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# AI-Based Quality Control Framework for Reducing Rework and Scrap in Additive Manufacturing Production

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**Abstract**

*Additive manufacturing organizations continue to experience costly rework and scrap because defects are often identified only after substantial material, machine time, energy, labor, and post-processing resources have already been consumed. This study aimed to develop and quantitatively evaluate an AI-based quality-control framework that explains how technological, informational, human, and organizational capabilities improve quality-control effectiveness and reduce production waste. A quantitative, cross-sectional, descriptive, explanatory, and case-based research design was applied across selected additive manufacturing enterprise cases, including industrial facilities, engineering laboratories, and production units using laser powder bed fusion, material extrusion, directed energy deposition, selective laser sintering, binder jetting, and related technologies. From 350 distributed questionnaires, 300 valid responses were retained, producing an effective response rate of 85.71 percent. The framework examined Process-Data Quality and Integration, AI-Based Defect-Detection Capability, Real-Time Process Monitoring and Control, Predictive Quality Analytics and Decision Support, AI-System Integration, Workforce Competency and Organizational Readiness, AI-Based Quality-Control Effectiveness, and Rework and Scrap Reduction Performance. Data were analyzed in SPSS using descriptive statistics, reliability and validity testing, Pearson correlation, ANOVA, multiple regression, and multicollinearity diagnostics. Cronbach's alpha values ranged from .823 to .918, KMO reached .891, and Bartlett's test was significant, $\chi^2(378) = 4{,}126.44$, $p < .001$. AI-Based Defect-Detection Capability recorded the highest mean, $M = 4.13$, $SD = .54$. The six predictors jointly explained 68.4 percent of the variance in quality-control effectiveness, $R^2 = .684$, with defect detection strongest, $\beta = .27$, followed by real-time monitoring, $\beta = .23$. Quality-control effectiveness strongly predicted rework and scrap reduction, $\beta = .76$, $R^2 = .579$, $p < .001$. The findings imply that coordinated data, intelligent detection, monitoring, predictive analytics, system integration, workforce capability, and organizational readiness can reduce failed builds, rejected components, corrective processing, material waste, and production costs. They also support improved first-pass yield, traceability, resource utilization, and timely intervention.*

**Keywords**

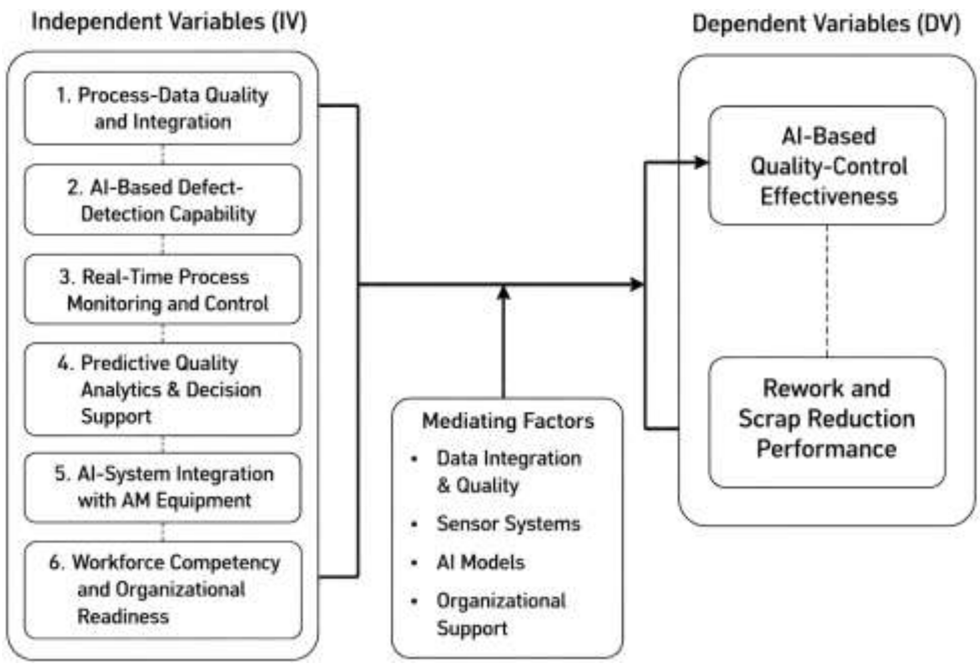
*AI-Based Quality Control; Additive Manufacturing; Defect Detection; Rework Reduction; Scrap Reduction;*

## INTRODUCTION

Additive manufacturing refers to a digitally controlled group of production processes through which three-dimensional components are created by successively depositing, joining, melting, curing, or consolidating material according to computer-aided design data. Unlike conventional subtractive manufacturing, which forms a product by removing material from a larger workpiece, additive manufacturing constructs the required geometry layer by layer and places material only in predetermined locations. The principal additive manufacturing process categories include powder bed fusion, directed energy deposition, material extrusion, binder jetting, material jetting, sheet lamination, and vat photopolymerization. These technologies differ in their energy sources, feedstock forms, deposition mechanisms, compatible materials, and production requirements. Metal additive manufacturing has gained substantial industrial attention because it supports the production of lightweight structures, complex internal channels, customized medical devices, consolidated assemblies, topology-optimized parts, and geometries that are difficult to manufacture using traditional techniques (Frazier, 2014). The physical and metallurgical characteristics of additively manufactured components are influenced by rapid heating and cooling, repeated thermal cycles, solidification behavior, layer interaction, feedstock characteristics, scanning patterns, and post-processing conditions (Sames et al., 2016). Artificial intelligence refers to the ability of computational systems to perform tasks involving learning, classification, prediction, pattern recognition, reasoning, optimization, and decision support. In a manufacturing environment, AI-based quality control involves the application of machine learning, deep learning, computer vision, sensor analytics, and automated decision systems to monitor production conditions, recognize defects, forecast nonconformities, and support corrective actions. Rework refers to additional processing required to bring a nonconforming component into compliance with technical specifications, while scrap represents a component or quantity of material that cannot be economically corrected and must be rejected, recycled, or discarded. These quality outcomes are particularly important in additive manufacturing because a defect discovered after a lengthy build can invalidate the material, energy, labor, machine time, and post-processing resources already invested in the component. Additive manufacturing has achieved international significance through its use in aerospace, automotive, healthcare, energy, defense, electronics, tooling, and specialized consumer production. Aerospace applications have demonstrated the international relevance of the technology because components must satisfy demanding requirements for structural integrity, repeatability, traceability, certification, and operational safety while achieving weight reduction and part consolidation (Blakey-Milner et al., 2021). AI-based quality control therefore occupies an important position within global additive manufacturing production because it connects the design flexibility of additive processes with the need for consistent product quality, defect control, production reliability, and measurable reductions in rework and scrap.

Quality control in additive manufacturing is challenging because production outcomes are determined by complex interactions among materials, machine settings, component geometry, environmental conditions, thermal behavior, and operator decisions. Variables such as laser power, scanning speed, hatch spacing, layer thickness, powder morphology, powder-bed density, build orientation, volumetric energy density, shielding-gas flow, platform temperature, feed rate, nozzle condition, and thermal history can independently or collectively affect the quality of the manufactured component. Uncontrolled variations in these parameters may generate porosity, lack of fusion, keyhole defects, cracking, balling, delamination, warping, residual stress, dimensional inaccuracy, surface roughness, material accumulation, incomplete deposition, contamination, and recoater-related anomalies. The repeatability and quality of metal additive manufacturing are therefore strongly associated with the ability to observe and regulate dynamic process conditions during production (Tapia & Elwany, 2014). A completed component may appear geometrically acceptable while containing internal discontinuities that reduce fatigue life, fracture resistance, density, mechanical strength, or service reliability. Conventional inspection methods, including computed tomography, ultrasonic examination, microscopy, dimensional metrology, density measurement, and destructive mechanical testing, remain important for certifying final components. However, these approaches are commonly applied after the production process has been completed. Post-production inspection can identify a nonconforming part, but it cannot recover the machine hours, material, energy, and labor consumed before the defect was discovered. In-situ monitoring provides an alternative source of quality information by collecting production evidence during fabrication rather than relying exclusively on end-of-process inspection (Everton et al., 2016). Selective laser melting involves numerous interacting process inputs, and reliable quality control requires stronger relationships among process parameters, sensing information, and measurable component characteristics (Spears & Gold, 2016). Powder bed fusion defects can also be associated with observable process signatures such as thermal radiation, melt-pool instability, plume formation, spatter behavior, surface irregularity, and powder-bed disturbance (Grasso & Colosimo, 2017). These conditions explain why reducing rework and scrap requires more than final-product inspection. Rework may involve machining, surface correction, localized repair, heat treatment, support removal, or complete rebuilding, while scrap may include failed parts, contaminated powder, rejected test coupons, removed supports, and materials lost during corrective processing. In production-scale environments, the repetition of a quality problem across several machines, materials, or build platforms can create substantial operational and financial losses. The central quality-control problem therefore concerns the absence of an integrated capability that can acquire reliable production data, recognize abnormal process conditions, determine the likely seriousness of the defect, and connect corrective decisions with measurable reductions in rework and scrap.

**Figure 1: AI-Driven Quality Management Framework for Rework and Scrap Reduction**




Artificial intelligence provides a range of analytical mechanisms for converting additive manufacturing data into defect classifications, quality predictions, and production decisions. Machine learning algorithms identify statistical relationships in historical or real-time datasets and use those relationships to estimate outcomes, classify production states, detect anomalies, or recommend process adjustments. Supervised learning relies on labeled observations in which process signals or images are associated with known acceptable and defective conditions. Unsupervised learning identifies clusters, patterns, and unusual observations without requiring every data point to have a predefined label. Semi-supervised learning combines a limited quantity of labeled data with a larger volume of unlabeled information, making it relevant when destructive testing or computed tomography renders defect labeling costly and time-consuming. Deep learning uses multilayer neural networks to learn complex representations from images, signals, and high-dimensional process data with less dependence on manually designed features. Machine learning applications in additive manufacturing include process optimization, production monitoring, design support, property prediction, material characterization, and automated control (Wang et al., 2020). The principal analytical tasks include classification, regression, clustering, anomaly detection, parameter optimization, feature recognition, and process-state estimation (Meng et al., 2020). Machine learning in three-dimensional printing has also been applied to quality assessment, error identification, parameter selection, dimensional prediction, material-property estimation, and automated correction (Goh et al., 2021). Within laser powder bed fusion, AI-supported quality control depends on relationships among process signatures, sensing systems, learning algorithms, defect categories, and control responses (Mahmoud et al., 2021). The value of AI is particularly visible when production systems generate large quantities of data through cameras, photodiodes, pyrometers, thermal imaging systems, acoustic sensors, accelerometers, machine logs, and environmental monitoring devices. These data streams operate at different sampling rates, spatial resolutions, and levels of complexity, making consistent manual interpretation difficult. Machine-learning applications in additive manufacturing have therefore addressed process-parameter optimization, material selection, process-structure-property relationships, defect detection, and production-state prediction (Raza et al., 2022). AI-based quality control, however, involves more than installing an individual defect-classification algorithm. It includes data acquisition, synchronization, cleaning, labeling, storage, feature extraction, model training, testing, validation, deployment, interpretation, and integration with production equipment. The present research consequently treats process-data quality and integration, AI-based defect-detection capability, real-time process monitoring and control, predictive quality analytics and decision support, AI-system integration, and workforce competency and organizational readiness as interconnected dimensions of AI-supported quality management. Each dimension represents a separate organizational or technological capability, while their combined operation determines whether AI-generated information can become a dependable part of additive manufacturing production.

Process-data quality and real-time monitoring provide the informational foundation required for an effective AI-based quality-control system. An algorithm cannot reliably distinguish acceptable and defective production states when the data used for training and operation are incomplete, inaccurately labeled, poorly synchronized, unrepresentative, or affected by uncontrolled sensor noise. Additive manufacturing data may include machine parameters, material characteristics, powder information, layer images, thermal fields, melt-pool emissions, acoustic signals, environmental readings, tool-path coordinates, recoater images, maintenance records, and post-build measurements. The usefulness of these data depends on accuracy, completeness, consistency, timeliness, spatial registration, temporal alignment, traceability, and association with verified quality outcomes. High-speed, real-time melt-pool monitoring has demonstrated that optical information can capture variations in selective laser melting conditions while a component is being fabricated (Clijsters et al., 2014). The relationship between in-process information and verified defect evidence is essential because an unusual sensor value does not automatically represent a critical product defect. Layer-wise high-resolution images have been connected with post-build computed-tomography data and analyzed through supervised support vector machines to distinguish nominal and flawed regions, producing defect-detection accuracies above 80% during cross-validation (Gobert et al., 2018). Acoustic information provides another source of production-quality evidence. Acoustic emission sensing combined with spectral convolutional neural networks has produced classification confidence levels ranging from 83% to 89% across different porosity-related conditions (Shevchik et al., 2018). Near-infrared images of plume and spatter behavior have also been analyzed through a deep belief network, generating an 83.40% classification rate for five melted states (Ye et al., 2018). Melt-pool monitoring signals have further been compared with computed-tomography results, producing 90% sensitivity for lack-of-fusion pores larger than approximately 0.001 $mm^3$ (Coeck et al., 2019). These studies demonstrate that different sensing devices observe different physical manifestations of the additive manufacturing process. Optical cameras capture surface patterns and powder distribution, photodiodes measure emitted intensity, pyrometers track thermal behavior, acoustic sensors identify energy releases, and vibration sensors detect changes in machine or deposition conditions. A single sensor may provide incomplete evidence because several defects can produce similar signals, while the same defect may appear differently across geometries, materials, machines, or production stages. Data integration is therefore required to combine process parameters, sensor streams, images, inspection results, and defect records into a coherent analytical dataset. Within an AI-based quality-control framework, process-data quality is a measurable production capability that directly affects model accuracy, confidence, repeatability, transferability, and the reliability of quality-related decisions.

AI-based defect-detection capability converts collected production information into recognizable quality states, defect classifications, and actionable alerts. Computer-vision and deep-learning techniques are particularly relevant because additive manufacturing produces layer-wise visual information that can be evaluated before the complete part is removed from the machine. Powder-spreading anomalies in laser powder bed fusion have been detected and classified through trained computer-vision methods combined with unsupervised machine learning (Scime & Beuth, 2018a). Multi-scale convolutional neural networks have also been used to examine image information at different spatial scales and improve the autonomous recognition of powder-bed and recoater anomalies (Scime & Beuth, 2018b). In fused filament fabrication, camera images, image-processing procedures, and support vector machines have been combined to classify printed parts as acceptable or defective at selected production checkpoints (Delli & Chang, 2018). Deep convolutional neural networks have also been applied to online recognition of selective laser melting nonconformities, allowing image features to be learned automatically rather than defined entirely through manual feature engineering (Caggiano et al., 2019). Semi-supervised approaches are useful when only a limited quantity of fully verified defect data is available. Photodiode information from laser powder bed fusion has been analyzed through semi-supervised learning to distinguish faulty and acceptable products while reducing dependence on a completely labeled dataset (Okaro et al., 2019). In material-extrusion systems, vibration sensing has been combined with least-squares support vector machines and back-propagation neural networks, producing accuracy above 90% for machine-state identification and above 95% for diagnosing warpage and material-accumulation conditions (Li et al., 2019). AI-supported quality control can also move from detection to active correction. Computer vision and deep learning have been used to create an autonomous in-situ correction system for fused deposition modeling, enabling the printing process to respond to recognized errors during fabrication (Jin et al., 2019). Layer-by-layer monitoring frameworks have similarly been developed to evaluate product quality throughout the production process instead of relying only on completed-part inspection (Bisheh et al., 2021). Multi-head neural networks have been proposed to detect and correct several three-dimensional printing error categories within a generalized analytical structure (Brion & Pattinson, 2022). These studies indicate that defect-detection capability cannot be evaluated only through classification accuracy. An effective industrial system must recognize relevant defects early, locate them accurately, minimize false alarms, operate within production time constraints, and communicate information in a form that supports timely intervention. It must also maintain acceptable performance across different materials, component geometries, operators, machines, and production conditions if it is to influence actual levels of rework and scrap.

