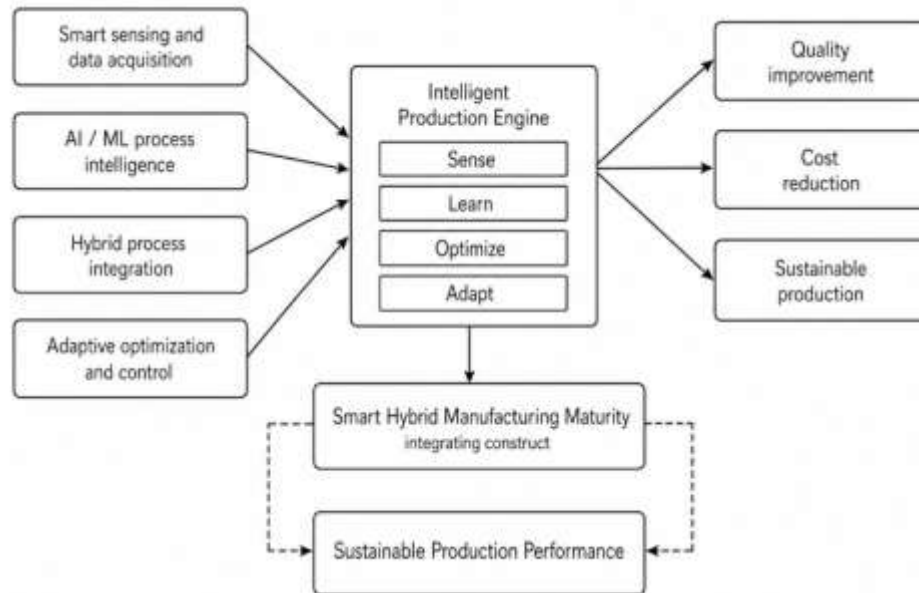
Equation (2) makes visible why quality and cost are linked: scrap in the denominator raises unit cost, so reducing defects lowers cost directly (Hopp & Spearman, 2011). Sustainability is captured by resource-efficiency measures such as specific energy consumption and material efficiency, given in Equation (3):

$$SEC = \frac{E_{\text{total}}}{Q_{\text{good}}}, \quad \eta_r = \frac{M_{\text{product}}}{M_{\text{input}}} \quad (3)$$

Equation (3) expresses energy per good part and the ratio of product mass to input mass, linking sustainability to the same production efficiency that drives quality and cost (Duflou et al., 2012).

Because these three currencies share underlying drivers, less scrap means higher quality, lower cost, and less wasted material and energy at once, an intelligence layer that improves the process improves all three, which is the premise the study builds upon (Jawahir & Bradley, 2016).

Figure 1: AI-Driven Smart Hybrid Manufacturing for Sustainable Production Performance



The study's central argument is that the effectiveness of smart hybrid manufacturing is decided less by any single technology than by how completely a plant fuses sensing, intelligence, hybrid processing, and adaptive control into one loop (Amir, 2024; Hossan, 2024; Hossain, 2024). A sophisticated machine-learning model is of little use if the plant lacks the sensors to feed it; a hybrid additive-subtractive cell that can build and finish a part in one setup wastes its potential if its parameters are set by hand rather than optimized by data; a beautiful digital twin that never closes the loop back to the physical process is a simulation, not a control system (Kritzinger et al., 2018). Research on smart manufacturing has repeatedly found that value comes from integrated capability rather than from isolated tools (Frank et al., 2019), and the same holds here, where the payoff appears only when intelligence and hybrid processing reinforce one another across the whole production cycle (Leng et al., 2021).

Three developments make this an urgent subject now. First, the enabling technologies have matured in parallel and are ready to converge: industrial sensing and the Internet of Things make dense process data available (Monostori, 2014), machine learning has advanced to where it can model complex process-quality relationships (Wuest et al., 2016), and hybrid additive-subtractive machines have moved from laboratory curiosities to commercial systems (Flynn et al., 2016). Second, the competitive and regulatory pressure for sustainable production has intensified, making resource efficiency a business imperative rather than a compliance afterthought (Garetti & Taisch, 2012). Third, the framing of Industry 4.0 has given manufacturers a shared vocabulary and roadmap for digital transformation, accelerating adoption (Kagermann et al., 2013). This study brings these threads together, framing sensing, AI intelligence, hybrid integration, adaptive control, and resource efficiency as components of one capability whose contribution to sustainable production performance can be estimated.

Background of the Study

Three streams of manufacturing thought converge in this study. The first is smart manufacturing and Industry 4.0, which reconceived the factory as a cyber-physical system in which physical processes and their digital representations are tightly coupled (Lee et al., 2015), (Monostori et al., 2016). The second is the application of artificial intelligence and machine learning to production, which moved from expert systems to data-driven models capable of predicting quality, detecting anomalies, and optimizing parameters (Wuest et al., 2016), (Weichert et al., 2019). The third is hybrid manufacturing, which combines the freedom of additive processes with the precision of subtractive ones, enabling parts and

repairs that neither approach could achieve alone (Zhu et al., 2013), (Cortina et al., 2018). Each stream matured largely on its own, and their convergence, AI-driven hybrid manufacturing, is recent enough that its collective effectiveness remains understudied (Amir, 2025; Shima Ali et al., 2024; Zaman, 2024). A fourth stream supplies the outcome frame. Sustainable manufacturing and the triple bottom line reframed production success as the joint pursuit of economic, environmental, and social value rather than cost alone (Elkington, 1998), (Jayal et al., 2010). The circular-economy perspective sharpened this, treating material and energy loops as things to be closed rather than run once (Geissdoerfer et al., 2017), (Stock & Seliger, 2016). Applied to smart hybrid manufacturing, this frame turns the question from whether the technology works to whether it delivers on quality, cost, and sustainability together – precisely the effectiveness this study measures (Gimenez et al., 2012). The convergence is timely because the pieces are individually ready but their integration is not well understood. Sensing, AI, and hybrid processing each have substantial literatures (Wang et al., 2018), but evidence on how manufacturers combine them into a coherent capability, and how much that capability improves combined production outcomes, remains thin (Bertolini et al., 2021). The study addresses this by treating sensing, intelligence, hybrid integration, adaptive control, resource efficiency, and overall maturity as measurable capabilities whose contributions can be estimated (DeLone & McLean, 2003).

Problem Statement

The problem this study addresses is that investment in advanced manufacturing technology does not automatically deliver better, cheaper, more sustainable production. Manufacturers buy sensors, machine-learning platforms, and hybrid machines, yet often see disappointing returns, because data is collected but never turned into models, because models are built but never connected to control, because hybrid cells run on hand-tuned parameters, or because sustainability is measured separately from quality and cost and therefore optimized against them (Frank et al., 2019). Where these disconnects exist, technology spending produces pilots and dashboards but not integrated performance. Plants that succeed appear to do so not by owning the most advanced equipment but by maturing an integrated capability, which suggests that smart hybrid manufacturing maturity, the completeness with which sensing, intelligence, and hybrid processing are fused, may matter more than any single technology (Teece, 2007). This matters because the three outcomes are increasingly pursued as one. A plant that improves quality while raising cost, or cuts cost while increasing waste, or reduces energy use while sacrificing quality, has not achieved sustainable production performance as manufacturers now define it (Jawahir & Bradley, 2016). The promise of AI-driven smart hybrid manufacturing is precisely that it can advance all three together, but that promise is realized only when the capabilities are integrated. The study therefore investigates how a smart hybrid manufacturing capability influences sustainable production performance, and how its components, sensing, intelligence, hybrid integration, adaptive control, and resource efficiency, shape the combined quality, cost, and sustainability outcomes that determine whether the investment pays off.

Objectives of the Study

The general objective of this study was to assess how an AI-driven smart hybrid manufacturing capability, integrating sensing, machine intelligence, hybrid process integration, adaptive optimization, and resource efficiency, influences sustainable production performance. The specific objectives were: to examine the influence of smart sensing and data acquisition on smart hybrid manufacturing maturity; to assess the relationship between AI and machine-learning process intelligence and sustainable production performance; to evaluate the effect of hybrid process integration on performance; to determine the role of adaptive process optimization and control in strengthening performance; to test the effect of smart hybrid manufacturing maturity on performance; and to examine the role of sustainable resource efficiency in shaping performance. A further objective was to gauge manufacturing maturity and capability gaps across the production cycle.