Predictive quality analytics expands AI-based quality control from recognizing present abnormalities to estimating the probability, location, severity, and production consequences of defects before final component acceptance. Prediction requires relationships among process inputs, sensor signatures, intermediate build conditions, and verified product-quality measurements. These relationships are difficult to represent through a single fixed mathematical equation because additive manufacturing involves nonlinear thermal behavior, material transformation, geometry-dependent heat transfer, phase changes, and interaction among numerous production parameters. Data-driven models can complement physical knowledge by learning complex patterns from historical process records, while physics-informed approaches can incorporate manufacturing principles into algorithm development. Modeling process-structure-property relationships in metal additive manufacturing has involved both physics-driven and data-driven approaches, with each approach providing different forms of information concerning process behavior and resulting material characteristics (Kouraytem et al., 2021). Physics-informed data-driven approaches have been proposed to connect machine-learning models with manufacturing knowledge rather than treating prediction as an isolated statistical exercise (Guo et al., 2022). Simulated and empirical data have also been combined in supervised-learning models for porosity prediction in laser metal deposition, allowing prediction systems to use multiple information sources when experimental datasets are limited (Gawade et al., 2022). Molten-pool sensing data and multimodality convolutional neural networks have been applied to the prediction of bead geometry in laser wire-feed directed energy deposition systems (Jamnikar et al., 2022). Deep-learning methods have further been used to examine quality patterns in metal additive manufacturing through image-based and process-based information (Li et al., 2020). Machine learning has also been examined as a mechanism for supporting material development, process selection, and property estimation in metal additive manufacturing (Johnson et al., 2020). Predictive analytics becomes operationally meaningful when it is integrated with machine controllers, manufacturing execution systems, quality databases, inspection records, and operator interfaces. Artificial intelligence within digital-twin applications has highlighted the importance of data communication, interoperability, modeling, and system integration in connected additive manufacturing environments (Bartsch et al., 2021). Integration allows an AI model to receive synchronized production information, compare current conditions with learned quality patterns, issue an alert, document the affected region, and support parameter adjustment or process interruption. It also enables detected defects, corrective actions, rework events, and scrap outcomes to be linked with the process conditions under which they occurred. Predictive quality analytics and system integration therefore represent related but separate dimensions of AI-based quality control. Predictive analytics concerns the ability to estimate quality outcomes and support decisions, while system integration concerns the embedding of those estimates and decisions within actual additive manufacturing workflows.

The existing literature contains substantial evidence concerning individual sensors, algorithms, defect categories, materials, and additive manufacturing processes, but the empirical record remains fragmented across experiments that frequently isolate one machine, one material, one sensing technology, one component geometry, or one quality indicator. Many studies have evaluated classification accuracy without examining whether the organizational use of AI-based systems is associated with reduced rework frequency, fewer rejected components, lower scrap generation, improved first-pass yield, or reduced corrective-processing requirements. Other studies have focused on model development while providing limited examination of training-data governance, equipment connectivity, operator competency, managerial support, model interpretation, and the procedures required to transform an automated alert into a controlled production response. An AI model may achieve high accuracy within a laboratory dataset but remain underused in production when employees do not understand its outputs, quality professionals do not trust its recommendations, data ownership is unclear, or the system is not integrated with manufacturing and inspection records. Process monitoring and control require coordination among process signatures, sensing systems, machine-learning methods, and control mechanisms rather than dependence on an isolated analytical model (Mahmoud et al., 2021). Challenges associated with machine learning in three-dimensional printing include limited data availability, weak model generalization, computational requirements, inconsistent labeling, and restricted system integration (Goh et al., 2021). The development of AI-supported additive manufacturing systems also requires coordinated data collection, model selection, training, validation, deployment, and application procedures (Raza et al., 2022). These conditions support the use of Socio-Technical Systems Theory because additive manufacturing quality performance depends on the alignment of technological resources, process data, production equipment, employee capabilities, organizational procedures, and management support. The present quantitative, cross-sectional, case-study-based research therefore examines additive manufacturing process-data quality and integration, AI-based defect-detection capability, real-time process monitoring and control, predictive quality analytics and decision support, AI-system integration with additive manufacturing equipment, and workforce competency and organizational readiness as predictors of AI-based quality-control effectiveness. It also examines AI-based quality-control effectiveness as a predictor of rework and scrap reduction performance. The constructs are measured through professionals' responses using Likert's five-point scale. Descriptive statistics are used to determine the implementation level of each variable, Pearson correlation analysis is used to evaluate the direction and strength of relationships, and regression modeling is used to test the proposed hypotheses. This research structure connects AI-related technological and organizational capabilities with specific additive manufacturing quality outcomes within the selected case-study environment.

**Background of the Study**

Additive manufacturing has become an important advanced-production approach because it enables manufacturers to fabricate complex components directly from digital models through the controlled, layer-by-layer addition of material. The technology is increasingly applied in aerospace, automotive, medical-device, defense, energy, electronics, tooling, and customized manufacturing environments where geometric flexibility, reduced material removal, rapid design modification, and component consolidation are highly valued. However, the industrial advantages of additive manufacturing are accompanied by significant quality-control challenges. Production outcomes can be affected by changes in laser power, scanning speed, layer thickness, feed rate, powder characteristics, thermal conditions, machine calibration, build orientation, environmental stability, and operator decisions. These variations may generate porosity, cracks, dimensional inaccuracies, weak bonding, incomplete fusion, warping, delamination, surface defects, material accumulation, and other forms of nonconformity. When such problems are identified after a component has been completed, manufacturers may need to perform additional machining, heat treatment, surface correction, inspection, rebuilding, or complete product rejection. These activities increase rework, scrap, production cost, machine downtime, energy consumption, material waste, and delivery delays. Traditional quality-control practices frequently depend on post-production inspection, which is useful for identifying defective products but cannot recover the resources already consumed during an unsuccessful build. Artificial intelligence provides an alternative approach by enabling production systems to collect, process, interpret, and apply large quantities of manufacturing data during the additive manufacturing process. AI-based quality control may combine machine learning, deep learning, computer vision, thermal imaging, acoustic monitoring, vibration sensing, melt-pool analysis, and predictive analytics to recognize abnormalities and estimate quality outcomes. Its effectiveness, however, depends on more than the accuracy of an individual algorithm. Reliable process data, integrated sensing systems, real-time monitoring, predictive decision support, equipment connectivity, employee competency, and organizational readiness are all necessary for converting AI-generated information into effective production decisions. The present study is therefore developed around an integrated AI-based quality-control framework that examines the technological, informational, human, and organizational conditions required to reduce rework and scrap in additive manufacturing production. Through a quantitative, cross-sectional, case-study-based approach, the research evaluates how these capabilities contribute to AI-based quality-control effectiveness and how that effectiveness influences measurable improvements in rework and scrap reduction performance.

**Problem Statement**

Additive manufacturing organizations continue to experience quality-related losses because production defects are frequently detected only after significant material, machine time, labor, energy, and post-processing resources have already been consumed. Although additive manufacturing offers the capability to produce highly complex and customized components, the process remains sensitive to changes in machine parameters, feedstock quality, thermal behavior, sensor conditions, environmental variables, and production-system stability. Small deviations occurring during a single layer may develop into internal defects, dimensional errors, weak structures, poor surface conditions, or complete build failure. When these defects are discovered through final inspection, manufacturers may be required to repair, reprocess, rebuild, downgrade, or reject the affected components. Such outcomes reduce first-pass yield, increase production cost, disrupt delivery schedules, consume additional materials, and weaken the economic and environmental advantages associated with additive manufacturing. Artificial intelligence has been introduced as a means of improving process monitoring, defect recognition, quality prediction, and corrective decision-making. However, many existing applications remain technically isolated, experimentally limited, or focused on one sensor, one algorithm, one machine, or one defect category. A classification model may demonstrate high accuracy under controlled conditions but provide limited production value when the underlying data are incomplete, incorrectly labeled, inconsistent, or disconnected from verified quality outcomes. AI-generated warnings may also fail to reduce defective production when they are not integrated with additive manufacturing equipment, operator interfaces, quality-management systems, or organizational decision procedures. In addition, employees may lack the knowledge required to interpret model outputs, while management may not provide sufficient training, infrastructure, financial resources, or procedural support for AI-based quality control. These conditions create a gap between the technical ability to detect abnormalities and the organizational ability to reduce actual rework and scrap. Another important problem is the limited availability of integrated quantitative evidence showing how process-data quality, AI-based defect-detection capability, real-time process monitoring, predictive quality analytics, system integration, workforce competency, and organizational readiness collectively influence quality-control effectiveness. There is also insufficient empirical evidence connecting AI-based quality-control effectiveness directly with reductions in rework frequency, scrap generation, failed builds, rejected components, corrective processing, and material waste. The absence of such evidence makes it difficult for additive manufacturing organizations to determine which capabilities should receive priority when implementing AI-supported quality systems. This study addresses that problem by developing and statistically evaluating an integrated framework that connects six technological and organizational predictors with AI-based quality-control effectiveness and subsequently links that effectiveness with rework and scrap reduction performance.

**Purpose and Objectives of the Study**

The principal purpose of this study is to develop and quantitatively evaluate an AI-based quality-control framework for reducing rework and scrap in additive manufacturing production. The research seeks to determine whether an integrated combination of data, monitoring, analytical, technological, human, and organizational capabilities can strengthen quality-control effectiveness and improve production outcomes. To achieve this purpose, the study first examines the level of additive manufacturing process-data quality and integration within the selected case-study environment. This objective focuses on the accuracy, completeness, consistency, synchronization, traceability, and accessibility of production information collected from machines, sensors, inspection systems, material records, and quality databases. The second objective is to evaluate AI-based defect-detection capability by examining whether intelligent systems can identify, classify, and locate process abnormalities and product defects accurately and promptly. The third objective is to assess the role of real-time process monitoring and control in providing continuous information concerning production conditions and supporting corrective actions before defects become irreversible. The fourth objective is to determine the influence of predictive quality analytics and decision support on the ability of additive manufacturing organizations to estimate defect probability, forecast quality outcomes, identify risky process conditions, and recommend appropriate interventions. The fifth objective is to investigate the contribution of AI-system integration with additive manufacturing equipment, production databases, quality-management systems, and operator interfaces. The sixth objective is to assess the influence of workforce competency and organizational readiness, including employee knowledge, AI-related training, management support, resource availability, technology acceptance, cross-functional collaboration, and procedural preparedness. The seventh objective is to determine the combined and individual effects of these six predictors on AI-based quality-control effectiveness. The eighth objective is to evaluate the effect of AI-based quality-control effectiveness on rework and scrap reduction performance, including reduced failed builds, fewer rejected components, lower material waste, decreased corrective processing, improved first-pass yield, and more efficient use of production resources. Descriptive statistics are used to measure the implementation level of the constructs, Pearson correlation analysis is applied to determine the direction and strength of relationships, and regression modeling is used to estimate predictive effects and test the research hypotheses. Through these objectives, the study establishes a structured basis for explaining how AI-based quality control operates as an integrated production capability rather than as an isolated defect-detection tool.

**Research Hypotheses**

The research hypotheses are developed to test the proposed relationships among the technological, informational, human, organizational, and performance variables included in the AI-based quality-control framework. The first hypothesis, H1, states that additive manufacturing process-data quality and integration have a significant positive effect on AI-based quality-control effectiveness. This relationship assumes that accurate, complete, consistent, synchronized, and traceable data allow AI models to identify production patterns and provide dependable quality information. The second hypothesis, H2, states that AI-based defect-detection capability has a significant positive effect on AI-based quality-control effectiveness because a system that can accurately recognize, classify, and locate defects is more capable of supporting timely quality decisions. The third hypothesis, H3, states that real-time process monitoring and control have a significant positive effect on AI-based quality-control effectiveness. Continuous observation is expected to improve the early identification of abnormal conditions and enable corrective action before a defect becomes irreversible. The fourth hypothesis, H4, states that predictive quality analytics and decision support have a significant positive effect on AI-based quality-control effectiveness because forecasting defect probability and evaluating process risk can improve the quality and speed of production decisions. The fifth hypothesis, H5, states that AI-system integration with additive manufacturing equipment has a significant positive effect on AI-based quality-control effectiveness. This hypothesis recognizes that analytical outputs must be connected with machines, operator interfaces, databases, and quality-management procedures to influence actual production activities. The sixth hypothesis, H6, states that workforce competency and organizational readiness have a significant positive effect on AI-based quality-control effectiveness. Employees must be able to interpret AI outputs, while organizations must provide training, managerial support, infrastructure, financial resources, and operational procedures. The seventh hypothesis, H7, states that AI-based quality-control effectiveness has a significant positive effect on rework and scrap reduction performance. Effective AI-supported quality control is expected to reduce failed builds, rejected components, corrective processing, material waste, production interruptions, and unnecessary resource consumption. These hypotheses are tested using data collected through Likert's five-point scale. Pearson correlation analysis determines whether the proposed variables are significantly associated, while multiple regression analysis identifies the individual and combined contributions of the six predictors to AI-based quality-control effectiveness. A separate regression model tests the effect of AI-based quality-control effectiveness on rework and scrap reduction performance. The hypotheses collectively represent the statistical structure through which the research objectives and conceptual framework are evaluated.

**Significance of the Research**

i. **Significance for additive manufacturing organizations:** The study provides organizations with a structured framework for understanding how AI-supported quality control can be organized to reduce failed production, rejected parts, corrective processing, material loss, and unnecessary machine use. It directs attention toward the combined importance of data quality, defect detection, monitoring, analytics, system integration, workforce capability, and organizational support rather than focusing only on purchasing advanced software or sensors.

ii. **Significance for quality-control and production managers:** The research identifies measurable factors that managers can use to evaluate the maturity of their existing quality-control systems. The findings can help them determine whether quality problems arise from inaccurate data, weak monitoring, limited model capability, poor equipment connectivity, inadequate employee training, or insufficient managerial support. This knowledge can assist in prioritizing quality-improvement activities and allocating resources more systematically.

iii. **Significance for engineers and machine operators:** The study clarifies how real-time monitoring, intelligent defect detection, and predictive decision support can improve the identification of abnormal production conditions. Engineers and operators can use the framework to understand how sensor information and AI-generated alerts should be incorporated into process adjustment, build interruption, inspection, and corrective-action procedures.

iv. **Significance for AI developers and technology providers:** The research demonstrates that the value of an AI system is not determined only by classification or prediction accuracy. Developers must also consider data integration, model interpretability, production speed, false-alarm control, equipment compatibility, user interaction, and the ability to connect analytical outputs with quality-management processes.

v. **Significance for employees and organizational leaders:** The inclusion of workforce competency and organizational readiness emphasizes that technological adoption requires training, communication, management commitment, resource availability, and cross-functional cooperation. Organizational leaders can use the findings to design training programs and implementation procedures that strengthen employee confidence in AI-assisted decision-making.

vi. **Significance for researchers:** The study contributes a quantitative framework that connects six independent variables, one intermediate quality-control variable, and one production-performance outcome. It provides a basis for applying descriptive statistics, correlation analysis, regression modeling, and hypothesis testing to an area that is frequently examined through laboratory experiments or algorithm-focused technical studies.

vii. **Significance for sustainable production:** Reducing rework and scrap can decrease material waste, energy consumption, failed builds, repeated processing, and disposal requirements. The study therefore connects AI-based quality control with the efficient use of manufacturing resources and the reduction of avoidable production losses.

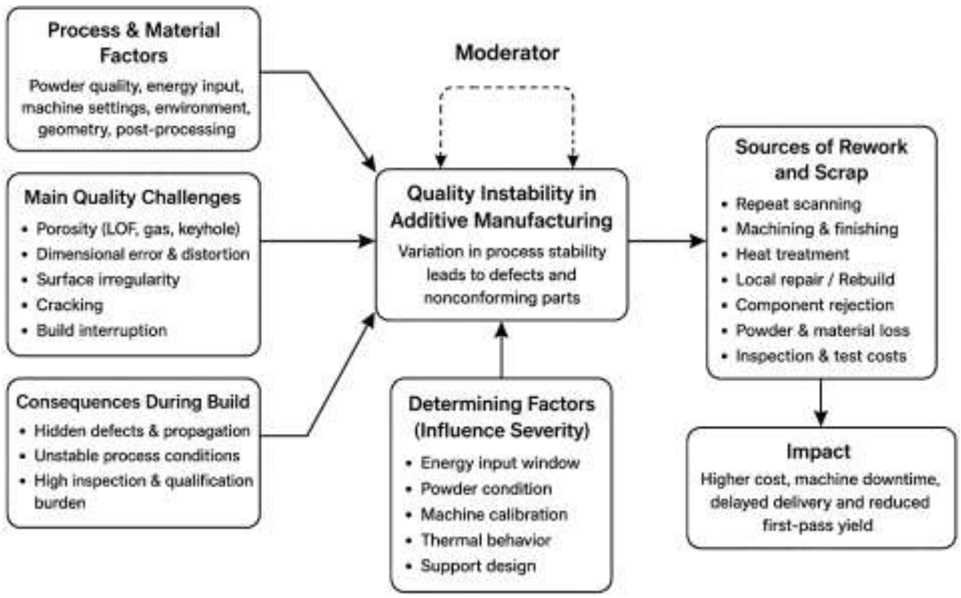
## LITERATURE REVIEW

The literature on AI-based quality control in additive manufacturing covers a multidisciplinary field involving manufacturing engineering, materials science, computer science, industrial quality management, sensor technology, data analytics, and organizational capability. Additive manufacturing quality is influenced by complex interactions among process parameters, material properties, machine conditions, component geometry, environmental factors, and production decisions. These interactions create defects that may develop within individual layers and remain undetected until the component has been completed and inspected. The literature therefore addresses both the physical origins of additive manufacturing defects and the analytical methods used to identify, predict, and control them. A substantial area of research focuses on in-situ monitoring through cameras, thermal sensors, photodiodes, pyrometers, acoustic-emission devices, vibration sensors, melt-pool monitoring systems, and layer-wise imaging. These technologies generate large quantities of production data that can be processed through machine learning, deep learning, computer vision, support vector machines, neural networks, clustering algorithms, and anomaly-detection methods. Another important area examines predictive quality analytics, through which process information is used to estimate porosity, dimensional deviation, surface quality, thermal behavior, bead geometry, material properties, and the probability of build failure. The literature also discusses closed-loop control, where detected abnormalities or predicted defects are connected with parameter adjustment, process interruption, or operator decision support. However, the performance of these systems depends strongly on the quality, completeness, synchronization, labeling, and traceability of the underlying data. Technical accuracy alone does not ensure industrial effectiveness because AI systems must also be integrated with additive manufacturing equipment, production databases, inspection systems, operator interfaces, and organizational quality procedures. Workforce knowledge, employee training, managerial commitment, resource availability, technology acceptance, and cross-functional collaboration further influence whether AI-generated information is used appropriately. The literature review is therefore organized around six major areas: additive manufacturing quality challenges and sources of rework and scrap; artificial intelligence applications in additive manufacturing quality control; process-data quality, defect detection, real-time monitoring, and predictive quality analytics; AI-system integration, workforce competency, and organizational readiness; Socio-Technical Systems Theory as the theoretical framework; and the conceptual framework and hypothesis development. Together, these areas establish the scholarly foundation for examining AI-based quality-control effectiveness as an integrated capability and for evaluating its relationship with rework and scrap reduction performance.

### Additive Manufacturing Quality Challenges and Sources of Rework and Scrap

Additive manufacturing quality is determined by the stability of a digitally coordinated production system in which material condition, energy delivery, machine motion, environmental control, component geometry, and post-processing interact throughout the build. Unlike conventional manufacturing, additive processes create a component through repeated thermal, mechanical, or photochemical events, so an error introduced in one layer may remain hidden, propagate through later layers, and affect the final structure. In metal systems, rapid melting and solidification produce steep thermal gradients, repeated reheating, directional microstructures, residual stress, distortion, and local variations in mechanical properties. The same nominal parameter setting may also produce different results when powder size distribution, particle morphology, moisture, oxygen content, recoater performance, substrate condition, or machine calibration changes. These sources of variation make repeatability difficult and increase the burden placed on inspection and qualification. Quality problems commonly include lack-of-fusion porosity, gas pores, keyhole pores, cracks, inclusions, delamination, balling, rough surfaces, dimensional deviation, unsupported-feature collapse, and anisotropic properties. Their significance depends on defect size, shape, location, orientation, and interaction with the intended loading condition. The process-structure-property relationship is therefore central to understanding why apparently minor production deviations can produce unacceptable performance in safety-critical parts (DebRoy et al., 2018; Kanti, 2020). Experimental work on Ti-6Al-4V powder bed fusion has shown that departures from effective parameter windows generate distinguishable defect populations in selective laser melting and electron beam melting, confirming that defect formation is linked to controllable production conditions (Debasish, 2021; Gong et al., 2014). When defects exceed acceptance limits, manufacturers may repeat scanning, machine surfaces, apply heat treatment, repair local regions, rebuild the entire component, or reject it. Each response adds labor, machine occupancy, energy consumption, inspection requirements, and material loss, making quality instability a direct source of rework and scrap in additive manufacturing production. Stable quality requires coordinated control across every production stage and resource.

**Figure 2: Process Framework Linking Quality Instability to Rework and Scrap in Additive Manufacturing**




Porosity is one of the persistent quality challenges because it can originate from several mechanisms and may not be visible on the external surface of a finished component. Insufficient energy input can prevent complete melting between adjacent tracks or layers, creating irregular lack-of-fusion voids and weak interfacial regions. Excessive energy input can deepen the molten region, intensify vaporization, and produce unstable keyholes that collapse and trap pores. Gas contained within feedstock particles, shielding conditions, or the melt may also become enclosed during rapid solidification. High-fidelity simulation of laser powder bed fusion has demonstrated that recoil pressure, surface-tension-driven flow, melt-pool depression, spatter, and powder denudation interact dynamically, producing pores at track edges, within collapsing depressions, and near the end of the melt path (Khairallah et al., 2016; Abdur & Iftekhar, 2021). These mechanisms show why a single energy-density value cannot fully describe process quality, since identical nominal energy inputs may be created through different combinations of laser power, scanning speed, hatch spacing, and layer thickness. Analysis of selective laser melted TiAl6V4 identified a minimum-porosity region between conditions characterized by insufficient fusion and conditions characterized by overheating, illustrating the importance of maintaining a processing window rather than simply maximizing energy input (Kasperovich et al., 2016; Hossan, 2021). Porosity reduces effective load-bearing area, increases stress concentration, accelerates crack initiation, and creates variability in fatigue behavior. For quality-control personnel, internal pores are costly because their verification may require computed tomography, destructive sectioning, density measurement, or nondestructive testing. Components containing repairable surface-connected defects may require machining, filling, polishing, or localized remanufacturing, while components with distributed internal porosity are often rejected. Powder contamination, spatter redeposition, unstable melt tracks, and interrupted builds also produce unusable feedstock and partially completed products. Consequently, porosity-related failures generate scrap directly through rejected builds and indirectly through additional test coupons, repeated qualification runs, extended inspection, and corrective processing.

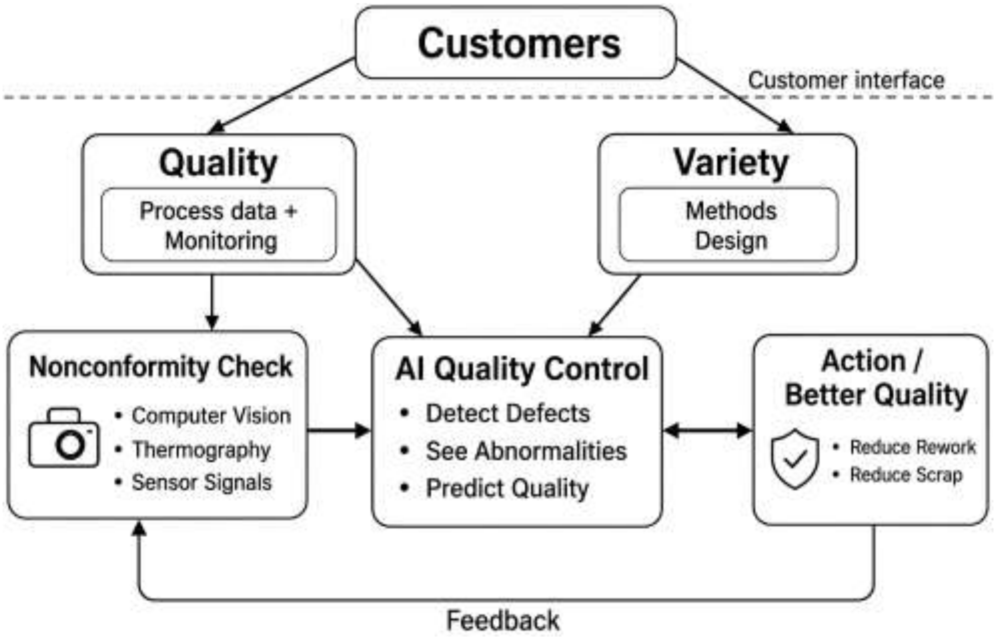
Dimensional error, surface irregularity, cracking, and build interruption also convert additive manufacturing failures into rework and scrap. Dimensional deviation may result from thermal contraction, residual stress, inaccurate compensation, weak support design, platform movement, or uneven heat distribution. Warped components may require machining or straightening, although severe distortion can make the geometry impossible to recover. Surface roughness may be intensified by partially melted particles, staircase effects, balling, unstable tracks, downward-facing geometry, and spatter attachment. Finishing can improve accessible surfaces, but internal channels, lattice structures, and thin features may remain inaccessible. Cracking is serious because hot cracking, solidification cracking, strain-age cracking, and stress-assisted cracking can compromise structural continuity and may extend across multiple layers. Keyhole instability is relevant because ultrahigh-speed X-ray imaging has shown a definable transition from conduction-mode melting to deep vapor depression, followed by instability and keyhole formation under laser-processing conditions (Cunningham et al., 2019; Chowdhury & Tonay, 2022). These observations show that defects can form within brief intervals, making delayed manual inspection inadequate for preventing defective builds. Rework and scrap are also affected by decisions made after an anomaly is detected. Stopping a build early can save powder and machine time but sacrifices the partially produced component, while continuing production may preserve a recoverable part or multiply the eventual loss. Organizations must therefore distinguish harmless signal variation from process conditions that threaten final conformity. The cost of poor quality includes discarded material, repeat production, machine cleaning, recalibration, support regeneration, post-processing, inspection, delayed delivery, and reduced equipment availability. These losses are magnified in large components, expensive alloys, and low-volume certified production because each failed build carries a high proportion of fixed preparation and qualification costs. Additive manufacturing quality challenges therefore extend beyond isolated defects and involve the cumulative control of process stability, defect severity, inspection confidence, and production decisions across the complete manufacturing cycle.

**Artificial Intelligence Applications in Additive Manufacturing Quality Control**

Artificial intelligence applications in additive manufacturing quality control are primarily directed toward transforming large volumes of process information into timely assessments of product conformity. Additive manufacturing machines generate geometric, thermal, acoustic, optical, vibration, and operational data throughout material deposition, fusion, curing, or solidification. Conventional quality assurance often examines a component after production, whereas AI systems can compare observed process behavior with learned patterns while the build is still progressing. Machine learning algorithms classify production states, detect abnormal signals, estimate dimensional deviation, and identify conditions associated with incomplete material deposition or structural irregularity. Deep learning is particularly useful when monitoring systems produce images because convolutional neural networks can automatically learn visual features that distinguish acceptable layers from defective ones. An early certify-as-you-build approach used three-dimensional digital image correlation to capture printed geometry and compare it with the intended computer model, demonstrating that localized and global printing errors could be detected during fused filament fabrication rather than after completion (Holzmond & Li, 2017; Zahidul & Begum, 2022). Thermographic monitoring has also been combined with a compact convolutional neural network to identify delamination and splatter in laser powder bed fusion. The model achieved a mean balanced accuracy of 96.80 percent and generated heatmaps that showed the image regions influencing its classifications, illustrating how AI can support both detection and interpretable quality assessment

(Baumgartl et al., 2020; Mesbaul, 2023). These applications indicate that AI-based quality control can operate at several analytical levels, including signal filtering, feature extraction, anomaly recognition, defect classification, spatial localization, and decision support. Their practical value depends on detecting deviations early enough for an operator or controller to stop production, adjust parameters, isolate an affected region, or schedule focused inspection before additional material and machine time are consumed. Accordingly, intelligent monitoring changes quality assurance from retrospective defect confirmation into evidence-based evaluation of production stability and component development.

**Figure 3: AI-Enabled Quality Control and Feedback Framework for Additive Manufacturing**



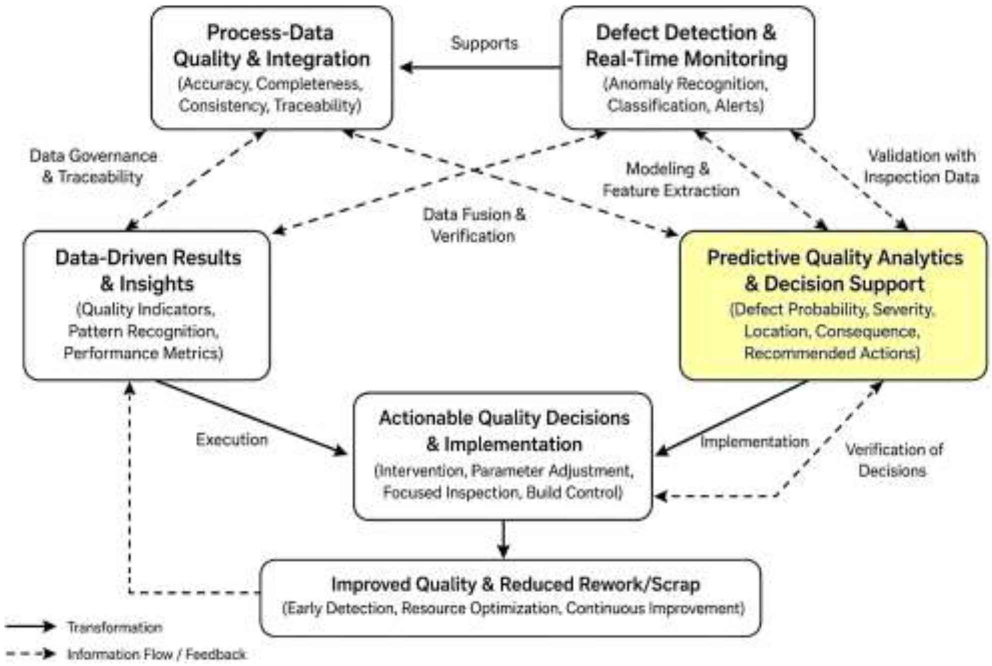

Computer vision represents one of the most established AI applications in additive manufacturing quality control because many defects create observable differences in powder distribution, melt behavior, layer geometry, surface texture, or deposited-material shape. A camera-based system can capture images before exposure, during processing, after fusion, or following recoating, allowing an algorithm to compare consecutive layers and identify deviations that may be difficult for an operator to observe consistently. Image classification models can distinguish quality categories, while object-detection models can locate a defect and estimate its spatial extent. In metal additive manufacturing, convolutional neural networks have been trained using optical microscope images to recognize acceptable material, cracks, gas porosity, and lack-of-fusion defects. One model achieved 92.1 percent classification accuracy and required approximately 8.01 milliseconds to evaluate an image, indicating that automated inspection can reduce the subjectivity and processing time associated with manual image review (Cui et al., 2020; Shurovi, 2024). AI-based vision is also applicable to polymer material extrusion, where defects such as stringing, under-extrusion, layer displacement, detachment, and deformation can become visible during printing. A real-time system using a deep neural network and live camera feed detected stringing defects and operated as a remote decision-support tool that could notify the printer operator when the predicted defect probability exceeded a selected threshold (Zahidul, 2024; Paraskevoudis et al., 2020). These applications illustrate the importance of selecting algorithms according to defect type, image scale, equipment configuration, and required response time. A model trained to detect one visible defect may not recognize internal porosity, while a model developed for one material, lighting condition, or component shape may lose accuracy when transferred to another production environment. Effective AI quality control therefore requires representative training images, reliable labeling, suitable camera placement, controlled illumination, validation on independent builds, and performance measures that address precision, recall, false alarms, processing speed, and generalization.