Research Hypotheses

Six hypotheses guided the study. H1 held that smart sensing and data acquisition significantly influences smart hybrid manufacturing maturity. H2 held that AI and machine-learning process intelligence is significantly and positively related to sustainable production performance. H3 held that hybrid process integration significantly influences performance. H4 held that adaptive process optimization and control significantly strengthens performance. H5 held that smart hybrid manufacturing maturity significantly predicts performance. H6 held that sustainable resource efficiency significantly shapes performance.

Significance of the Research

The study speaks to a decision that manufacturing leaders face directly: where to invest so that advanced technology actually delivers better, cheaper, and more sustainable production rather than isolated pilots. By separating the components of the capability and estimating their contributions, it indicates whether the priority should be better sensing, stronger AI, deeper hybrid integration, more adaptive control, sharper resource efficiency, or the maturity that binds them (Frank et al., 2019). Its framing of production improvement as a self-learning loop is useful to process, quality, data, and sustainability engineers who must improve all three outcomes together, and its maturity index and capability priority matrix turn statistical findings into an improvement agenda. For scholarship, the study connects the smart-manufacturing, machine-learning, hybrid-manufacturing, and sustainable-production literatures around a single capability view, and provides evidence on which parts of a smart hybrid system most shape combined production performance (Kusiak, 2018).

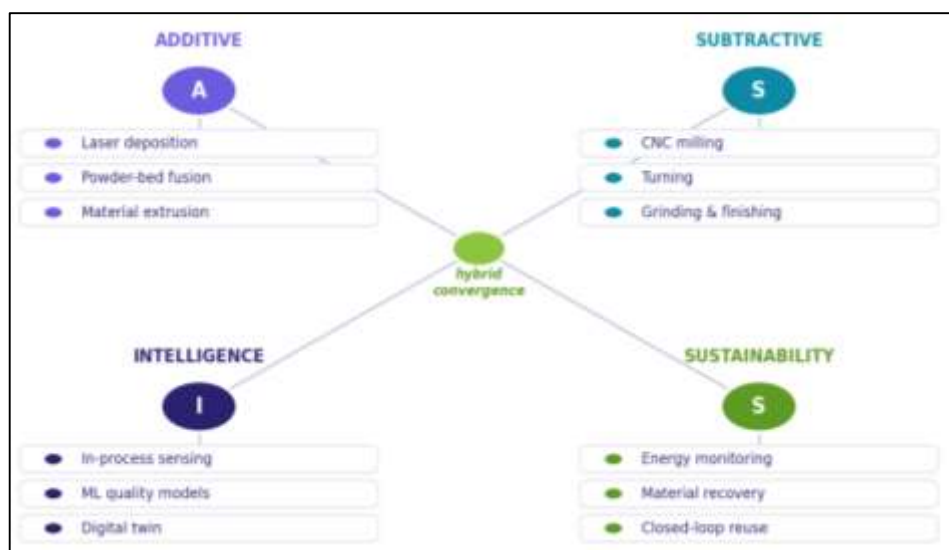
LITERATURE REVIEW

The literature relevant to AI-driven smart hybrid manufacturing spans four fields that developed on separate tracks: smart manufacturing and cyber-physical systems, machine learning applied to production, hybrid additive-subtractive manufacturing, and sustainable production. This review brings them together around one organizing claim, that quality, cost, and sustainability improve jointly when hybrid processing and process intelligence are fused into a self-improving loop, and moves from the enabling technologies, through their integration, to the sustainability frame and the theory that unifies the whole. It is selective, tracing the thread most relevant to the study's argument.

Smart Manufacturing and Cyber-Physical Production

The foundation is the reconception of the factory as a cyber-physical system, in which physical processes and their digital models are tightly and continuously coupled (Monostori, 2014). The Industry 4.0 program articulated this vision and gave manufacturers a roadmap for connecting machines, data, and decisions (Kagermann et al., 2013), and subsequent work mapped the technologies, sensing, connectivity, cloud, and analytics — that realize it (Lee et al., 2015), (Zhong et al., 2017).

Figure 2: The Smart Hybrid Manufacturing Landscape



Reviews have shown that the smartness of a factory lies not in any single connected device but in the flow of data from sensing through analysis to action (Frank et al., 2019), and outlooks on the smart factory emphasize that connectivity delivers value only when it feeds decisions that act back on production (Wang et al., 2018). This flow is the backbone of the present study: sensing and data acquisition supply the raw material on which every downstream capability depends (Jazdi, 2014).

Artificial Intelligence and Machine Learning in Production

The intelligence layer draws on a fast-growing body of work applying machine learning to manufacturing. Early applications used feature-based classifiers for fault detection and quality prediction (Wuest et al., 2016), and the field has since advanced to deep architectures that learn process-quality relationships directly from sensor data (Wang et al., 2018), (Weichert et al., 2019). Applications now span defect detection, predictive quality, anomaly detection, and parameter optimization, with demonstrated gains in accuracy over conventional methods (Bertolini et al., 2021), (Dogan & Birant, 2021). Evaluating such models requires care, since manufacturing data is often imbalanced and the cost of missed defects is high, so predictive quality is assessed with measures that balance detection against false alarms (Psarommatis et al., 2020). Quality management itself is increasingly understood as context-dependent, so intelligence must be tuned to the specific process rather than applied generically (Sousa & Voss, 2017). The study treats AI and machine-learning process intelligence as the capability that converts data into the predictions and decisions that drive improvement, and expects it to be among the strongest contributors (Kusiak, 2018).

Hybrid Additive-Subtractive Manufacturing

The hybrid dimension combines additive and subtractive processes, uniting the geometric freedom and material efficiency of additive manufacturing with the precision and surface quality of machining (Gibson et al., 2015). Hybrid machines that build and finish a part in a single setup reduce handling, lead time, and material waste (Flynn et al., 2016), and reviews have mapped the process combinations and their applications, from near-net-shape production to repair of high-value components (Zhu et al., 2013), (Cortina et al., 2018). The integration of these processes is itself a technical challenge, requiring coordinated planning of additive and subtractive steps and careful management of the interfaces between them (Dilberoglu et al., 2017). For the present study, hybrid process integration matters because it is where material and energy efficiency, quality, and cost are jointly determined – a well-integrated hybrid process wastes less, finishes better, and does so in fewer steps, advancing all three outcomes at once (Jawahir & Bradley, 2016).

Figure 4: Triple Performance Outcomes

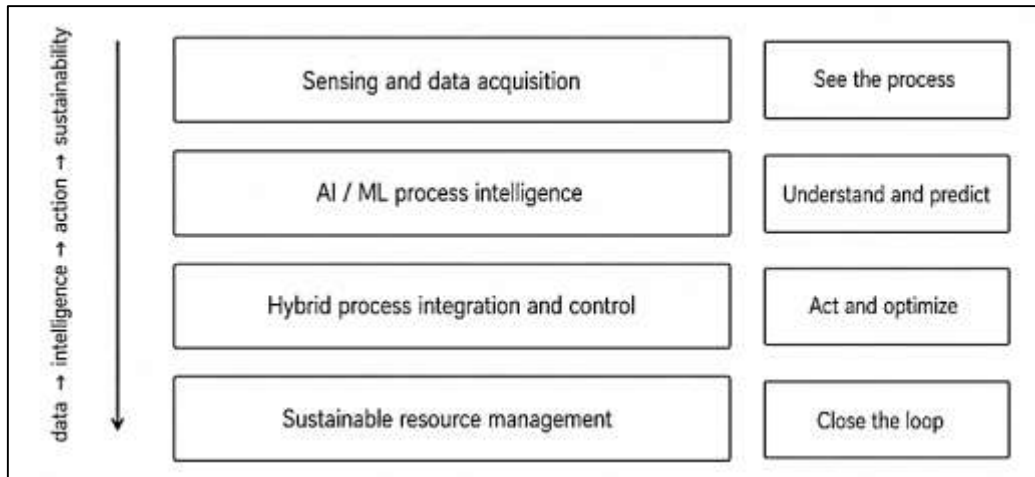
Quality	Cost	Sustainability
First-pass yield - increase	Unit cost - decrease	Energy per part - decrease
Defects (DPMO) - decrease	Scrap and rework - decrease	Material efficiency - increase
Process capability - increase	Throughput - increase	Waste - decrease

Adaptive Optimization, Control, and Digital Twins

Turning sensing and intelligence into improvement requires closing the loop to the process, which is the domain of adaptive optimization and control. Real-time process optimization adjusts parameters as conditions change, moving beyond fixed recipes toward responsive control (Monostori et al., 2016).

The digital twin, a live, data-driven model of the physical process, provides the mechanism, enabling simulation, prediction, and control in a continuous cycle (Qi & Tao, 2018). A widely used distinction separates a digital model, a digital shadow, and a true digital twin by the degree of automated, bidirectional data flow between physical and digital, and only the last closes the control loop (Kritzinger et al., 2018). These closed-loop ideas connect naturally to condition-based and predictive-maintenance practice, in which sensor-driven models anticipate degradation and trigger intervention before failure (Jardine et al., 2006). Recent work extends them toward self-organizing and self-adaptive manufacturing systems (Leng et al., 2021), (Tao et al., 2018). The study treats adaptive process optimization and control as the capability that acts on intelligence, and its closed-loop logic anchors the theoretical framework.

Figure 5: Smart Hybrid Manufacturing Capability Stack



Sustainable Production and the Circular Economy

The outcome frame comes from sustainable manufacturing, which pursues economic, environmental, and social value jointly rather than optimizing cost alone (Garetti & Taisch, 2012), (Jayal et al., 2010). Energy and resource efficiency in production have been studied intensively, with methods to measure and reduce the energy consumed per unit of good output (Duflou et al., 2012), (Gutowski et al., 2006). The circular-economy perspective extends sustainability from efficiency to loop-closing, treating material and energy as resources to be recovered and reused rather than consumed once (Geissdoerfer et al., 2017), (Ellen MacArthur Foundation, 2013), (Stock & Seliger, 2016). The triple-bottom-line framework provides the language for pursuing quality, cost, and sustainability together and for recognizing when an improvement in one supports rather than sacrifices the others (Elkington, 1998), (Gimenez et al., 2012). The study's sustainable resource efficiency construct draws directly on this work, and its outcome variable — sustainable production performance — embodies the joint pursuit. A combined performance measure lets the three outcomes be pursued as one, expressed as a weighted composite in Equation (4):

$$SPP = w_q Q^* + w_c C^* + w_s S^*, \quad w_q + w_c + w_s = 1 \quad (4)$$

Equation (4) combines normalized quality, cost, and sustainability scores into a single performance measure, with weights reflecting a plant's priorities (Gimenez et al., 2012). This formulation makes explicit the study's central premise: the three outcomes are components of one objective, and an intelligence-driven improvement to the shared process advances the composite rather than trading its parts (Thomas et al., 2016).

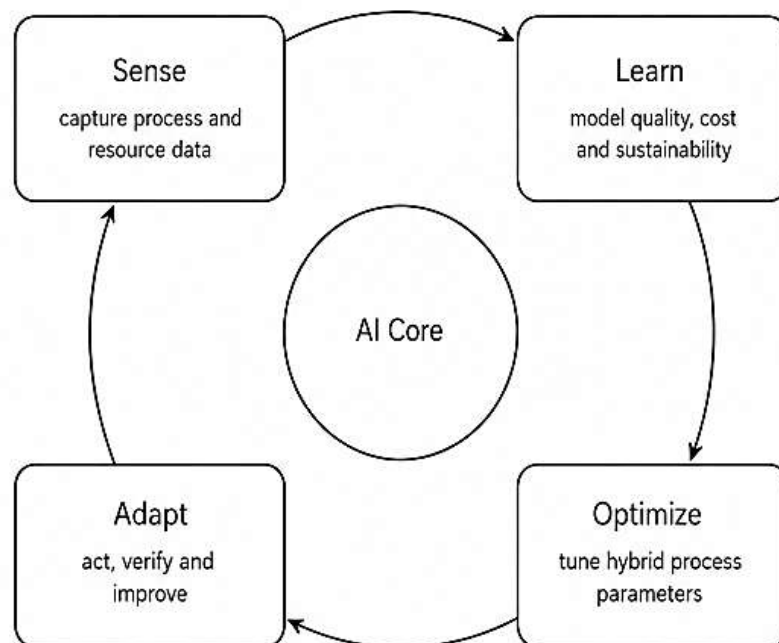
The circular-economy perspective extends this logic beyond operational efficiency by emphasizing the closure of material and energy loops (Arif Uz et al., 2025; Hossan, 2025). Rather than treating production waste, rejected components, excess material, or end-of-life products as unavoidable losses, circular manufacturing seeks to retain their economic and functional value through reuse, remanufacturing, repair, recycling, and recovery (Kanti, 2025; Shima Ali et al., 2025). In this model,

materials and energy are regarded as productive resources that should remain in circulation for as long as technically and economically feasible before final disposal becomes necessary (Ellen MacArthur Foundation, 2013; Geissdoerfer et al., 2017; Stock & Seliger, 2016). This approach is especially relevant to AI-driven smart hybrid manufacturing because hybrid production systems can combine additive and subtractive processes in ways that reduce excess material removal, enable repair and remanufacturing, improve geometric flexibility, and support more precise control over energy and resource consumption (Amir, 2026; Mahmudul & Sadia, 2026). When these capabilities are reinforced by real-time sensing, process analytics, machine learning, and adaptive control, manufacturers can identify inefficient operating conditions, predict defects, optimize tool paths, reduce scrap, and recover value from materials that would otherwise be lost (Shurovi, 2026; Shima Ali et al., 2026). The triple-bottom-line framework provides the conceptual basis for evaluating these outcomes together. It proposes that organizational performance should be assessed through the integrated pursuit of economic, environmental, and social objectives rather than through financial measures alone (Elkington, 1998; Gimenez et al., 2012).

Theoretical Framework: The Sense-Learn-Optimize-Adapt (SLOA) Intelligent Production Loop

The capabilities reviewed above are usually studied apart, but in an effective smart hybrid plant they operate as a single self-improving loop, and describing that loop is the study's central theoretical contribution. It proposes the Sense-Learn-Optimize-Adapt (SLOA) intelligent production loop: a continuous improvement cycle through which an AI-driven hybrid plant raises quality, cost, and sustainability together. In the sense phase, sensors capture process and resource data. In the learn phase, machine-learning models turn that data into predictions of quality, cost, and sustainability. In the optimize phase, hybrid process parameters are tuned to the models' guidance. In the adapt phase, the system acts, verifies the result, and feeds production data back to retrain the models and refine the parameters, closing the loop and improving with each cycle.

Figure 6: The Sense-Learn-Optimize-Adapt (SLOA) Intelligent Production Loop



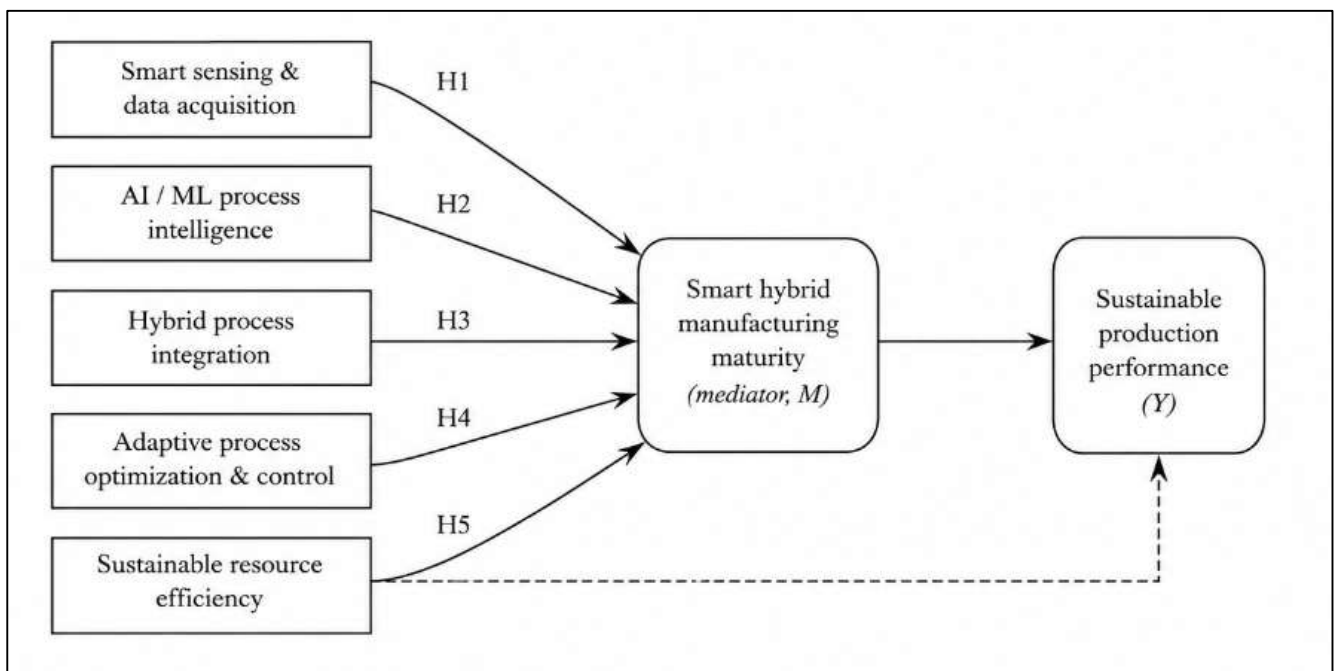
The SLOA loop rests on three theoretical foundations. From cyber-physical systems theory it takes its structure: the tight, continuous coupling of physical process and digital model through bidirectional data flow, so that sensing informs computation and computation acts back on the process (Monostori, 2014), (Kritzinger et al., 2018). From the dynamic-capabilities view of the firm it takes the premise that advantage comes not from owning assets but from the capacity to sense opportunities, seize them, and