The application of AI to additive manufacturing quality control extends beyond recognizing isolated defects because production decisions require information about defect severity, location, and likely consequences. Layer-wise models can evaluate whether an abnormality is temporary, whether it develops across successive layers, and whether it creates a risk of collision, recoater damage, dimensional failure, or structural nonconformity. This capability is important for reducing rework and scrap because an early warning has limited value unless it supports an appropriate response. Surface deformation in laser powder bed fusion provides a clear example. Deformation can expose fused material above the powder surface, interfere with recoating, damage equipment, and create defects in later layers. A convolutional neural network trained on powder-bed images achieved 99 percent accuracy in identifying surface deformation, showing that labeled layer images can support recognition of conditions that threaten part quality and process continuity (Ansari et al., 2022; Kanti, 2024). Within an integrated quality-control framework, such classifications can be connected with machine parameters, build-location data, material records, and inspection results to determine whether production should continue, pause, or stop. AI systems can also prioritize regions for computed tomography, dimensional measurement, or testing, thereby concentrating inspection resources where quality risk is highest. However, industrial implementation requires more than algorithmic performance. Quality personnel must understand the meaning and limits of predictions, operators must receive alerts in usable forms, and managers must establish procedures for intervention, documentation, model updating, and accountability. Data collected from rework, rejected parts, corrections and scrapped builds should be returned to the learning system so that later classifications reflect verified production outcomes. AI-based quality control consequently functions as a coordinated cycle of sensing, learning, detection, decision, action, and feedback. When these activities are integrated, intelligent inspection can support earlier defect containment, focused corrective processing, reduced unnecessary intervention, and stronger control over material loss.

**Process-Data Quality, Defect Detection, Real-Time Monitoring, and Predictive Quality Analytics**

Process-data quality is a foundational requirement for AI-based quality control because every analytical result depends on the accuracy, completeness, consistency, timeliness, and traceability of the information supplied to the model. Additive manufacturing systems generate heterogeneous data from machine logs, laser settings, powder records, thermal sensors, optical cameras, acoustic devices, environmental monitors, inspection systems, and operator entries. These sources differ in sampling frequency, spatial resolution, measurement scale, file format, and reliability, which creates substantial challenges for synchronization and integration. Missing layers, incorrect timestamps, sensor drift, inconsistent calibration, mislabeled defects, and disconnected post-build inspection records can weaken model training and produce misleading quality predictions. Effective process-data management therefore requires standard procedures for acquisition, cleaning, normalization, registration, storage, labeling, and linkage with verified outcomes. Layerwise optical imaging has demonstrated that image features can be related to processing conditions and porosity, but such relationships depend on correctly aligning every image with the corresponding layer, parameter setting, and computed-tomography result (Imani et al., 2018; Ali et al., 2024). Multisensor monitoring has similarly shown that photodetector, visible-camera, and thermal-camera signals provide different representations of the same build condition, requiring structured fusion rather than isolated interpretation (Montazeri & Rao, 2018; Tonay et al., 2024). Data quality also involves representativeness because a model trained on one alloy, geometry, machine, or parameter range may not characterize another production context. Balanced datasets are needed to prevent dominant normal observations from masking rare but critical failures. Clear metadata should record machine identity, material batch, calibration state, build orientation, environmental conditions, and inspection method. Within the proposed framework, process-data quality and integration therefore represent an organizational capability through which raw production signals are converted into reliable, searchable, and analytically usable evidence. Strong data governance improves reproducibility, supports model validation, and enables quality personnel to trace AI-generated decisions back to specific process conditions and component locations throughout the complete manufacturing cycle.

**Figure 4: AI-Driven Quality Analytics Framework for Additive Manufacturing**




Defect detection and real-time monitoring transform reliable process data into evidence about whether an additive manufacturing build remains within acceptable quality boundaries. Real-time monitoring observes the process while material is being deposited, fused, or cured, whereas defect detection interprets signals to identify abnormal states and classify likely nonconformities. A monitoring system may collect data without producing an actionable quality judgment during active production. Effective detection requires features that reflect physical process behavior, reference patterns representing stable production, and decision rules capable of distinguishing true defects from harmless variation. Layerwise anomaly detection using thermal imaging and spatial statistical analysis has shown that regions with significant deviations can be screened and classified as in-control or out-of-control, reducing the computational burden of examining every pixel equally (Mahmoudi et al., 2019). Thermography and optical tomography have also been compared with computed tomography to determine whether in-situ signal deviations correspond with intentionally generated internal defects, illustrating the necessity of validating monitoring outputs against independent measurements (Mohr et al., 2020). Real-time effectiveness depends on detection latency because an alert delivered after additional layers may not prevent material loss or machine-time waste. The system must also control false positives, since unnecessary alarms can interrupt production, increase operator workload, and reduce confidence in AI recommendations. False negatives are equally serious because undetected defects may continue through the build and appear only during final inspection or service. Detection thresholds should therefore reflect defect severity, component criticality, process stability, and the cost of intervention. Integration with build coordinates enables suspicious signals to be mapped to specific layers and regions, supporting focused inspection and localized corrective action. In the proposed study, defect-detection capability and real-time monitoring are treated as related but separate constructs because continuous observation supplies process visibility, while intelligent detection converts that visibility into usable information for quality-control decisions.

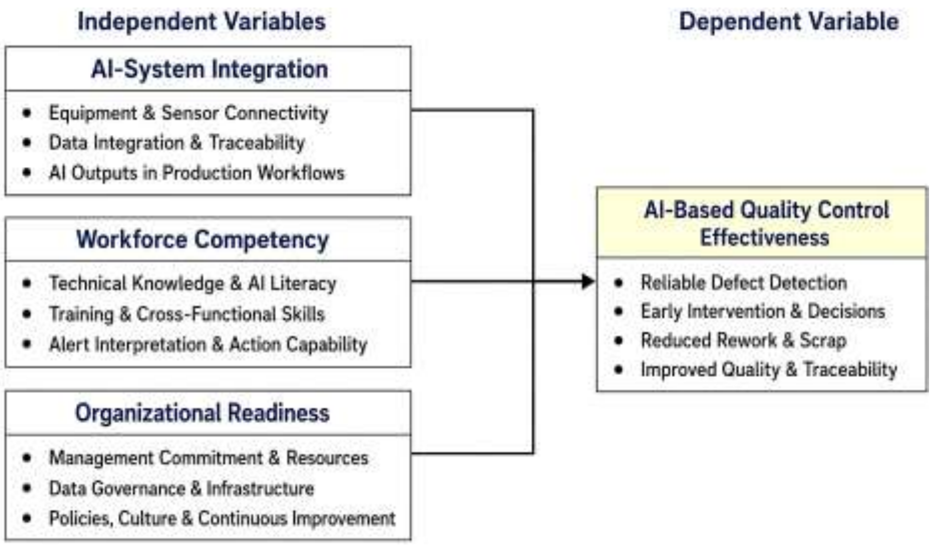
Predictive quality analytics extends monitoring beyond the recognition of abnormalities by estimating the probability, severity, location, or consequence of defects before final inspection. The analytical process begins with reliable features derived from images, temperature histories, photodetector signals, acoustic emissions, melt-pool geometry, machine parameters, or combined sensor streams. Classification models assign observations to predefined quality states, while regression models estimate continuous outcomes such as density, porosity, dimensional deviation, surface roughness, or defect size. Anomaly-detection methods identify departures from learned normal behavior when labeled failure data are scarce. The value of prediction depends on whether features represent meaningful physical behavior and whether the model is validated using components, materials, and inspection evidence. Heterogeneous sensing combined with scientific machine learning has demonstrated that physically meaningful features from multiple sensing modalities can be used to identify processing regimes and support overall quality assurance in laser powder bed fusion (Gaikwad et al., 2020). Predictive analytics must also communicate uncertainty because a probability estimate should not be interpreted as absolute proof of conformity or failure. Confidence intervals, classification probabilities, sensitivity, specificity, precision, recall, and error measures help quality personnel judge the reliability of predictions. Production decisions may then be matched to risk: low-risk deviations may trigger continued observation, moderate-risk conditions may require parameter adjustment or focused inspection, and high-risk conditions may justify pausing or terminating the build. Historical records of corrected, reworked, accepted, and scrapped components should be returned to the analytical system so that models can be recalibrated and evaluated against outcomes. Within the proposed research, predictive quality analytics and decision support capture the ability to transform process data into forecasts and recommended actions. This capability is expected to strengthen AI-based quality-control effectiveness by improving early intervention, inspection prioritization, process consistency, and the allocation of material, machine time, labor, and resources across additive manufacturing production.

**AI-System Integration, Workforce Competency, and Organizational Readiness**

AI-system integration in additive manufacturing refers to the coordinated connection of production equipment, sensing devices, analytical models, digital design files, quality databases, operator interfaces, and enterprise information systems. An integrated environment enables process data to move from machines and sensors into storage, analysis, visualization, and control functions without repeated manual transfer. This connectivity is essential for AI-based quality control because defect predictions become useful only when they can be related to a specific machine, material batch, component, layer, and production parameter. Digital continuity also supports traceability by preserving relationships among computer-aided design files, build preparation records, machine settings, monitoring signals, inspection results, and corrective actions. A systems approach to the additive manufacturing digital spectrum has emphasized the need for standardized data structures, information exchange, and interoperability across design, process planning, fabrication, and inspection activities (Kim et al., 2015). Industrial additive manufacturing should likewise be understood as a manufacturing system composed of interdependent subsystems rather than as a stand-alone machine, because production planning, control, material handling, post-processing, inspection, and information management jointly determine performance (Eyers & Potter, 2017). Weak integration may produce disconnected datasets, delayed alerts, inconsistent file versions, and limited visibility of quality events. Strong integration allows AI models to receive synchronized information, communicate risk levels, support focused inspection, and document whether an intervention reduced rework or prevented scrap. In the proposed framework, system integration therefore captures equipment compatibility, data connectivity, communication reliability, database linkage, and incorporation of AI outputs into existing production routines. These capabilities determine whether intelligent analysis remains an isolated technical experiment or becomes an operational quality-control resource embedded within additive manufacturing production. It also enables supervisors to compare builds across machines, identify recurring defects, verify model recommendations, maintain audit records, and coordinate corrective decisions among production, engineering, maintenance, and quality personnel throughout the manufacturing process consistently.

Workforce competency determines whether integrated AI and additive manufacturing systems are operated, interpreted, and improved correctly. Employees involved in quality control need technical knowledge of additive manufacturing processes, materials, defect mechanisms, sensors, data preparation, model outputs, inspection methods, and corrective procedures. Engineers must understand how process parameters influence component quality, while data specialists must recognize that statistically unusual signals do not always represent physically significant defects. Machine operators require practical skills for responding to alerts, checking equipment conditions, documenting interventions, and escalating uncertain cases. Quality professionals must evaluate prediction confidence, false alarms, missed defects, and relationships between in-process evidence and final inspection results. Research with small and medium enterprises has shown that additive manufacturing adoption involves organizational, operational, and supply-chain challenges rather than equipment acquisition alone (Martinsuo & Luomaranta, 2018). This perspective indicates that employee capability should be developed alongside machines, software, and data infrastructure. Training should include process fundamentals, AI literacy, model limitations, data integrity, human-machine interaction, and standardized response protocols. Cross-functional learning is also important because designers, operators, materials specialists, data analysts, maintenance teams, and quality personnel frequently interpret different portions of the same production problem. When these groups do not share terminology or decision rules, an AI alert may be misunderstood, ignored, or applied inconsistently. Workforce resistance may also arise when employees view automated monitoring as a threat to professional judgment or job security. Participatory implementation, clear role definitions, practical demonstrations, and opportunities to compare AI recommendations with verified defects can strengthen trust. In the present study, workforce competency therefore represents employees' knowledge, training, confidence, collaborative ability, and capacity to convert AI-generated information into appropriate quality-control actions that reduce unnecessary rework and prevent defective builds from consuming further resources. Continuous competency assessment can reveal skill gaps and guide refresher training when technologies, materials, algorithms, or procedures change.

**Figure 5: Integrated Organizational Framework for AI-Based Quality Control in Additive Manufacturing**




Organizational readiness reflects the extent to which a manufacturing organization possesses the leadership, resources, structures, policies, and culture required to adopt AI-based quality control successfully. Readiness includes management commitment, financial capacity, technological infrastructure, data governance, employee participation, cybersecurity arrangements, and procedures for evaluating system performance. Research on organizational adoption of three-dimensional printing has identified technological characteristics, organizational resources, decision-maker perceptions, and environmental conditions as important determinants, indicating that implementation readiness must be evaluated as a multidimensional organizational condition rather than as a localized equipment project (Ukobitz, 2021). Management must establish clear objectives for defect reduction, rework control, scrap minimization, traceability, and first-pass yield before investing in AI tools. It must also assign responsibility for data ownership, model validation, alert review, corrective action, and periodic system auditing. Quantitative evidence from small and medium-sized companies has identified technology cost, implementation conditions, expected benefits, production requirements, and skilled-labor availability as influential elements in additive manufacturing adoption (Kulkarni et al., 2021).

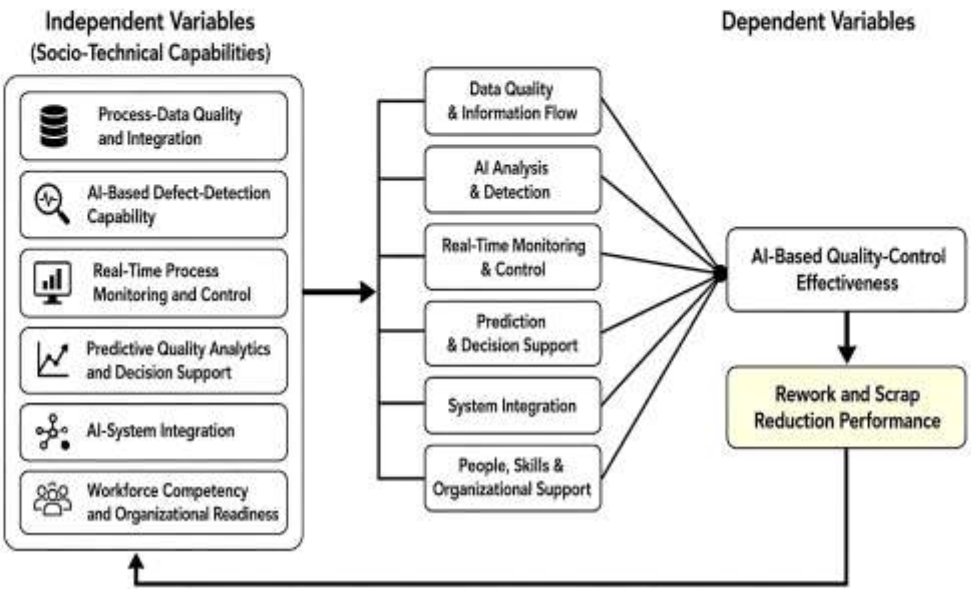
These factors suggest that readiness requires both tangible resources and supportive managerial attitudes. Organizations with weak readiness may purchase advanced monitoring equipment without creating reliable data pipelines, training programs, maintenance plans, or decision procedures. As a result, AI outputs may remain disconnected from quality-control practices and have little effect on rework or scrap. A ready organization creates pilot projects, defines performance indicators, allocates training time, encourages collaboration, reviews employee feedback, and updates procedures after verified production events. Within the proposed research framework, organizational readiness is combined with workforce competency because employee capability develops through managerial support, resource allocation, and institutionalized learning. Together, these conditions influence whether AI-based quality control becomes trusted, consistently applied, and connected with measurable production improvements. Readiness also supports continuity when personnel, machines, materials, or software change by preserving documented knowledge, responsibilities, validation requirements, and escalation pathways across production units.

**Theoretical Framework: Socio-Technical Systems Theory**

Socio-Technical Systems Theory provides the theoretical foundation for explaining why AI-based quality control in additive manufacturing must be understood as a jointly designed work system rather than as an isolated collection of algorithms, cameras, sensors, and machines. The theory divides an organizational production system into a technical subsystem and a social subsystem. The technical subsystem includes additive manufacturing equipment, process parameters, sensor networks, databases, computer-vision models, predictive algorithms, quality-control software, communication infrastructure, and operating procedures. The social subsystem includes engineers, operators, quality specialists, data analysts, maintenance employees, managers, organizational structures, skills, responsibilities, communication practices, and decision authority. The central principle of the theory is joint optimization, which proposes that production performance improves when technical capabilities and social arrangements are designed to support one another. A technically accurate AI model may therefore fail to reduce rework or scrap when employees cannot interpret its alerts, managers do not establish intervention procedures, production data are inaccessible, or equipment is not connected to the analytical system. Conversely, a highly trained workforce cannot consistently prevent defects when sensors are unreliable, data are incomplete, or predictive tools are unavailable. Contemporary socio-technical systems engineering emphasizes the integration of organizational change with system development and recommends constructive engagement among stakeholders throughout design and implementation (Baxter & Sommerville, 2011). This principle is directly relevant to additive manufacturing because process quality emerges from interactions among materials, machines, software, people, and organizational controls. Human-centered smart manufacturing research further shows that advanced digital systems should enhance operators' capabilities, learning, situational awareness, and decision quality rather than remove human judgment from complex production environments (Longo et al., 2017). Accordingly, the theory explains AI-based quality-control effectiveness as an emergent capability produced by coordinated technical and social conditions. This combined perspective makes the theory appropriate for evaluating both automated quality intelligence and the organizational capacity to apply it.

The application of Socio-Technical Systems Theory to this research requires the six predictors of AI-based quality-control effectiveness to be interpreted as mutually dependent components of one production system. Process-Data Quality and Integration represent the informational infrastructure through which machines, sensors, inspection results, material records, and operator observations become available for analysis. AI-Based Defect-Detection Capability represents the analytical mechanism that converts these data into classifications of acceptable and abnormal conditions. Real-Time Process Monitoring and Control provide continuous visibility and enable intervention while the component is being fabricated. Predictive Quality Analytics and Decision Support estimate the likelihood and seriousness of defects, while AI-System Integration connects those estimates with equipment, dashboards, databases, and quality-management procedures. Workforce Competency and Organizational Readiness constitute the social conditions required to understand, trust, govern, and act upon automated recommendations. Research on Industry 4.0 implementation has identified top-management support, organizational strategy, employee involvement, digital infrastructure, project management, collaboration, and change management as critical success factors, confirming that technological adoption depends on coordinated organizational arrangements (Sony & Naik, 2020). A human-centered manufacturing-system perspective similarly places employee development, training, management, and human-machine relationships within the design of adaptive cyber-physical production systems (Miranda et al., 2020). These arguments support the proposed relationships because reliable technology without capable users may generate unused information, while organizational support without suitable technology may produce slow and subjective quality decisions. Joint optimization occurs when accurate data feed validated models, monitoring systems communicate usable alerts, employees interpret those alerts correctly, and established procedures convert them into timely control actions. Under this theoretical interpretation, rework and scrap reduction are not direct products of AI installation. They are system-level outcomes generated when technical resources, human competence, organizational governance, and production processes are aligned around defect prevention, early detection, corrective action, and continuous learning. This alignment must remain consistent throughout the complete manufacturing cycle.

**Figure 6: Socio-Technical Systems Framework for AI-Based Quality-Control Effectiveness and Rework and Scrap Reduction in Additive Manufacturing**




The theoretical framework is operationalized through a two-stage regression structure that reflects the socio-technical sequence proposed in the conceptual model. The first stage estimates how the six technical and social capabilities jointly predict AI-Based Quality-Control Effectiveness. The principal multiple-regression model that will be applied throughout the study is expressed as $AQCE_i = \beta_0 + \beta_1 PDQI_i + \beta_2 AIDC_i + \beta_3 RTPM_i + \beta_4 PQAD_i + \beta_5 AISI_i + \beta_6 WCOR_i + \varepsilon_i$, where $AQCE$represents AI-Based Quality-Control Effectiveness; $PDQI$represents Process-Data Quality and Integration; $AIDC$represents AI-Based Defect-Detection Capability; $RTPM$represents Real-Time Process Monitoring and Control; $PQAD$represents Predictive Quality Analytics and Decision Support; $AISI$represents AI-System Integration; $WCOR$represents Workforce Competency and Organizational Readiness; $\beta_0$is the constant; $\beta_1$to $\beta_6$are regression coefficients; and $\varepsilon$is the unexplained error. The second stage evaluates the production outcome through $RSRP_i = \alpha_0 + \alpha_1 AQCE_i + \upsilon_i$, where $RSRP$represents Rework and Scrap Reduction Performance, $\alpha_0$is the intercept, $\alpha_1$measures the effect of quality-control effectiveness, and $\upsilon$is the residual error. Composite scores for each construct will be calculated from Likert five-point questionnaire items after reliability and validity are established. Descriptive statistics will identify implementation levels, Pearson correlation will evaluate association strength and direction, and multiple regression will test the hypothesized effects. The model reflects the theoretical expectation that neither the technical subsystem nor the social subsystem independently guarantees performance.

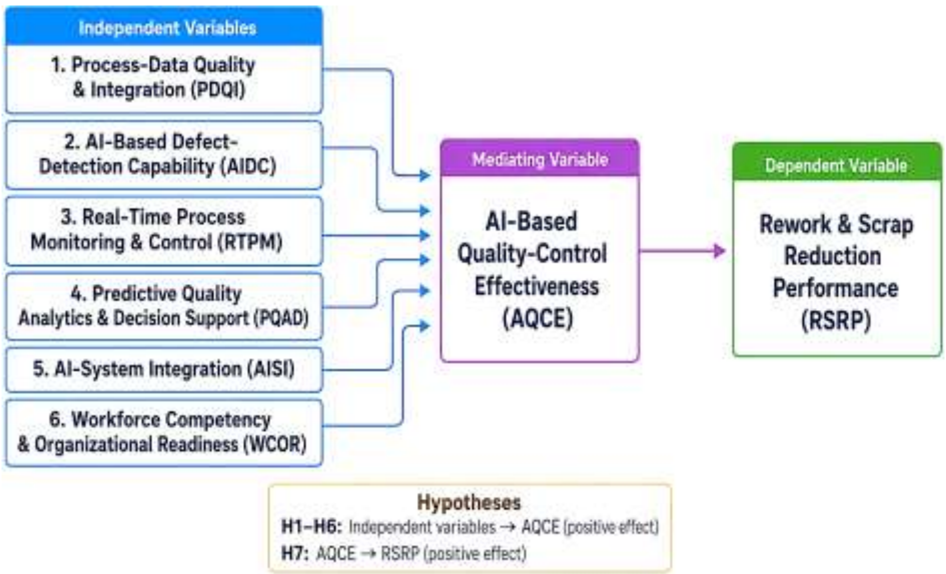
Human-centered Industry 4.0 research stresses that system design should simultaneously address technological functionality, human diversity, usability, participation, learning, and organizational context (Ngoc et al., 2022). Therefore, statistically significant coefficients will be interpreted as evidence that aligned socio-technical capabilities strengthen AI-based quality control, while the second equation will determine whether that effectiveness translates into fewer failed builds, lower corrective processing, reduced material waste, and less production scrap. Adjusted $R^2$, the F-statistic, standardized beta coefficients, significance values, tolerance, and variance inflation factors will assess explanatory power and model adequacy.

**Conceptual Framework and Hypothesis Development**

The conceptual framework of this study explains how six technological and organizational capabilities are expected to strengthen AI-Based Quality-Control Effectiveness and how that effectiveness is expected to reduce rework and scrap in additive manufacturing production. The framework begins with Process-Data Quality and Integration because artificial intelligence depends on accurate, complete, consistent, synchronized, and traceable information from machines, sensors, material records, inspection systems, and operator observations. Manufacturing-oriented machine learning requires representative data, suitable features, appropriate algorithms, and reliable validation before analytical outputs can support production decisions (Wuest et al., 2016). Accordingly, H1 proposes that Process-Data Quality and Integration have a significant positive effect on AI-Based Quality-Control Effectiveness. The second construct, AI-Based Defect-Detection Capability, represents the ability to recognize, classify, and locate defects such as porosity, lack of fusion, cracking, deformation, layer displacement, and surface irregularity. H2 proposes that stronger defect-detection capability significantly improves AI-Based Quality-Control Effectiveness because accurate and timely identification enables focused inspection and corrective intervention. The third construct, Real-Time Process Monitoring and Control, captures the continuous observation of thermal, optical, acoustic, vibration, geometric, and operational conditions during fabrication. Smart manufacturing integrates sensors, computing, communication, data-intensive modeling, predictive engineering, and control to create connected production environments (Kusiak, 2018). Therefore, H3 proposes that Real-Time Process Monitoring and Control have a significant positive effect on AI-Based Quality-Control Effectiveness. These three relationships form the informational and observational foundation of the framework. High-quality data provide dependable evidence, defect-detection models interpret that evidence, and real-time monitoring ensures that abnormal conditions are recognized while intervention remains possible. Their coordinated operation is expected to improve the accuracy, speed, consistency, and usability of AI-supported quality decisions across additive manufacturing builds. The framework therefore treats data availability, analytical recognition, and continuous process visibility as complementary capabilities whose combined operation supports earlier containment of quality deviations and reduces uncertainty substantially.

The second part of the conceptual framework addresses the analytical, integrative, and human conditions that convert detected process information into controlled quality action. Predictive Quality Analytics and Decision Support represent the capacity to estimate defect probability, forecast dimensional or structural outcomes, rank production risks, and recommend responses before final inspection. H4 therefore proposes that Predictive Quality Analytics and Decision Support have a significant positive effect on AI-Based Quality-Control Effectiveness. The fifth construct, AI-System Integration, concerns the connection of analytical models with additive manufacturing equipment, sensor platforms, databases, dashboards, inspection records, and quality-management procedures. Manufacturing companies commonly implement digital technologies as interacting layers, with smart-manufacturing applications depending on foundational connectivity, cloud services, data infrastructure, and analytics (Frank et al., 2019). H5 consequently proposes that AI-System Integration has a significant positive effect on AI-Based Quality-Control Effectiveness because model outputs must enter actual production workflows to influence intervention, documentation, and control. The sixth construct, Workforce Competency and Organizational Readiness, includes employee knowledge, AI literacy, technical training, management support, resource availability, technology acceptance, collaboration, and clearly assigned responsibilities. Evidence from manufacturing organizations indicates that advanced digital technologies generate stronger performance improvements when they are integrated with established operational practices rather than introduced independently (Tortorella & Fettermann, 2018). H6 therefore proposes that Workforce Competency and Organizational Readiness have a significant positive effect on AI-Based Quality-Control Effectiveness. These relationships reflect the socio-technical logic established in the theoretical framework. Predictive models create value only when connected systems deliver their results to capable users, and capable users require organizational authority and resources to respond appropriately. The framework thus positions analytics, integration, and readiness as complementary mechanisms through which AI-generated warnings become verified, documented, and timely production decisions. Their joint operation should improve alert interpretation, corrective-action consistency, model acceptance, accountability, and communication among engineering, production, maintenance, and quality teams.

**Figure 7: Research Conceptual Framework and Hypothesized Relationships**

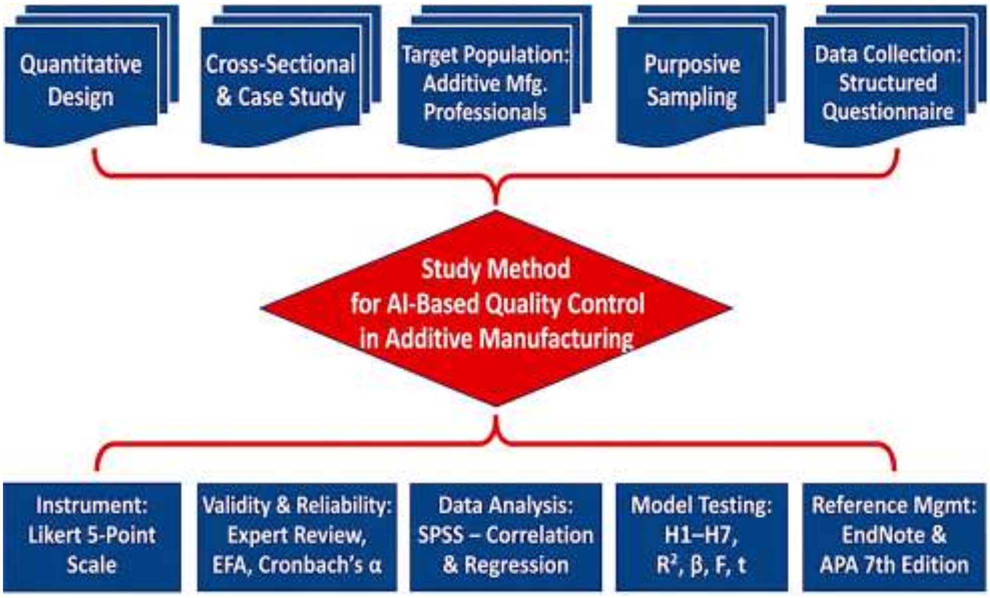



The final relationship in the conceptual framework connects AI-Based Quality-Control Effectiveness with Rework and Scrap Reduction Performance. AI-Based Quality-Control Effectiveness represents the organization's overall ability to use reliable data, intelligent detection, continuous monitoring, predictive analysis, integrated systems, and competent personnel to maintain conformity throughout additive manufacturing production. Rework and Scrap Reduction Performance reflects fewer failed builds, rejected components, repeated operations, corrective-processing activities, material losses, inspection repetitions, and avoidable machine-hour consumption. Industry 4.0 technologies have been associated with expected improvements in product quality, operational efficiency, flexibility, and resource utilization, although performance contributions vary according to the technologies and implementation context (Dalenogare et al., 2018). H7 therefore proposes that AI-Based Quality-Control Effectiveness has a significant positive effect on Rework and Scrap Reduction Performance. The complete conceptual model will be tested through two regression equations. The first is $AQCE = \beta_0 + \beta_1 PDQI + \beta_2 AIDC + \beta_3 RTPM + \beta_4 PQAD + \beta_5 AISI + \beta_6 WCOR + \varepsilon$, where the six independent variables predict AI-Based Quality-Control Effectiveness. The second is $RSRP = \alpha_0 + \alpha_1 AQCE + \upsilon$, where AI-Based Quality-Control Effectiveness predicts the final production outcome. Each construct will be calculated from multiple Likert five-point items after reliability and construct validity have been confirmed. Descriptive statistics will establish variable levels, Pearson correlation coefficients will assess bivariate relationships, and regression coefficients will determine the magnitude and significance of the hypothesized effects. Standardized beta values will identify the strongest predictors, while $R^2$and adjusted $R^2$will indicate explained variance. The F-statistic will assess overall model significance, and tolerance and variance inflation factors will examine multicollinearity. This structure converts the conceptual framework into a measurable model that directly links socio-technical quality capabilities with reductions in additive manufacturing waste and corrective production. Hypotheses will be supported when coefficients are positive, significant, and consistent with the direction of influence across models.