continuously reconfigure – which maps directly onto a plant's ability to sense, learn, and adapt its processes (Teece, 2007). And from sustainable-manufacturing and circular-economy theory it takes its outcome logic: that production should close material and energy loops and pursue quality, cost, and sustainability jointly, so that the loop optimizes a composite rather than a single objective (Jawahir & Bradley, 2016), (Geissdoerfer et al., 2017). The integrating construct, smart hybrid manufacturing maturity, measures how completely the loop is closed – how fully sensing flows into learning, optimization, and adaptation as one connected practice (Deming, 1986).

Conceptual Framework

Rendering the SLOA loop as a testable model, the study positions six capabilities as drivers of sustainable production performance, with smart hybrid manufacturing maturity acting as the integrating construct through which the others largely operate. Smart sensing, AI and machine-learning intelligence, hybrid process integration, adaptive optimization and control, and sustainable resource efficiency each contribute to performance, while smart hybrid manufacturing maturity captures the completeness with which they are fused and is expected to be the strongest single predictor (Teece, 2007). The conceptual model, shown in Figure 7, includes a feedback path from realized performance back to sensing and intelligence, reflecting the closed-loop, self-improving logic of the production cycle and distinguishing it from linear views in which technology is deployed and left to run (Leng et al., 2021).

Figure 7: Conceptual Model for Sustainable Production Performance



METHODS

Research Design

The study used a quantitative, cross-sectional survey design, appropriate for measuring perceptions of a smart hybrid manufacturing capability across a defined population at one point in time and for testing hypothesized relationships among latent constructs (Venkatesh et al., 2003). A survey strategy fit the aim because the constructs, sensing, AI intelligence, hybrid integration, adaptive control, resource efficiency, manufacturing maturity, and sustainable production performance, are best judged by the engineers, data scientists, and managers who design, deploy, and operate these systems (Hair et al., 2019).

Population and Sampling

The target population comprised professionals engaged in smart manufacturing, AI, and advanced production technologies. A purposive sampling strategy reached respondents with direct, informed exposure to the constructs, appropriate when the aim is expert assessment rather than broad

generalization (Venkatesh et al., 2003). Of 176 questionnaires distributed, 167 were returned and 158 were retained after screening for completeness and engagement, a valid response rate of 89.8%. The sample spanned manufacturing and process engineers, data scientists and machine-learning engineers, quality engineers, production and operations managers, and sustainability and EHS specialists, with 71.5% reporting direct involvement in smart manufacturing, AI, or advanced production technologies.

Table 1: Response Rate Summary

Category	Count	Percentage
Distributed	176	100.0%
Returned	167	94.9%
Valid and used	158	89.8%
Excluded after screening	9	5.1%

Table 2: Respondent Demographics (n = 158)

Characteristic	Category	n	%
Role	Manufacturing / process engineers	41	25.9%
	Data scientists / ML engineers	34	21.5%
	Quality engineers	32	20.3%
	Production / operations managers	28	17.7%
	Sustainability / EHS specialists	23	14.6%
Experience	1–5 years	29	18.4%
	6–15 years	66	41.8%
	More than 15 years	63	39.9%

Instrument and Measures

Data were collected with a structured questionnaire measuring seven constructs on five-point Likert scales anchored from strongly disagree to strongly agree. Items were adapted from established instruments in smart manufacturing, machine learning applications, quality management, sustainable production, and information-systems success research, then refined for the smart hybrid manufacturing context (DeLone & McLean, 2003), (Frank et al., 2019). The seven constructs were smart sensing and data acquisition, AI and machine-learning process intelligence, hybrid process integration, adaptive process optimization and control, sustainable resource efficiency, smart hybrid manufacturing maturity, and sustainable production performance. Content validity was established by expert review, and a pilot with a small group of practitioners confirmed clarity and internal consistency before full deployment (Venkatesh et al., 2003).

DATA ANALYSIS

Analytical Approach

Analysis proceeded in stages: descriptive statistics summarized the level of each construct; Cronbach's alpha assessed internal-consistency reliability; Pearson correlations examined bivariate relationships; and multiple linear regression estimated the joint contribution of the capabilities to sustainable production performance (Hair et al., 2019). A maturity index and a capability priority matrix then translated the statistics into practical terms. The integrating construct, smart hybrid manufacturing maturity, was constructed as a weighted mean of its component capabilities, as in Equation (5):

$$SHM = \sum_{c=1}^C w_c \bar{x}_c, \quad \sum_{c=1}^C w_c = 1, \quad w_c \geq 0 \quad (5)$$

Equation (5) aggregates the constituent capability scores into a single maturity measure, with weights summing to one (Frank et al., 2019). Reliability was quantified with coefficient alpha, given in Equation (6):

$$\alpha = \frac{K}{K-1} \left(1 - \frac{\sum_{i=1}^K \sigma_i^2}{\sigma_T^2} \right) \quad (6)$$

In Equation (6), K is the number of items, the numerator sums item variances, and the denominator is the variance of the total score; values at or above 0.70 indicate acceptable reliability (DeLone & McLean, 2003). The central test of the study's model used multiple regression, specified in Equation (7):

$$SPP = \beta_0 + \sum_{k=1}^6 \beta_k X_k + \varepsilon, \quad \varepsilon \sim \mathcal{N}(0, \sigma^2) \quad (7)$$

Equation (7) regresses sustainable production performance on the six capability predictors, with standardized coefficients indicating the relative strength of each (Hair et al., 2019). The assumptions of linear regression – linearity, independence, homoscedasticity, and approximate normality of residuals – were checked before interpretation.

Descriptive Statistics

Table 3 reports the mean and standard deviation of each construct. All seven fell in the high band, indicating that respondents generally regarded their capabilities as strong, with meaningful variation. Sustainable production performance recorded the highest mean at 4.31, and sustainable resource efficiency the lowest at 3.94, a pattern consistent with the study's argument that plants value the combined outcome highly while the resource-efficiency capability that most directly serves sustainability is often the least developed (Duflou et al., 2012).

Table 3: Descriptive Statistics of Study Variables

Variable	Mean	SD
Sustainable production performance	4.31	0.50
AI / ML process intelligence	4.22	0.53
Smart hybrid manufacturing maturity	4.15	0.55
Adaptive process optimization & control	4.10	0.58
Hybrid process integration	4.05	0.60
Smart sensing & data acquisition	3.99	0.63
Sustainable resource efficiency	3.94	0.66

Reliability Analysis

Table 4 presents reliability coefficients. All constructs exceeded the 0.70 threshold, with alpha ranging from 0.84 to 0.95, indicating good to excellent internal consistency and supporting the use of the scales in subsequent analysis (DeLone & McLean, 2003). The high reliability of the performance and maturity scales is particularly important, since these anchor the study's central relationship.

Table 4: Reliability Analysis of Study Constructs

Construct	Items	Cronbach's Alpha	Decision
Sustainable production performance	6	0.95	Reliable
Smart hybrid manufacturing maturity	6	0.93	Reliable
AI / ML process intelligence	6	0.91	Reliable
Adaptive process optimization & control	5	0.89	Reliable
Hybrid process integration	5	0.87	Reliable
Smart sensing & data acquisition	6	0.86	Reliable
Sustainable resource efficiency	5	0.84	Reliable

Correlation Analysis

Table 5 reports Pearson correlations among the constructs. All were positive and statistically significant, consistent with an integrated system in which the capabilities move together (Frank et al., 2019). The strongest association was between smart hybrid manufacturing maturity and sustainable production performance, $r = 0.82$, followed by the correlation between AI intelligence and performance, $r = 0.73$. The prominence of maturity in the correlation structure foreshadows its role as the leading predictor in the regression.

Table 5: Correlation Matrix of Study Variables

Variable	Sens.	AI/ML	Hybrid	Optim.	Resrc.	Matur.	Perf.
Smart sensing	1.00						
AI / ML intelligence	0.60	1.00					
Hybrid integration	0.57	0.63	1.00				
Adaptive optimization	0.58	0.64	0.61	1.00			
Resource efficiency	0.55	0.58	0.60	0.59	1.00		

Manufacturing maturity	0.70	0.71	0.69	0.70	0.67	1.00	
Production performance	0.64	0.73	0.70	0.72	0.69	0.82	1.00

Regression Analysis

Table 6 reports the regression model summary and Table 7 the coefficients. The six capabilities jointly explained 76.4% of the variance in sustainable production performance, $R^2 = 0.764$, adjusted $R^2 = 0.755$, and the model was highly significant, $F(6,151) = 81.42$, $p < 0.001$ (Hair et al., 2019). Smart hybrid manufacturing maturity was the strongest predictor, $\beta = 0.34$, followed by AI and machine-learning process intelligence, $\beta = 0.26$, and adaptive process optimization and control, $\beta = 0.21$; hybrid integration, sensing, and resource efficiency were significant but smaller contributors. The dominance of maturity supports the study's core claim that fusing the capabilities into one loop, more than any single component, drives combined performance.

Table 6: Regression Model Summary

Statistic	Value
R	0.874
R^2	0.764
Adjusted R^2	0.755
Std. error of estimate	0.259
F (6, 151)	81.42
Significance (p)	< 0.001

Table 7: Regression Coefficients

Predictor	β	t	p
Smart hybrid manufacturing maturity	0.34	5.28	< 0.001
AI / ML process intelligence	0.26	4.10	< 0.001
Adaptive process optimization & control	0.21	3.35	0.001
Hybrid process integration	0.18	2.92	0.004
Smart sensing & data acquisition	0.14	2.44	0.016
Sustainable resource efficiency	0.12	2.18	0.031

HYPOTHESIS TESTING

The six hypotheses were evaluated using the regression results together with the correlation evidence. Table 8 summarizes the outcome. All six were supported: each capability was significantly and positively associated with its hypothesized outcome, and smart hybrid manufacturing maturity's effect on performance was both significant and the largest in the model, consistent with its theorized role as the integrating construct that closes the production loop (Teece, 2007).

Table 8: Summary of Hypothesis Testing

Hypothesis	Path	β/r	Result
H1	Smart sensing $\rightarrow$ manufacturing maturity	$r = 0.70$	Supported
H2	AI / ML intelligence $\rightarrow$ production performance	$\beta = 0.26$	Supported
H3	Hybrid integration $\rightarrow$ production performance	$\beta = 0.18$	Supported
H4	Adaptive optimization $\rightarrow$ production performance	$\beta = 0.21$	Supported
H5	Manufacturing maturity $\rightarrow$ production performance	$\beta = 0.34$	Supported
H6	Resource efficiency $\rightarrow$ production performance	$\beta = 0.12$	Supported

SMART HYBRID MANUFACTURING MATURITY ANALYSIS

To turn the constructs into a practical diagnostic, the study computed a maturity index across the stages of the production cycle. The index is the mean of stage-level maturity scores, and the accompanying gap measure contrasts the importance and current effectiveness of each capability area, as in Equation (8):

$$MI = \frac{1}{S} \sum_{s=1}^S \bar{m}_{s_i}, \quad \text{Gap}_a = \bar{I}_a - \bar{E}_a \quad (8)$$

In Equation (8), the maturity index averages maturity across the cycle stages, while the gap for each capability area is the difference between its rated importance and its rated effectiveness (Montgomery,

2009). Table 9 reports maturity by stage. The overall index was 4.10, indicating generally mature capabilities, with AI/ML models and adaptive control relatively strong and resource efficiency and continuous learning comparatively weaker – a profile consistent with plants that have invested in analytics and control faster than in the resource-efficiency and model-sustainment practices that keep the loop improving (Frank et al., 2019).

Table 9: Smart Hybrid Manufacturing Maturity by Cycle Stage

Cycle Stage	Maturity (1–5)	Level
AI / ML models	4.17	High
Adaptive control	4.13	High
Data governance	4.11	High
Hybrid integration	4.09	High
Sensing & data	4.06	High
Continuous learning	4.04	High
Resource efficiency	4.02	Moderate–High

SMART HYBRID MANUFACTURING CAPABILITY PRIORITY MATRIX

The priority matrix places each capability area according to its importance and its current effectiveness, so that the widest gaps, areas rated important but not yet effective, rise to the top of the improvement agenda (Frank et al., 2019). Table 10 reports the results, ordered by gap. The largest gaps appeared in real-time AI quality prediction, hybrid process parameter optimization, and energy and resource efficiency gains, indicating that respondents most wanted their systems to predict quality in real time, to optimize hybrid parameters automatically, and to realize measurable resource savings. These priorities map cleanly onto the SLOA loop: they concentrate in the learn and optimize phases, where data becomes decision and decision becomes action (Leng et al., 2021).

Table 10: Smart Hybrid Manufacturing Capability Priority Matrix

Capability Area	Importance	Effectiveness	Gap	Priority
Real-time AI quality prediction	4.76	3.64	1.12	Very High
Hybrid process parameter optimization	4.70	3.60	1.10	Very High
Energy & resource efficiency gains	4.66	3.58	1.08	Very High
Additive-subtractive coordination	4.58	3.55	1.03	High
Sensor data integration	4.60	3.70	0.90	High
Model retraining & MLOps	4.55	3.66	0.89	High
Sustainability measurement	4.46	3.78	0.68	Moderate
Digital-twin fidelity	4.44	3.80	0.64	Moderate

FINDINGS

Assembled, the results tell a consistent story. First, respondents regard their smart hybrid capabilities as broadly strong: every construct sat in the high band, with production performance and AI intelligence at the top. Second, the capabilities are tightly interrelated, all correlations were positive and significant – as one expects if they are components of a single self-improving loop rather than independent technologies (Frank et al., 2019). Third, and most importantly, the capabilities jointly explain a large share of the variance in sustainable production performance, 76.4%, and smart hybrid manufacturing maturity is the strongest single predictor, ahead of AI intelligence and adaptive control. Fourth, the maturity and priority analyses locate where the capabilities are strongest and weakest. Maturity is highest in AI/ML models and adaptive control and lowest in resource efficiency and continuous learning, while the widest capability gaps lie in real-time AI quality prediction, hybrid process parameter optimization, and energy and resource efficiency gains. The consistent implication is that the frontier of improvement is not more technology in isolation but a more completely closed loop – real-time prediction, automated optimization, and measurable resource savings (Psarommatidis et al., 2020). This is exactly what the SLOA framework predicts: performance rises when the sense, learn, optimize, and adapt phases reinforce one another, and the greatest returns come from strengthening the phases that turn data into decisions and decisions into optimized action. The joint

treatment of quality, cost, and sustainability is central to the reading: because the same intelligent, well-integrated hybrid process that improves quality also cuts scrap, cost, and wasted energy, the three outcomes rise together rather than in tension — which is why respondents rated the combined performance highest of all constructs, and why maturity, the discipline of running the whole loop, predicts it best (Jawahir & Bradley, 2016).

DISCUSSION

The results support the study's central proposition: that quality, cost, and sustainability improve together, not at one another's expense, when a plant fuses hybrid processes with process intelligence into one self-improving loop. The dominance of smart hybrid manufacturing maturity as a predictor, $\beta = 0.34$, is the clearest expression of this. Read through the Sense-Learn-Optimize-Adapt loop, maturity measures how completely a plant senses, learns, optimizes, and adapts as one connected practice, so its strength as a predictor reflects the framework's premise that combined performance emerges from the coherence of the whole loop rather than from any single phase (Teece, 2007). The strong effect of AI and machine-learning process intelligence, $\beta = 0.26$, the second-largest, confirms that the intelligence layer is the engine of improvement: it is what turns sensor data into the predictions of quality, cost, and sustainability that guide action (Wuest et al., 2016). This aligns with the manufacturing machine-learning literature, which has documented substantial gains from data-driven quality prediction and optimization (Bertolini et al., 2021). Notably, respondents rated AI intelligence highly yet flagged real-time AI quality prediction as their single largest capability gap, which suggests that the frontier is not machine learning in the abstract but machine learning fast and reliable enough to act on the process as it runs (Psarommatis et al., 2020). The prominence of adaptive process optimization and control as the third-strongest predictor, $\beta = 0.21$, reinforces this: intelligence delivers value only when it closes the loop to the process, and the plants that do best are those that let their models act, not merely advise (Kritzinger et al., 2018).