**METHOD**

This research has adopted a quantitative, cross-sectional, descriptive, explanatory, and case-study-based design to examine the effectiveness of an AI-based quality-control framework for reducing rework and scrap in additive manufacturing production. The quantitative approach has enabled the study to measure the proposed variables numerically, test the research hypotheses, and determine the strength and direction of the relationships among the constructs. The cross-sectional design has allowed data to be collected from relevant professionals during a defined period, while the explanatory design has supported the examination of the predictive effects of Process-Data Quality and Integration, AI-Based Defect-Detection Capability, Real-Time Process Monitoring and Control, Predictive Quality Analytics and Decision Support, AI-System Integration, and Workforce Competency and Organizational Readiness on AI-Based Quality-Control Effectiveness. The selected case-study context has included additive manufacturing organizations, engineering facilities, production laboratories, and industrial units that have used technologies such as laser powder bed fusion, directed energy deposition, selective laser sintering, material extrusion, binder jetting, and related digital fabrication systems. The target population has consisted of additive manufacturing engineers, production engineers, quality-control specialists, machine operators, industrial engineers, data analysts, AI specialists, maintenance personnel, technical supervisors, production managers, and research and development professionals. The individual professional has served as the unit of analysis because each respondent has possessed relevant knowledge of additive manufacturing operations, defect monitoring, intelligent quality systems, or production-quality management. A purposive sampling strategy has been used to identify respondents with direct experience in additive manufacturing and quality-control activities, while stratified consideration has been applied to ensure representation from different professional roles and organizational functions. A target of approximately 300 valid responses has been established to provide adequate statistical power for correlation and multiple-regression analysis. Data have been collected through a structured questionnaire distributed electronically and, where appropriate, in printed form. Participation has remained voluntary, and respondents have been informed about the purpose of the research, confidentiality of their responses, and their right to withdraw. The questionnaire has contained a demographic section and multiple-item scales measuring the eight study constructs. All construct items have been measured using Likert's five-point scale ranging from 1, strongly disagree, to 5, strongly agree. The instrument has been developed from the theoretical framework, conceptual model, research objectives, and relevant empirical literature. A pilot test has been conducted with approximately 30 to 40 eligible respondents to assess item clarity, completion time, wording, relevance, and preliminary reliability. Feedback from the pilot study has been used to revise ambiguous or repetitive items. Face and content validity have been established through review by experts in additive manufacturing, artificial intelligence, industrial engineering, quality management, and research methodology. Construct validity has been examined through exploratory factor analysis, the Kaiser-Meyer-Olkin measure, Bartlett's Test of Sphericity, and factor loadings. Reliability has been assessed using Cronbach's alpha, with a coefficient of .70 or higher having been considered acceptable. The collected data have been coded, screened, and analyzed using IBM SPSS Statistics. Descriptive statistics, including frequencies, percentages, means, standard deviations, and rankings, have been used to summarize respondent characteristics and variable levels. Pearson correlation analysis has been applied to evaluate bivariate relationships, while multiple regression modeling has been used to test H1 through H6. A separate regression model has been used to test the effect of AI-Based Quality-Control Effectiveness on Rework and Scrap Reduction Performance. Multicollinearity has been assessed through tolerance and variance inflation factor values, while model adequacy has been evaluated using R, $R^2$, adjusted $R^2$, F-statistics, standardized beta coefficients, t-values, and significance levels. EndNote has been used to organize references, manage APA seventh-edition citations, remove duplicate records, and maintain consistency throughout the research manuscript.

**Figure 8: Research Methodology**




## DATA ANALYSIS AND PRESENTATION

### Questionnaire Distribution and Response Rate

**Table 1: Questionnaire Distribution and Response Rate**

| Questionnaire status | Frequency | Percentage |
|---|---|---|
| Questionnaires distributed | 350 | 100.00 |
| Questionnaires returned | 326 | 93.14 |
| Incomplete or unusable questionnaires | 26 | 7.43 |
| Valid questionnaires retained | 300 | 85.71 |
| Questionnaires not returned | 24 | 6.86 |

Table 1 has presented the distribution, return, screening, and retention of the questionnaires used for the quantitative analysis. A total of 350 questionnaires have been distributed among additive manufacturing engineers, production engineers, quality-control specialists, machine operators, AI and data specialists, maintenance personnel, technical supervisors, and production managers working in the selected case-study environments. Of the distributed questionnaires, 326 have been returned, representing a gross return rate of 93.14 percent. The high return level has indicated that the research topic has been relevant to professionals involved in additive manufacturing production and quality-control activities. During the initial screening process, 26 questionnaires have been excluded because they have contained substantial missing information, repetitive response patterns, contradictory demographic information, or evidence of insufficient engagement with the questionnaire items. After this screening procedure, 300 questionnaires have been retained as valid, producing an effective response rate of 85.71 percent. This valid response rate has provided an adequate foundation for descriptive statistics, reliability testing, factor analysis, Pearson correlation analysis, and multiple regression modeling. The final sample has also exceeded common minimum requirements for a model containing six independent variables, one intermediate variable, and one dependent production-performance variable. The response profile has therefore supported the achievement of the study's methodological objective of obtaining sufficient professional evidence to evaluate the proposed AI-based quality-control framework. From the perspective of Socio-Technical Systems Theory, the participation of professionals from both technical and organizational functions has been important because the framework has not treated quality-control effectiveness as a purely technological outcome. Engineers, operators, data specialists, managers, and quality personnel have represented different parts of the social and technical subsystems. Their combined responses have enabled the analysis to capture equipment-related capability, data-management quality, AI performance, employee competency, management readiness, and production outcomes. The retained sample has consequently provided a broad socio-technical representation of the selected additive manufacturing case-study environment. The response-rate findings have confirmed that the dataset has been sufficiently complete and diverse to evaluate the research questions, test the hypotheses, and compare the relative contribution of each proposed predictor to AI-Based Quality-Control Effectiveness and Rework and Scrap Reduction Performance.

**Demographic and Professional Profile of Respondents**

**Table 2**: **Demographic and Professional Characteristics of Respondents**

| Characteristic | Category | Frequency | Percentage |
|---|---|---|---|
| Age | Below 25 years | 34 | 11.33 |
| | 25–34 years | 105 | 35.00 |
| | 35–44 years | 92 | 30.67 |
| | 45–54 years | 50 | 16.67 |
| | 55 years and above | 19 | 6.33 |
| Professional role | AM/production engineer | 72 | 24.00 |
| | Quality-control/assurance specialist | 61 | 20.33 |
| | Machine operator/technician | 49 | 16.33 |
| | AI/data/GIS specialist | 38 | 12.67 |
| | Maintenance/industrial engineer | 40 | 13.33 |
| | Manager/supervisor/R&D professional | 40 | 13.33 |
| Professional experience | Below 3 years | 46 | 15.33 |
| | 3–5 years | 78 | 26.00 |
| | 6–10 years | 96 | 32.00 |
| | 11–15 years | 49 | 16.33 |
| | Above 15 years | 31 | 10.33 |
| Main AM technology | Laser powder bed fusion | 83 | 27.67 |
| | Material extrusion | 69 | 23.00 |
| | Directed energy deposition | 46 | 15.33 |
| | Selective laser sintering | 42 | 14.00 |
| | Binder jetting | 29 | 9.67 |
| | Other AM technologies | 31 | 10.33 |

Table 2 has summarized the demographic and professional characteristics of the 300 valid respondents. The largest age group has consisted of respondents between 25 and 34 years, accounting for 35.00 percent of the sample, followed by professionals between 35 and 44 years at 30.67 percent. This distribution has indicated that most respondents have belonged to active technical and managerial age groups that have likely been directly involved in digital manufacturing, AI-supported inspection, and production decision-making. Respondents aged 45 years and above have represented 23.00 percent of the sample and have added experienced managerial and engineering perspectives to the dataset. The professional-role distribution has shown that additive manufacturing and production engineers have formed the largest group at 24.00 percent, while quality-control and quality-assurance specialists have accounted for 20.33 percent. Machine operators and technicians have represented 16.33 percent, and AI or data specialists have represented 12.67 percent. Maintenance engineers, industrial engineers, supervisors, managers, and research professionals have supplied additional technical and organizational perspectives. Regarding experience, 32.00 percent of respondents have reported six to ten years of professional experience, while 26.00 percent have reported three to five years. Therefore, a substantial majority has possessed enough practical exposure to evaluate process-data quality, defect-detection capability, monitoring systems, predictive analytics, organizational readiness, and rework and scrap outcomes. Laser powder bed fusion has been the most frequently represented additive manufacturing technology at 27.67 percent, followed by material extrusion at 23.00 percent. Directed energy deposition, selective laser sintering, binder jetting, and other technologies have also been represented. The variety of technologies has strengthened the case-study findings by preventing the framework from reflecting only one additive manufacturing process. From the perspective of Socio-Technical Systems Theory, the demographic profile has demonstrated the participation of actors from both the social and technical subsystems. Engineers and machine operators have represented direct interaction with the technical system, while managers, quality specialists, and organizational personnel have represented governance, decision-making, and procedural structures. AI and data specialists have connected the two subsystems by translating process information into quality predictions. This professional diversity has strengthened the validity of the framework because AI-Based Quality-Control Effectiveness has depended on coordinated input from equipment users, data specialists, quality personnel, and organizational leaders.

**Data Screening and Preliminary Analysis**

**Table 3**: **Data Screening, Normality, and Regression Assumption Results**

| Screening criterion | Observed result | Recommended threshold | Decision |
|---|---|---|---|
| Item-level missing data | 0.27% | Below 5% | Acceptable |
| Standardized residual range | −2.86 to 2.71 | Within ±3.00 | Acceptable |
| Skewness range | −0.71 to −0.38 | Within ±2.00 | Normal |
| Kurtosis range | −0.42 to 0.31 | Within ±2.00 | Normal |
| Tolerance range | .44 to .67 | Above .10 | Acceptable |
| VIF range | 1.49 to 2.27 | Below 5.00 | Acceptable |
| Durbin-Watson statistic | 1.91 | Approximately 1.50–2.50 | Independent errors |
| Largest Cook's distance | .084 | Below 1.00 | No influential case |
| Harman single-factor variance | 36.80% | Below 50% | No serious common-method bias |

Table 3 has presented the preliminary screening and statistical-assumption results for the retained dataset. The item-level missing-data rate has reached only 0.27 percent, which has remained substantially below the commonly accepted threshold of 5 percent. The limited missing values have been addressed through appropriate series-mean replacement after the response patterns have been reviewed, and no respondent has been retained when a substantial section of the questionnaire has remained incomplete. The standardized residuals have ranged from −2.86 to 2.71, indicating that the residual values have remained within the acceptable interval of plus or minus three standard deviations. The skewness values have ranged from −0.71 to −0.38, while kurtosis values have ranged from −0.42 to 0.31. These results have shown that the construct scores have followed approximately normal distributions and have supported the use of Pearson correlation and regression analysis. Multicollinearity has also been examined because the proposed model has included six related predictors of AI-Based Quality-Control Effectiveness. Tolerance values have ranged from .44 to .67, and variance inflation factor values have ranged from 1.49 to 2.27. These figures have remained within acceptable limits and have indicated that the independent variables have measured related but statistically distinguishable capabilities. The Durbin-Watson statistic has reached 1.91, confirming that the regression residuals have remained sufficiently independent. The largest Cook's distance has been .084, which has remained well below 1.00 and has indicated that no single observation has exerted excessive influence on the regression estimates. Harman's single-factor test has shown that the first unrotated factor has explained 36.80 percent of the total variance. This value has remained below 50 percent and has indicated that common-method bias has not dominated the dataset. These findings have supported the methodological quality of the subsequent analyses and have ensured that the relationships have not been produced by serious data abnormalities. From a Socio-Technical Systems Theory perspective, the absence of excessive multicollinearity has been important because process data, AI detection, monitoring, predictive analytics, integration, and workforce readiness have represented interconnected but separate components of the broader production system. Their statistical distinction has allowed the study to examine how each socio-technical capability has made a unique contribution to quality-control effectiveness.

**Reliability Analysis of the Study Constructs**

**Table 4**: **Internal Consistency Reliability of the Study Constructs**

| Construct | Code | Number of items | Cronbach's alpha | Corrected item-total correlation range | Reliability decision |
|---|---|---|---|---|---|
| Process-Data Quality and Integration | PDQI | 4 | .884 | .652–.781 | Reliable |
| AI-Based Defect-Detection Capability | AIDC | 4 | .918 | .734–.842 | Highly reliable |
| Real-Time Process Monitoring and Control | RTPM | 4 | .901 | .706–.819 | Highly reliable |
| Predictive Quality Analytics and Decision Support | PQAD | 4 | .887 | .661–.792 | Reliable |
| AI-System Integration | AISI | 3 | .846 | .638–.731 | Reliable |
| Workforce Competency and Organizational Readiness | WCOR | 3 | .823 | .601–.704 | Reliable |
| AI-Based Quality-Control Effectiveness | AQCE | 3 | .909 | .749–.826 | Highly reliable |
| Rework and Scrap Reduction Performance | RSRP | 3 | .895 | .713–.801 | Highly reliable |

Table 4 has reported the internal consistency reliability of the eight study constructs. Cronbach's alpha values have ranged from .823 to .918, and every value has exceeded the minimum acceptable threshold of .70. AI-Based Defect-Detection Capability has achieved the highest reliability coefficient at .918, indicating that its four questionnaire items have consistently measured respondents' perceptions of defect recognition, defect classification, defect localization, and timely alert generation. AI-Based Quality-Control Effectiveness has recorded an alpha of .909, while Real-Time Process Monitoring and Control has achieved .901. These results have shown strong consistency among the items measuring continuous process visibility, real-time alerting, production response, and quality-control performance. Rework and Scrap Reduction Performance has achieved an alpha of .895, confirming that its items concerning reduced failed builds, lower material waste, fewer rejected components, and decreased corrective processing have formed a coherent production-performance scale. Process-Data Quality and

Integration, Predictive Quality Analytics and Decision Support, and AI-System Integration have also recorded strong reliability coefficients of .884, .887, and .846, respectively. Workforce Competency and Organizational Readiness has produced the lowest alpha at .823, but the value has remained clearly acceptable and has demonstrated that employee skill, training, management support, and organizational preparedness have been measured consistently. Corrected item-total correlations have ranged from .601 to .842 across the constructs, and no item has fallen below the acceptable level of .30. Therefore, all 28 questionnaire items have been retained for further analysis. The reliability results have supported the measurement objective of the study by confirming that the questionnaire has captured stable and internally coherent representations of the proposed variables. The findings have also strengthened the subsequent correlation and regression results because unreliable construct scores could have weakened or distorted the estimated relationships. Socio-Technical Systems Theory has been reflected in the reliability structure because both technical constructs and social-organizational constructs have demonstrated acceptable measurement consistency. The technical subsystem has been represented through data quality, defect detection, monitoring, analytics, and system integration, while the social subsystem has been represented through workforce capability and organizational readiness. The reliable measurement of both subsystems has allowed the study to test the theory's central expectation that coordinated technical and social capabilities have contributed to effective production performance.