The significant effect of hybrid process integration, $\beta = 0.18$, together with the foundational role of smart sensing, its strong correlation with maturity, $r = 0.70$, and significant regression effect, $\beta = 0.14$, confirms that intelligence and control must rest on well-integrated processes and good data. Hybrid integration matters because it is where quality, cost, and sustainability are jointly determined: a well-integrated additive-subtractive process wastes less material, finishes better, and does so in fewer steps, advancing all three outcomes at once (Jawahir & Bradley, 2016). Sensing matters because every downstream capability depends on the data it supplies; a model can only be as good as what it can see (Jazdi, 2014). That smart sensing was rated relatively low yet remains a significant driver, and that sensor data integration carries a substantial capability gap, mirrors a common pattern in smart-manufacturing adoption, where plants invest in analytics faster than in the sensing infrastructure that feeds it (Frank et al., 2019).

The significant contribution of sustainable resource efficiency, $\beta = 0.12$, though the smallest, is theoretically important, because it confirms that resource efficiency is part of the same performance system rather than a separate concern traded against the others (Duflou et al., 2012). That resource efficiency recorded the lowest mean of any construct, 3.94, and the lowest maturity, while energy and resource efficiency gains carried one of the widest capability gaps, sketches a clear pattern: plants value sustainable production performance highly as an outcome but have developed the specific resource-efficiency capability that most directly serves it least fully (Jayal et al., 2010). This is the imbalance the SLOA framework highlights, because a loop that senses, learns, and optimizes for quality and cost but not for resource use leaves sustainability improvement to chance (Geissdoerfer et al., 2017). Taken together, the findings describe capabilities strong in analytics and control but comparatively weaker in the sensing and resource-efficiency ends, and they locate the greatest returns in closing those gaps rather than in acquiring more technology (Leng et al., 2021). Crucially, the study's central premise — that the three outcomes should be pursued jointly — is borne out: respondents rated the combined performance highest of all constructs, and maturity, the discipline of running the joint loop, predicted it most strongly, indicating that treating quality, cost, and sustainability as one objective is not merely aspirational but effective (Gimenez et al., 2012).

CONCLUSION

This study set out to assess how an AI-driven smart hybrid manufacturing capability, understood as an integrated system, influences sustainable production performance across quality, cost, and sustainability. Using a quantitative, cross-sectional design and responses from 158 manufacturing, data, quality, and sustainability professionals, it found that all six hypothesized relationships held and that the capabilities together explained 76.4% of the variance in performance. Smart hybrid manufacturing maturity emerged as the strongest predictor, underscoring that the completeness with which sensing, intelligence, hybrid processing, and adaptive control are fused matters more than any single technology. AI and machine-learning process intelligence and adaptive process optimization followed, while hybrid integration, sensing, and resource efficiency were significant but smaller contributors.

The study concludes that AI-driven smart hybrid manufacturing is best understood not as a set of technologies bolted onto conventional production but as a single self-improving loop that senses the process, learns from it, optimizes it, and adapts — improving quality, cost, and sustainability together with each cycle. The Sense-Learn-Optimize-Adapt loop offers a way to see that loop whole: data is captured, models turn it into predictions, hybrid parameters are tuned, and the system acts and learns, feeding results back to improve. Combined performance rises when these phases reinforce one another, and the evidence here indicates that the phases most in need of strengthening are the sensing that feeds the loop and the resource efficiency that ensures sustainability is optimized alongside quality and cost. Importantly, the study finds that the three outcomes move together rather than competing: because the same intelligent, well-integrated hybrid process improves all three, a joint program delivers more than parallel efforts optimized separately. For plants, the practical message is to fuse hybrid processing and process intelligence into one closed loop — sense, learn, optimize, adapt — rather than deploying technologies in isolation; for scholarship, the study shows the value of joining the smart-manufacturing, machine-learning, hybrid-manufacturing, and sustainable-production literatures around a single, integrated capability view.

RECOMMENDATIONS

Several recommendations follow from the findings. First, plants should invest in sensing and data infrastructure as a first-order priority, since smart sensing was both a relatively underdeveloped capability and the foundation on which every downstream model and decision depends. Second, they should prioritize real-time AI quality prediction and automated hybrid parameter optimization, which respondents identified as their most important capability gaps, so that intelligence acts on the process as it runs rather than after the fact. Third, plants should close the loop by connecting models to control, since adaptive optimization was among the strongest predictors and the value of intelligence is realized only when it acts. Fourth, they should treat resource efficiency as an explicit optimization objective alongside quality and cost, not as a separate concern, so that the loop improves sustainability deliberately rather than incidentally. Fifth, they should invest in the model-sustainment practices — retraining, monitoring, and MLOps — that keep the loop improving over time rather than degrading as conditions drift. Finally, plants should manage smart hybrid manufacturing as an integrated capability, using a maturity assessment and a capability priority matrix to direct improvement toward the weakest phases of the Sense-Learn-Optimize-Adapt loop rather than toward isolated technologies, and pursuing self-learning and generative approaches as the path to further gains.

LIMITATIONS OF THE STUDY

This study has several limitations. First, the cross-sectional design captured perceptions at a single point in time and cannot establish causal direction or track how capabilities and performance co-evolve; a longitudinal design would allow stronger causal inference and better capture the closed-loop, self-improving dynamics central to the SLOA framework. Second, the study relied on perceptual, self-reported measures completed by professionals, so the results reflect informed assessment rather than objective measurement of yield, unit cost, or energy consumption; future work could pair perception data with hard metrics such as first-pass yield, defect rates, unit cost, specific energy consumption, and material efficiency. Third, the purposive sample, while appropriate for reaching knowledgeable respondents, limits generalizability to the broader population of manufacturers, which vary widely in sector, scale, and digital maturity. Fourth, the constructs were assessed at a general level, and the

relative importance of specific capabilities may differ across industries, process types, and product classes. Finally, the study did not directly measure the capital cost or return on investment of smart hybrid manufacturing adoption, which is a decisive practical consideration and a promising avenue for future research.