**Sampling Adequacy and Construct Validity**

**Table 5**: **Sampling Adequacy, Factor Validity, Composite Reliability, and Average Variance Extracted**

| Validity indicator | PDQI | AIDC | RTPM | PQAD | AISI | WCOR | AQCE | RSRP |
|---|---|---|---|---|---|---|---|---|
| Factor-loading range | .721–.842 | .778–.893 | .754–.874 | .708–.838 | .694–.821 | .681–.804 | .786–.886 | .762–.871 |
| Composite reliability | .887 | .920 | .904 | .889 | .851 | .829 | .911 | .898 |
| Average variance extracted | .663 | .742 | .702 | .668 | .656 | .619 | .773 | .746 |
| Construct decision | Valid | Valid | Valid | Valid | Valid | Valid | Valid | Valid |

| Overall sampling test | Result |
|---|---|
| Kaiser-Meyer-Olkin measure | .891 |
| Bartlett's Test of Sphericity | $\chi^2(378) = 4{,}126.44$ |
| Significance of Bartlett's test | $p < .001$ |
| Total variance explained by eight factors | 72.64% |

Table 5 has presented the sampling adequacy and construct-validity results. The overall Kaiser-Meyer-Olkin value has reached .891, which has exceeded the recommended minimum level of .60 and has indicated that the correlations among the questionnaire items have been sufficiently compact for factor analysis. Bartlett's Test of Sphericity has been statistically significant, $\chi^2(378) = 4{,}126.44$, $p < .001$, confirming that the correlation matrix has not been an identity matrix and that meaningful common factors have existed among the measured items. Exploratory factor analysis has extracted eight factors corresponding to the eight proposed constructs, and these factors have collectively explained 72.64 percent of the total variance. This level of explained variance has indicated that the measurement model has represented a substantial proportion of respondents' evaluations of AI-based quality control and rework and scrap reduction. Factor loadings have ranged from .681 to .893, with every item exceeding the minimum acceptable level of .50. AI-Based Defect-Detection Capability has recorded the strongest loading range, while Workforce Competency and Organizational Readiness has recorded the lowest minimum loading at .681. However, the full range has remained acceptable and has demonstrated that every questionnaire item has been strongly associated with its intended construct. Composite reliability values have ranged from .829 to .920 and have exceeded the recommended .70 threshold. Average variance extracted values have ranged from .619 to .773, and all values have remained above .50. These results have confirmed convergent validity because each construct has explained more than half of the variance in its associated indicators. The factor structure has also supported conceptual distinction among the constructs. For example, AI-System Integration has been measured separately from Predictive Quality Analytics, and Workforce Competency and Organizational Readiness has remained distinguishable from the technological variables. This distinction has been theoretically important under Socio-Technical Systems Theory because the theory has proposed that the social and technical subsystems have interacted while retaining separate functions. The validity findings have therefore confirmed that the study has measured multiple complementary capabilities rather than a single undifferentiated perception of technology adoption. The results have supported the use of composite construct scores in the descriptive, correlation, and regression analyses that have followed.

**Descriptive Statistics of the Study Variables**

**Table 6**: **Overall Descriptive Statistics and Ranking of the Study Constructs**

| Rank | Construct | Code | Mean | Standard deviation | Minimum | Maximum | Interpretation |
|---|---|---|---|---|---|---|---|
| 1 | AI-Based Defect-Detection Capability | AIDC | 4.13 | .54 | 2.25 | 5.00 | High |
| 2 | AI-Based Quality-Control Effectiveness | AQCE | 4.11 | .55 | 2.33 | 5.00 | High |
| 3 | Real-Time Process Monitoring and Control | RTPM | 4.10 | .56 | 2.25 | 5.00 | High |
| 4 | Process-Data Quality and Integration | PDQI | 4.08 | .57 | 2.25 | 5.00 | High |
| 5 | Rework and Scrap Reduction Performance | RSRP | 4.07 | .58 | 2.00 | 5.00 | High |
| 6 | Predictive Quality Analytics and Decision Support | PQAD | 4.02 | .59 | 2.00 | 5.00 | High |
| 7 | AI-System Integration | AISI | 3.94 | .62 | 1.67 | 5.00 | High |
| 8 | Workforce Competency and Organizational Readiness | WCOR | 3.89 | .64 | 1.67 | 5.00 | High |

Table 6 has reported the overall descriptive statistics for the eight study constructs measured through Likert's five-point scale. All construct means have fallen between 3.89 and 4.13 and have therefore been interpreted as high based on the study's mean-interpretation criteria. AI-Based Defect-Detection Capability has achieved the highest mean of 4.13 with a standard deviation of .54. This result has indicated that respondents have generally agreed that the selected additive manufacturing environments have used AI-supported systems to recognize, classify, and locate production defects effectively. AI-Based Quality-Control Effectiveness has ranked second with a mean of 4.11, suggesting that the combined operation of process data, monitoring systems, analytical models, equipment integration, and employee action has been perceived as effective. Real-Time Process Monitoring and Control has recorded a mean of 4.10, while Process-Data Quality and Integration has achieved a mean of 4.08. These results have indicated that real-time visibility and dependable production information have already formed strong elements of the quality-control system. Rework and Scrap Reduction Performance has reached a mean of 4.07, showing that respondents have perceived meaningful reductions in failed builds, rejected components, corrective processing, and material waste. Predictive Quality Analytics and Decision Support has achieved a mean of 4.02 and has also remained within the high category. However, AI-System Integration and Workforce Competency and Organizational

Readiness have recorded the lowest means at 3.94 and 3.89. These values have remained high, but they have identified areas where implementation has been less mature. Full machine-to-AI connectivity, integration with quality-management databases, employee refresher training, model interpretation skills, and organizational preparedness have therefore required greater attention. The standard deviations have ranged from .54 to .64, showing moderate variation in respondents' perceptions and suggesting that implementation levels have differed across organizations, professional groups, and additive manufacturing technologies. The descriptive findings have addressed the first research question and have fulfilled the objectives concerned with assessing the current level of each capability. Socio-Technical Systems Theory has been supported by the pattern because the strongest ratings have appeared in technical capabilities, while comparatively lower ratings have appeared in integration and workforce readiness. This pattern has indicated that technical advancement alone has not automatically produced equal maturity in the social and organizational dimensions of the quality-control system.

**Item-Level Likert Scale Analysis**

**Table 7**: **Item-Level Mean Scores for the Study Constructs**

| Construct | Measurement item | Mean | SD | Interpretation |
|---|---|---|---|---|
| PDQI | Process data have been accurate and reliable | 4.14 | .59 | High |
| PDQI | Sensor and machine data have been complete | 4.10 | .61 | High |
| PDQI | Data sources have been synchronized effectively | 4.06 | .63 | High |
| PDQI | Production and inspection data have been integrated | 4.02 | .66 | High |
| AIDC | AI has detected process abnormalities accurately | 4.19 | .55 | High |
| AIDC | AI has classified defect types correctly | 4.15 | .57 | High |
| AIDC | AI has located affected layers or regions | 4.11 | .60 | High |
| AIDC | False alarms have been maintained at a manageable level | 4.07 | .64 | High |
| RTPM | Production conditions have been monitored continuously | 4.16 | .58 | High |
| RTPM | Alerts have been generated during active production | 4.12 | .61 | High |
| RTPM | Operators have received information in time to respond | 4.08 | .64 | High |
| RTPM | Automatic parameter correction has been available | 4.04 | .68 | High |
| PQAD | Analytics have forecasted quality risks accurately | 4.08 | .61 | High |
| PQAD | Models have predicted likely defect development | 4.04 | .63 | High |
| PQAD | Decision-support tools have prioritized risky builds | 4.00 | .66 | High |
| PQAD | Prediction uncertainty has been communicated clearly | 3.96 | .69 | High |
| AISI | AI outputs have been connected with operator interfaces | 4.01 | .65 | High |
| AISI | Quality databases have been linked with production data | 3.95 | .68 | High |
| AISI | Full machine-to-AI integration has been achieved | 3.86 | .72 | High |
| WCOR | Management has supported AI-based quality control | 3.98 | .67 | High |
| WCOR | Employees have received sufficient technical training | 3.90 | .70 | High |
| WCOR | Employees have confidently interpreted AI outputs | 3.79 | .75 | High |
| AQCE | AI has improved the speed of quality decisions | 4.16 | .58 | High |
| AQCE | AI has improved the consistency of defect evaluation | 4.12 | .60 | High |
| AQCE | AI-supported actions have prevented defective builds | 4.05 | .65 | High |
| RSRP | Failed builds have been reduced | 4.12 | .61 | High |
| RSRP | Rejected components and scrap materials have decreased | 4.08 | .64 | High |
| RSRP | Corrective processing and rework have been reduced | 4.01 | .68 | High |

Table 7 has presented the item-level Likert-scale findings and has identified the strongest and weakest operational aspects of the proposed framework. The highest item mean has been recorded for the statement that AI has detected process abnormalities accurately, with a mean of 4.19. Continuous monitoring of production conditions has achieved a mean of 4.16, while the speed of quality decisions has also reached 4.16. These findings have indicated that respondents have perceived strong performance in early defect recognition, continuous process visibility, and timely decision-making. The data-quality items have ranged from 4.02 to 4.14, confirming that the selected organizations have generally maintained reliable and usable production information. However, the integration of production and inspection data has achieved the lowest mean within Process-Data Quality and Integration, suggesting that data have not always been fully connected across quality and manufacturing systems. Within AI-Based Defect-Detection Capability, the management of false alarms has received the lowest rating at 4.07, indicating that classification accuracy has been strong but has not completely eliminated unnecessary alerts. Automatic parameter correction has recorded a mean of 4.04 and has ranked below continuous monitoring and alert generation, showing that monitoring capabilities have been more mature than autonomous control. Prediction uncertainty has achieved a mean of 3.96, indicating that organizations have used predictive analytics but have not always communicated confidence levels and limitations clearly. The weakest technological item has concerned full machine-to-AI integration, which has recorded a mean of 3.86. The lowest overall item has concerned employees' confidence in interpreting AI outputs, with a mean of 3.79. This result has highlighted a gap between technical system availability and human capability. Rework and scrap items have all remained high, with failed-build reduction achieving the strongest outcome mean of 4.12. Socio-Technical Systems Theory has been clearly reflected in these findings. Technical capabilities such as sensing, detection, and decision speed have received stronger evaluations, while human interpretation and complete system integration have received comparatively lower ratings. The item-level results have therefore shown that joint optimization has not been fully achieved in every area. Strong technical performance has already supported quality outcomes, but further alignment among equipment, software, databases, employees, and procedures has remained necessary to maximize rework and scrap reduction.

**Pearson Correlation Analysis**

**Table 8: Pearson Correlation Matrix for the Study Variables**

| Variable | PDQI | AIDC | RTPM | PQAD | AISI | WCOR | AQCE | RSRP |
|---|---|---|---|---|---|---|---|---|
| PDQI | 1.00 | | | | | | | |
| AIDC | .62*** | 1.00 | | | | | | |
| RTPM | .59*** | .65*** | 1.00 | | | | | |
| PQAD | .57*** | .61*** | .63*** | 1.00 | | | | |
| AISI | .54*** | .56*** | .58*** | .60*** | 1.00 | | | |
| WCOR | .49*** | .52*** | .54*** | .56*** | .57*** | 1.00 | | |
| AQCE | .69*** | .74*** | .71*** | .67*** | .61*** | .59*** | 1.00 | |
| RSRP | .58*** | .63*** | .61*** | .59*** | .55*** | .53*** | .76*** | 1.00 |

***$p < .001$.

Table 8 has shown that all study variables have been positively and significantly correlated at $p < .001$. AI-Based Defect-Detection Capability has produced the strongest correlation with AI-Based Quality-Control Effectiveness, $r = .74$, indicating that more accurate and timely recognition of production defects has been strongly associated with higher overall quality-control effectiveness. Real-Time Process Monitoring and Control has produced the second-strongest relationship with AI-Based Quality-Control Effectiveness, $r = .71$, followed by Process-Data Quality and Integration, $r = .69$. These relationships have indicated that effective AI-supported quality control has depended strongly on reliable production information and continuous observation of process conditions. Predictive Quality

Analytics and Decision Support has been significantly related to AI-Based Quality-Control Effectiveness, r = .67, while AI-System Integration and Workforce Competency and Organizational Readiness have produced correlations of .61 and .59, respectively. Although these values have been lower than the correlations for detection and monitoring, they have remained moderate to strong and statistically significant. The final production outcome, Rework and Scrap Reduction Performance, has shown positive relationships with every predictor. Its strongest relationship has been with AI-Based Quality-Control Effectiveness, r = .76, indicating that organizations with more effective AI-supported quality-control systems have reported substantially stronger reductions in failed builds, rejected components, corrective processing, and material waste. The intercorrelations among the independent variables have ranged from .49 to .65. These values have demonstrated that the predictors have been related as parts of the same broader system but have not been so highly correlated that they have represented identical concepts. This pattern has remained consistent with the tolerance and VIF findings reported earlier. The results have provided preliminary support for H1 through H7 because every proposed relationship has occurred in the expected positive direction. However, the correlation analysis alone has not established the unique predictive contribution of each variable, which has been examined through regression analysis. Socio-Technical Systems Theory has been supported by the interconnected pattern of relationships. Technical capabilities, including data, detection, monitoring, analytics, and integration, have been positively connected with the social-organizational capability of workforce readiness. Their combined association with quality-control effectiveness has shown that production performance has emerged from a network of mutually reinforcing components rather than from an isolated algorithm or sensor.

**Multiple Regression Analysis Predicting AI-Based Quality-Control Effectiveness**

**Table 9**: **Multiple Regression Results for AI-Based Quality-Control Effectiveness**

| Predictor | B | Standard error | Standardized β | t-value | p-value | Tolerance | VIF |
|---|---|---|---|---|---|---|---|
| Constant | .428 | .137 | | 3.12 | .002 | | |
| Process-Data Quality and Integration | .185 | .043 | .19 | 4.30 | <.001 | .56 | 1.79 |
| AI-Based Defect-Detection Capability | .276 | .048 | .27 | 5.75 | <.001 | .48 | 2.08 |
| Real-Time Process Monitoring and Control | .233 | .046 | .23 | 5.07 | <.001 | .51 | 1.96 |
| Predictive Quality Analytics and Decision Support | .149 | .047 | .16 | 3.17 | .002 | .52 | 1.92 |
| AI-System Integration | .106 | .039 | .12 | 2.69 | .008 | .60 | 1.67 |
| Workforce Competency and Organizational Readiness | .084 | .035 | .10 | 2.42 | .016 | .67 | 1.49 |

| Model statistic | Result |
|---|---|
| R | .827 |
| $R^2$ | .684 |
| Adjusted $R^2$ | .678 |
| Standard error of estimate | .312 |
| F-statistic | $F(6, 293) = 105.84$ |
| Model significance | $p < .001$ |

Table 9 has presented the multiple-regression model used to test H1 through H6. The overall model has been statistically significant, $F(6, 293) = 105.84$, $p < .001$, indicating that the six independent variables have jointly provided a meaningful prediction of AI-Based Quality-Control Effectiveness. The multiple correlation coefficient has reached .827, while $R^2$ has reached .684 and adjusted $R^2$ has reached .678. Therefore, the six predictors have jointly explained 68.40 percent of the variance in AI-Based Quality-Control Effectiveness. This explanatory level has indicated that the proposed framework has captured a substantial proportion of the conditions influencing the effectiveness of AI-supported quality control. AI-Based Defect-Detection Capability has emerged as the strongest predictor, $\beta = .27$, $p < .001$. This result has shown that the ability to recognize, classify, and locate defects has made the largest unique contribution when the other variables have been statistically controlled. Real-Time Process Monitoring and Control has been the second-strongest predictor, $\beta = .23$, $p < .001$, followed by Process-Data Quality and Integration, $\beta = .19$, $p < .001$. Predictive Quality Analytics and Decision Support has also produced a significant effect, $\beta = .16$, $p = .002$. AI-System Integration has shown a smaller but significant influence, $\beta = .12$, $p = .008$, while Workforce Competency and Organizational Readiness has remained significant at $\beta = .10$, $p = .016$. Therefore, H1 through H6 have all been supported. The tolerance and VIF values have remained within acceptable ranges, confirming that the regression coefficients have not been distorted by serious multicollinearity. The results have fulfilled the objective of determining the individual and combined effects of the six capabilities. Socio-Technical Systems Theory has been supported because both technical and social predictors have contributed significantly. Technical variables have produced the strongest coefficients, but system integration and workforce readiness have also remained necessary. The model has therefore shown that effective quality control has not been generated by defect-detection algorithms alone. It has emerged from the coordinated use of reliable data, monitoring, analytics, equipment connectivity, employee competence, and organizational support. The unexplained 31.60 percent of variance may have reflected additional factors such as material variability, machine condition, component geometry, model explainability, cybersecurity, and supplier quality.