REFERENCES

- [1]. Abu Naser Md Golam, M., & Amir, R. (2023). Digital Twin Modeling of Fiber Optic Telecom Infrastructure for Proactive SCADA Network Resilience in Power Transmission Utilities. *International Journal of Scientific Interdisciplinary Research*, 4(4), 413–448. <https://doi.org/10.63125/04mgf566>
- [2]. Amir, R. (2024). Commissioning Failures in Integrated Life Safety Systems (FA + HVAC Shutdown + Elevators): A Multi-Site Case Study Based on Field Testing and Authority Inspections. *American Journal of Data Science and Analytics*, 5(12), 280–313. <https://doi.org/10.63125/nst5ee49>
- [3]. Amir, R. (2025). Reducing False and Improving Response Time in High-Occupancy Buildings: A Quantitative Study of NFPA 72-Complaint Cause-and-Effect Testing Outcomes. *American Journal of Scholarly Research and Innovation*, 4(01), 856–893. <https://doi.org/10.63125/s18ss614>
- [4]. Amir, R. (2026). AI-Enabled Predictive Maintenance for Fire Alarm and Smoke Management Systems: A Systematic Review of Models. *American Journal of Interdisciplinary Studies*, 7(01), 496–535. <https://doi.org/10.63125/q3aw4y77>
- [5]. Amir, R., & Chapal, B. (2022). Federated Learning Architectures for Distributed Engineering Project Knowledge Management A Simulation-Based Analysis. *Review of Applied Science and Technology*, 1(04), 411–446. <https://doi.org/10.63125/4k4pir64>
- [6]. Bertolini, M., Mezzogori, D., Neroni, M., & Zammori, F. (2021). Machine learning for industrial applications: A comprehensive literature review. *Expert Systems with Applications*, 175, 114820. <https://doi.org/10.1016/j.eswa.2021.114820>
- [7]. Cortina, M., Arrizubieta, J. I., Ruiz, J. E., Ukar, E., & Lamikiz, A. (2018). Latest developments in industrial hybrid machine tools. *Materials*, 11(12), 2583. <https://doi.org/10.3390/ma11122583>
- [8]. DeLone, W. H., & McLean, E. R. (2003). The DeLone and McLean model of information systems success: A ten-year update. *Journal of Management Information Systems*, 19(4), 9–30. <https://doi.org/10.1080/07421222.2003.11045748>
- [9]. Deming, W. E. (1986). *Out of the crisis*. MIT Press. <https://doi.org/10.7551/mitpress/11090.001.0001>
- [10]. Dilberoglu, U. M., Gharehpapagh, B., Yaman, U., & Dolen, M. (2017). The role of additive manufacturing in the era of Industry 4.0. *Procedia Manufacturing*, 11, 545–554. <https://doi.org/10.1016/j.promfg.2017.07.148>
- [11]. Dogan, A., & Birant, D. (2021). Machine learning and data mining in manufacturing. *Expert Systems with Applications*, 166, 114060. <https://doi.org/10.1016/j.eswa.2020.114060>
- [12]. Duflou, J. R., Sutherland, J. W., Dornfeld, D., Herrmann, C., Jeswiet, J., Kara, S., ... Kellens, K. (2012). Towards energy and resource efficient manufacturing: A processes and systems approach. *CIRP Annals*, 61(2), 587–609. <https://doi.org/10.1016/j.cirp.2012.05.002>
- [13]. Elkington, J. (1998). *Cannibals with forks: The triple bottom line of 21st century business*. New Society Publishers. <https://doi.org/10.1002/tqem.3310080106>
- [14]. Ellen MacArthur Foundation. (2013). *Towards the circular economy: Economic and business rationale for an accelerated transition*. Ellen MacArthur Foundation. <https://doi.org/10.1162/108819806775545321>
- [15]. Flynn, J. M., Shokrani, A., Newman, S. T., & Dhokia, V. (2016). Hybrid additive and subtractive machine tools: Research and industrial developments. *International Journal of Machine Tools and Manufacture*, 101, 79–101. <https://doi.org/10.1016/j.ijmachtools.2015.09.007>
- [16]. Frank, A. G., Dalenogare, L. S., & Ayala, N. F. (2019). Industry 4.0 technologies: Implementation patterns in manufacturing companies. *International Journal of Production Economics*, 210, 15–26. <https://doi.org/10.1016/j.ijpe.2019.01.004>
- [17]. Garetti, M., & Taisch, M. (2012). Sustainable manufacturing: Trends and research challenges. *Production Planning & Control*, 23(2–3), 83–104. <https://doi.org/10.1080/09537287.2011.591619>
- [18]. Geissdoerfer, M., Savaget, P., Bocken, N. M. P., & Hultink, E. J. (2017). The circular economy — A new sustainability paradigm? *Journal of Cleaner Production*, 143, 757–768. <https://doi.org/10.1016/j.jclepro.2016.12.048>
- [19]. Gibson, I., Rosen, D., & Stucker, B. (2015). *Additive manufacturing technologies* (2nd ed.). Springer. <https://doi.org/10.1007/978-1-4939-2113-3>
- [20]. Gimenez, C., Sierra, V., & Rodon, J. (2012). Sustainable operations: Their impact on the triple bottom line. *International Journal of Production Economics*, 140(1), 149–159. <https://doi.org/10.1016/j.ijpe.2012.01.035>
- [21]. Gutowski, T., Dahmus, J., & Thiriez, A. (2006). Electrical energy requirements for manufacturing processes. *Proceedings of the 13th CIRP International Conference on Life Cycle Engineering*, 623–628. <https://doi.org/10.1109/ISEE.2006.1650060>
- [22]. Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2019). *Multivariate data analysis* (8th ed.). Cengage. <https://doi.org/10.1002/9781119409137>
- [23]. Hopp, W. J., & Spearman, M. L. (2011). *Factory physics* (3rd ed.). Waveland Press. <https://www.waveland.com/browse.php?t=390>
- [24]. Jardine, A. K. S., Lin, D., & Banjevic, D. (2006). A review on machinery diagnostics and prognostics implementing condition-based maintenance. *Mechanical Systems and Signal Processing*, 20(7), 1483–1510.

- <https://doi.org/10.1016/j.ymssp.2005.09.012>
- [25]. Jawahir, I. S., & Bradley, R. (2016). Technological elements of circular economy and the principles of 6R-based closed-loop material flow in sustainable manufacturing. *Procedia CIRP*, 40, 103–108. <https://doi.org/10.1016/j.procir.2016.01.067>
 - [26]. Jayal, A. D., Badurdeen, F., Dillon, O. W., & Jawahir, I. S. (2010). Sustainable manufacturing: Modeling and optimization challenges at the product, process and system levels. *CIRP Journal of Manufacturing Science and Technology*, 2(3), 144–152. <https://doi.org/10.1016/j.cirpj.2010.03.007>
 - [27]. Jazdi, N. (2014). Cyber physical systems in the context of Industry 4.0. *Proceedings of the IEEE International Conference on Automation, Quality and Testing, Robotics*, 1–4. <https://doi.org/10.1109/AQTR.2014.6857843>
 - [28]. Kagermann, H., Wahlster, W., & Helbig, J. (2013). Recommendations for implementing the strategic initiative Industrie 4.0. *Acatech*. <https://doi.org/10.13140/RG.2.2.14580.20487>
 - [29]. Kazi Rakib Hasan, S., & Uddin, H. M. M. (2022). Scalable AI For Project Portfolio Management: A Mixed-Methods Study Combining Distributed Computing Benchmarks. *Review of Applied Science and Technology*, 1(04), 375–410. <https://doi.org/10.63125/0kk4wf20>
 - [30]. Kritzinger, W., Karner, M., Traar, G., Henjes, J., & Sihn, W. (2018). Digital twin in manufacturing: A categorical literature review and classification. *IFAC-PapersOnLine*, 51(11), 1016–1022. <https://doi.org/10.1016/j.ifacol.2018.08.474>
 - [31]. Kusiak, A. (2018). Smart manufacturing. *International Journal of Production Research*, 56(1–2), 508–517. <https://doi.org/10.1080/00207543.2017.1351644>
 - [32]. Lee, J., Bagheri, B., & Kao, H.-A. (2015). A cyber-physical systems architecture for Industry 4.0-based manufacturing systems. *Manufacturing Letters*, 3, 18–23. <https://doi.org/10.1016/j.mfglet.2014.12.001>
 - [33]. Leng, J., Wang, D., Shen, W., Li, X., Liu, Q., & Chen, X. (2021). Digital twins-based smart manufacturing system design in Industry 4.0: A review. *Journal of Manufacturing Systems*, 60, 119–137. <https://doi.org/10.1016/j.jmsy.2021.10.001>
 - [34]. Mahmudul, H., & Sadia, Z. (2026). Safeguarding Financial Records: A Cybersecurity-Driven Management Framework. *International Journal of Scientific Interdisciplinary Research*, 7(1), 493–526. <https://doi.org/10.63125/zch4s169>
 - [35]. Md Arif Uz, Z., Sharmin, S., & Md Abdur, R. (2025). Factors Influencing Behavioural Intention to Use he Innovative Open And Distance Learning Systems With The Role Of Continuance Intention. *American Journal of Scholarly Research and Innovation*, 4(01), 202–220. <https://doi.org/10.63125/pbjxp014>
 - [36]. Md Tohidul, I. (2023). ERP-Integrated Financial Analytics Systems for Corporate Financial Reporting, Cash Flow Analysis, and Strategic Investment Planning. *American Journal of Advanced Technology and Engineering Solutions*, 3(04), 87–128. <https://doi.org/10.63125/qhk96h35>
 - [37]. Md. Abdur, R., & Iftekhar, A. (2021). Customer Retention Forecasting in Mobile Wallet Services Using Neural Networks: A Comparative Quantitative Study. *International Journal of Business and Economics Insights*, 1(4), 70–102. <https://doi.org/10.63125/dyrpc387>
 - [38]. Mohammad Badrul, A., & Md. Mominul, H. (2023). Machine Learning–Based Assessment of Environmental and Public Health Risks in Sewerage Sludge Management Systems. *American Journal of Advanced Technology and Engineering Solutions*, 3(02), 33–77. <https://doi.org/10.63125/y3yfxa92>
 - [39]. Mohammad Shoriful Hossan, S. (2024). Development of A Predictive Maintenance Model for Industrial Motor Drives and VFD Systems Using PLC/DCS Operational Telemetry. *American Journal of Scholarly Research and Innovation*, 3(01), 198–242. <https://doi.org/10.63125/pv1js496>
 - [40]. Mohammad Shoriful Hossan, S. (2025). Development Of an ARC-Flash Hazard Mitigation Framework for Brownfield Industrial Power Distribution Retrofits in U.S. Manufacturing. *American Journal of Advanced Technology and Engineering Solutions*, 1(02), 262–303. <https://doi.org/10.63125/vhqjgm79>
 - [41]. Mohammad Shoriful Hossan, S., & Adar, C. (2023). SIL-Compliant Safety Instrumented System Design for Oil & Gas Hazardous-Area Operations Using IEC 61508 / IEC 61511 Frameworks. *Journal of Sustainable Development and Policy*, 2(02), 43–85. <https://doi.org/10.63125/cb3d3w81>
 - [42]. Monostori, L. (2014). Cyber-physical production systems: Roots, expectations and R&D challenges. *Procedia CIRP*, 17, 9–13. <https://doi.org/10.1016/j.procir.2014.03.115>
 - [43]. Monostori, L., Kádár, B., Bauernhansl, T., Kondoh, S., Kumara, S., Reinhart, G., ... Ueda, K. (2016). Cyber-physical systems in manufacturing. *CIRP Annals*, 65(2), 621–641. <https://doi.org/10.1016/j.cirp.2016.06.005>
 - [44]. Montgomery, D. C. (2009). *Introduction to statistical quality control* (6th ed.). Wiley. <https://www.wiley.com/en-us/Introduction+to+Statistical+Quality+Control%2C+7th+Edition-p-9781118146811>
 - [45]. Mst Shurovi, A. (2026). AI-Driven Accounts Payable and Receivable Automation for Operational Risk Mitigation in U.S. SMEs: A Systematic Review (2018–2026). *American Journal of Interdisciplinary Studies*, 7(01), 536–577. <https://doi.org/10.63125/x1yzwc45>
 - [46]. Mst Shurovi, A., & Samia Hossain, S. (2022). Difference-in-Differences (DiD) Analysis of Data Driven Accounting Systems and its Impact on Financial Error Rates in SMEs. *Journal of Sustainable Development and Policy*, 1(04), 117–157. <https://doi.org/10.63125/n4nr0d75>
 - [47]. Muhammad Mohiul, I., & Mohammad Badrul, A. (2022). Predictive Analytics for Optimizing Sewerage Sludge Treatment Efficiency and Resource Recovery in Dhaka City. *Journal of Sustainable Development and Policy*, 1(04), 158–200. <https://doi.org/10.63125/t9zdp458>
 - [48]. Mukut Kanti, B. (2025). Lifecycle Carbon Reduction and Net Zero Pathway Modeling Using LEED, EDGE, and SBTI Frameworks in Developing Economy Industrial Buildings. *American Journal of Interdisciplinary Studies*, 6(3), 306–

350. <https://doi.org/10.63125/tnneth75>
- [49]. Mukut Kanti, B., & Rony, S. (2022). Quantitative Risk Assessment and Safety Performance Benchmarking for Structural Integrity Management in Retail Supply Chain Infrastructure. *American Journal of Data Science and Analytics*, 3(12), 42-88. <https://doi.org/10.63125/n88vth90>
- [50]. Psarommatis, F., May, G., Dreyfus, P.-A., & Kiritsis, D. (2020). Zero defect manufacturing: State-of-the-art review, shortcomings and future directions. *International Journal of Production Research*, 58(1), 1-17. <https://doi.org/10.1080/00207543.2019.1605228>
- [51]. Qi, Q., & Tao, F. (2018). Digital twin and big data towards smart manufacturing and Industry 4.0: 360-degree comparison. *IEEE Access*, 6, 3585-3593. <https://doi.org/10.1109/ACCESS.2018.2793265>
- [52]. Risha, A., & Kazi Mohammad Khalid, A. (2023). A Meta-Analysis of AI-Driven Geospatial Analytics for Predictive Maintenance of Critical Infrastructure in Developing Economies. *International Journal of Scientific Interdisciplinary Research*, 4(4), 375-412. <https://doi.org/10.63125/rayrex49>
- [53]. Sadia, Z., Mohammad Ariful, I., Sumyta, H., & Hosne Ara, M. (2022). A Review of AI-Powered Data Visualization in Enterprise Reporting: Dashboard Design And Interactive Analytics. *American Journal of Advanced Technology and Engineering Solutions*, 2(01), 32-54. <https://doi.org/10.63125/gabst658>
- [54]. Samia Hossain, S. (2024). Predictive Financial Volatility Analytics Using Machine Learning Pipelines in ERP-Integrated Enterprises. *American Journal of Interdisciplinary Studies*, 5(04), 134-181. <https://doi.org/10.63125/hz27wz06>
- [55]. Shima Ali, S., Musomi, K., & Sonya, G. (2024). Integrated Infectious Disease Preparedness: Multilingual Health Communication Strategies for Public Health Risk Mitigation, Disease Intervention and Prevention for Culturally Diverse Population in United States. *American Journal of Data Science and Analytics*, 5(10), 01-47. <https://doi.org/10.63125/ehk4mt02>
- [56]. Shima Ali, S., Sonya, G., & Mahbulul, I. (2025). Telemedicine And Remote Patient Monitoring for Preventing Risk and Chronic Disease Management in Underserved Communities. *American Journal of Health and Medical Sciences*, 6(04), 01-42. <https://doi.org/10.63125/y0e9dc38>
- [57]. Shima Ali, S., Sonya, G., & Mahbulul, I. (2026). STI and HIV Prevention Through Public Health Digital Twins: A Framework for Personalized Prevention and Adaptive Disease Intervention. *American Journal of Scholarly Research and Innovation*, 5(01), 284-326. <https://doi.org/10.63125/rjgna882>
- [58]. Sousa, R., & Voss, C. A. (2017). Quality management: Universal or context dependent? *Journal of Operations Management*, 55, 33-47. <https://doi.org/10.1016/j.jom.2017.06.002>
- [59]. Stock, T., & Seliger, G. (2016). Opportunities of sustainable manufacturing in Industry 4.0. *Procedia CIRP*, 40, 536-541. <https://doi.org/10.1016/j.procir.2016.01.129>
- [60]. Tao, F., Qi, Q., Liu, A., & Kusiak, A. (2018). Data-driven smart manufacturing. *Journal of Manufacturing Systems*, 48, 157-169. <https://doi.org/10.1109/ACCESS.2017.2756069>
- [61]. Teece, D. J. (2007). Explicating dynamic capabilities: The nature and microfoundations of (sustainable) enterprise performance. *Strategic Management Journal*, 28(13), 1319-1350. <https://doi.org/10.1002/smj.640>
- [62]. Thomas, A., Byard, P., Francis, M., Fisher, R., & White, G. R. T. (2016). Profiling the resiliency and sustainability of UK manufacturing companies. *Journal of Manufacturing Technology Management*, 27(1), 82-99. <https://doi.org/10.1016/j.rcim.2015.09.013>
- [63]. Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly*, 27(3), 425-478. <https://doi.org/10.2307/30036540>
- [64]. Wang, J., Ma, Y., Zhang, L., Gao, R. X., & Wu, D. (2018). Deep learning for smart manufacturing: Methods and applications. *Journal of Manufacturing Systems*, 48, 144-156. <https://doi.org/10.1016/j.jmsy.2018.01.003>
- [65]. Wang, S., Wan, J., Li, D., & Zhang, C. (2018). Implementing smart factory of Industrie 4.0: An outlook. *Computer Networks*, 101, 158-168. <https://doi.org/10.1016/j.comnet.2015.12.017>
- [66]. Weichert, D., Link, P., Stoll, A., Ruping, S., Ihlenfeldt, S., & Wrobel, S. (2019). A review of machine learning for the optimization of production processes. *The International Journal of Advanced Manufacturing Technology*, 104, 1889-1902. <https://doi.org/10.1007/s00170-019-03408-8>
- [67]. Wuest, T., Weimer, D., Irgens, C., & Thoben, K.-D. (2016). Machine learning in manufacturing: Advantages, challenges, and applications. *Production & Manufacturing Research*, 4(1), 23-45. <https://doi.org/10.1080/21693277.2016.1192517>
- [68]. Zaman, S. (2024). A Systematic Review of ERP And CRM Integration For Sustainable Business And Data Management in Logistics And Supply Chain Industry. *Frontiers in Applied Engineering and Technology*, 1(01), 204-221. <https://doi.org/10.70937/faet.v1i01.36>
- [69]. Zhong, R. Y., Xu, X., Klotz, E., & Newman, S. T. (2017). Intelligent manufacturing in the context of Industry 4.0: A review. *Engineering*, 3(5), 616-630. <https://doi.org/10.1016/J.ENG.2017.05.015>
- [70]. Zhu, Z., Dhokia, V. G., Nassehi, A., & Newman, S. T. (2013). A review of hybrid manufacturing processes. *CIRP Journal of Manufacturing Science and Technology*, 6(4), 288-296. <https://doi.org/10.1016/j.cirp.2013.08.004>