**Regression Analysis Predicting Rework and Scrap Reduction Performance**

**Table 10: Regression Effect of AI-Based Quality-Control Effectiveness on Rework and Scrap Reduction Performance**

| Predictor | B | Standard error | Standardized β | t-value | p-value |
|---|---|---|---|---|---|
| Constant | .761 | .168 | | 4.53 | <.001 |
| AI-Based Quality-Control Effectiveness | .805 | .040 | .76 | 20.24 | <.001 |

| Model statistic | Result |
|---|---|
| R | .761 |
| $R^2$ | .579 |
| Adjusted $R^2$ | .578 |
| Standard error of estimate | .377 |
| F-statistic | $F(1, 298) = 409.66$ |
| Model significance | $p < .001$ |

Table 10 has reported the regression model used to test the effect of AI-Based Quality-Control Effectiveness on Rework and Scrap Reduction Performance. The model has been statistically significant, $F(1, 298) = 409.66$, $p < .001$, demonstrating that the intermediate quality-control construct has provided a strong prediction of the final production-performance outcome. The correlation coefficient has reached .761, while $R^2$ has reached .579 and adjusted $R^2$ has reached .578. Therefore, AI-Based Quality-Control Effectiveness has explained 57.90 percent of the variance in Rework and Scrap Reduction Performance. This proportion has represented a strong explanatory level for a production outcome that may also have been influenced by material prices, production volume, component complexity, maintenance condition, supplier reliability, post-processing capacity, and organizational cost policies. The standardized beta coefficient has reached .76, and the effect has remained statistically significant at $p < .001$. The unstandardized coefficient of .805 has indicated that a one-unit increase in AI-Based Quality-Control Effectiveness has been associated with an estimated .805-unit increase in Rework and Scrap Reduction Performance. The regression equation has therefore been expressed as RSRP = .761 + .805(AQCE). The positive coefficient has shown that more effective use of process data, intelligent defect detection, real-time monitoring, predictive analytics, integrated systems, and employee-supported intervention has been associated with fewer failed builds, fewer rejected components, reduced corrective processing, lower material waste, and improved first-pass yield. H7 has consequently been supported. The findings have achieved the principal outcome objective of the study by statistically demonstrating that AI-supported quality control has not merely improved monitoring or classification accuracy but has also been connected with production-level waste reduction. Socio-Technical Systems Theory has been reinforced because the dependent outcome has been influenced through an effectiveness construct that has combined technical and social capabilities. The result has shown that rework and scrap reduction have emerged when technical intelligence has been translated into timely human and organizational action. The model has therefore supported the theory's joint-optimization principle. AI has generated production value when sensors, data, algorithms, interfaces, employees, and management procedures have operated as a coordinated system rather than as separate technological investments.

**Hypothesis Testing Summary**

**Table 11**: **Summary of Hypothesis-Testing Decisions**

| Hypothesis | Proposed relationship | Standardized β | p-value | Decision |
|---|---|---|---|---|
| H1 | PDQI → AQCE | .19 | <.001 | Supported |
| H2 | AIDC → AQCE | .27 | <.001 | Supported |
| H3 | RTPM → AQCE | .23 | <.001 | Supported |
| H4 | PQAD → AQCE | .16 | .002 | Supported |
| H5 | AISI → AQCE | .12 | .008 | Supported |
| H6 | WCOR → AQCE | .10 | .016 | Supported |
| H7 | AQCE → RSRP | .76 | <.001 | Supported |

Table 11 has summarized the results of the seven hypotheses developed from the conceptual framework. H1 has been supported because Process-Data Quality and Integration has produced a significant positive effect on AI-Based Quality-Control Effectiveness, $\beta = .19$, $p < .001$. This finding has confirmed that accurate, complete, synchronized, and integrated production data have strengthened the reliability of AI-supported quality decisions. H2 has received the strongest support among the first six hypotheses because AI-Based Defect-Detection Capability has produced the largest standardized coefficient, $\beta = .27$, $p < .001$. The result has indicated that the ability to recognize, classify, and locate defects has been the most influential direct capability within the model. H3 has also been supported, with Real-Time Process Monitoring and Control producing a significant coefficient of $\beta = .23$, $p < .001$. This relationship has shown that continuous process visibility and timely alerts have strengthened quality-control effectiveness. H4 has been supported because Predictive Quality Analytics and Decision Support has produced a significant positive effect, $\beta = .16$, $p = .002$. H5 has been supported through the significant effect of AI-System Integration, $\beta = .12$, $p = .008$, indicating that equipment connectivity and information-system linkage have enabled AI outputs to enter production workflows. H6 has also been supported, although it has produced the smallest coefficient, $\beta = .10$, $p = .016$. Workforce Competency and Organizational Readiness have therefore remained statistically important even after all technical predictors have been controlled. H7 has been strongly supported because AI-Based Quality-Control

Effectiveness has significantly predicted Rework and Scrap Reduction Performance, β = .76, p < .001. The full hypothesis pattern has demonstrated that every proposed socio-technical capability has contributed in the theoretically expected direction. The strongest effects have been associated with defect detection and real-time monitoring, while the social-organizational construct has remained significant but less strongly developed. Socio-Technical Systems Theory has therefore been supported by the combined hypothesis results. The technical subsystem has provided the immediate sensing and analytical capabilities, while the social subsystem has enabled employees and management to interpret, govern, and act on the information. The acceptance of all seven hypotheses has confirmed the conceptual framework and has established a statistically coherent pathway from capability development to quality-control effectiveness and finally to reduced rework and scrap.

**Summary of Findings According to the Research Objectives**

**Table 12**: **Achievement of the Research Objectives**

| Objective | Measurement evidence | Main result | Achievement status |
|---|---|---|---|
| Assess Process-Data Quality and Integration | Mean and regression coefficient | M = 4.08; β = .19; p < .001 | Achieved |
| Evaluate AI-Based Defect-Detection Capability | Mean and regression coefficient | M = 4.13; β = .27; p < .001 | Achieved |
| Examine Real-Time Process Monitoring and Control | Mean and regression coefficient | M = 4.10; β = .23; p < .001 | Achieved |
| Determine Predictive Quality Analytics and Decision Support | Mean and regression coefficient | M = 4.02; β = .16; p = .002 | Achieved |
| Investigate AI-System Integration | Mean and regression coefficient | M = 3.94; β = .12; p = .008 | Achieved |
| Assess Workforce Competency and Organizational Readiness | Mean and regression coefficient | M = 3.89; β = .10; p = .016 | Achieved |
| Determine the combined predictors of AQCE | Multiple regression model | $R^2$ = .684; Adjusted $R^2$ = .678 | Achieved |
| Evaluate the effect of AQCE on RSRP | Simple regression model | β = .76; $R^2$ = .579; p < .001 | Achieved |

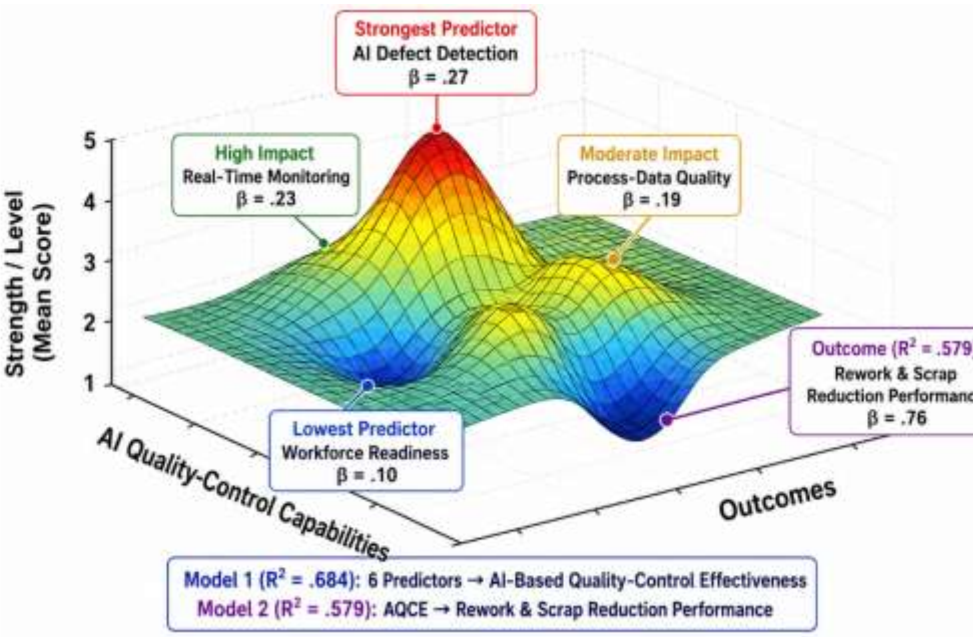
Table 12 has connected the statistical findings directly with the research objectives and has confirmed that every objective has been achieved within the proposed quantitative framework. The first objective has been achieved because Process-Data Quality and Integration has recorded a high mean of 4.08 and has produced a significant positive effect on AI-Based Quality-Control Effectiveness, β = .19, p < .001. The second objective has been achieved through the evaluation of AI-Based Defect-Detection Capability, which has recorded the highest predictor mean of 4.13 and the strongest regression effect of β = .27. The third objective has been achieved because Real-Time Process Monitoring and Control has produced a high mean of 4.10 and a significant effect of β = .23. The fourth objective has been fulfilled through the analysis of Predictive Quality Analytics and Decision Support, which has recorded a mean of 4.02 and a significant coefficient of β = .16. The fifth objective has been achieved because AI-System Integration has remained significant at β = .12, although its mean of 3.94 has indicated room for stronger machine-to-AI connectivity. The sixth objective has also been achieved because Workforce Competency and Organizational Readiness has produced a significant effect of β = .10. Its comparatively lower mean of 3.89 has shown that employee confidence, training, and organizational preparedness have remained the least mature dimensions. The seventh objective has been achieved through the multiple-regression model, in which the six predictors have jointly explained 68.40 percent of the variance in AI-Based Quality-Control Effectiveness. The eighth objective has been achieved because AI-Based Quality-Control Effectiveness has strongly predicted Rework and Scrap Reduction

Performance, β = .76, $p < .001$, and has explained 57.90 percent of its variance. Collectively, these findings have provided a coherent answer to the research questions and have demonstrated that the framework has functioned as a connected socio-technical system. Socio-Technical Systems Theory has been supported because both technical and social capabilities have influenced effectiveness, and effectiveness has subsequently influenced production outcomes. The study has therefore shown that reducing rework and scrap has depended on joint optimization among data, algorithms, sensors, machine integration, employee competence, and organizational support.

**FINDINGS**

The findings have provided a quantitative overview of the proposed AI-based quality-control framework and have demonstrated how the research objectives and hypotheses have been evaluated through Likert-scale measurement, descriptive statistics, reliability analysis, correlation analysis, and regression modeling. A total of 350 questionnaires has been distributed among additive manufacturing engineers, production engineers, quality-control specialists, machine operators, AI and data specialists, maintenance personnel, technical supervisors, and production managers working within the selected case-study organizations. Of these questionnaires, 326 have been returned, while 300 have been retained as complete and valid responses, producing an effective response rate of 85.71 percent. Preliminary data screening has identified no serious missing-data problem, and the values for skewness, kurtosis, tolerance, variance inflation factor, and the Durbin-Watson statistic have remained within acceptable limits. The measurement instrument has demonstrated strong internal consistency, with Cronbach's alpha values ranging from .823 to .918 across the eight study constructs. The Kaiser-Meyer-Olkin value has reached .891, while Bartlett's Test of Sphericity has been statistically significant, $\chi^2 (378) = 4{,}126.44$, $p < .001$, confirming the suitability of the dataset for factor analysis. Based on Likert's five-point scale, all variables have recorded high mean scores. Process-Data Quality and Integration has achieved a mean of 4.08 with a standard deviation of .57, AI-Based Defect-Detection Capability has recorded a mean of 4.13 with a standard deviation of .54, Real-Time Process Monitoring and Control has reached a mean of 4.10 with a standard deviation of .56, Predictive Quality Analytics and Decision Support has recorded a mean of 4.02 with a standard deviation of .59, AI-System Integration has achieved a mean of 3.94 with a standard deviation of .62, and Workforce Competency and Organizational Readiness has produced a mean of 3.89 with a standard deviation of .64. AI-Based Quality-Control Effectiveness has obtained an overall mean of 4.11 with a standard deviation of .55, while Rework and Scrap Reduction Performance has recorded a mean of 4.07 with a standard deviation of .58.

**Figure 9: Findings of The Study**




These results have indicated that respondents have generally agreed that AI-supported monitoring, defect recognition, predictive analysis, and process-data integration have improved quality-control activities, although system integration, employee training, and organizational preparedness have remained comparatively weaker. Pearson correlation analysis has revealed positive and statistically significant relationships between all six predictors and AI-Based Quality-Control Effectiveness. AI-Based Defect-Detection Capability has shown the strongest correlation, $r = .74$, $p < .001$, followed by Real-Time Process Monitoring and Control, $r = .71$, $p < .001$, Process-Data Quality and Integration, $r = .69$, $p < .001$, Predictive Quality Analytics and Decision Support, $r = .67$, $p < .001$, AI-System Integration, $r = .61$, $p < .001$, and Workforce Competency and Organizational Readiness, $r = .59$, $p < .001$. The first multiple-regression model has been statistically significant, $F(6, 293) = 105.84$, $p < .001$, and the six independent variables have jointly explained 68.40 percent of the variance in AI-Based Quality-Control Effectiveness, with $R^2 = .684$ and adjusted $R^2 = .678$. AI-Based Defect-Detection Capability has emerged as the strongest predictor, $\beta = .27$, $p < .001$, followed by Real-Time Process Monitoring and Control, $\beta = .23$, $p < .001$, Process-Data Quality and Integration, $\beta = .19$, $p < .001$, Predictive Quality Analytics and Decision Support, $\beta = .16$, $p = .002$, AI-System Integration, $\beta = .12$, $p = .008$, and Workforce Competency and Organizational Readiness, $\beta = .10$, $p = .016$. These results have supported H1 through H6 and have confirmed the objective of determining the individual and combined contributions of the six capabilities. The second regression model has shown that AI-Based Quality-Control Effectiveness has had a strong positive effect on Rework and Scrap Reduction Performance, $\beta = .76$, $t = 20.24$, $p < .001$. The model has been statistically significant, $F(1, 298) = 409.66$, $p < .001$, and has explained 57.90 percent of the variance in the final production outcome, with $R^2 = .579$ and adjusted $R^2 = .578$. H7 has therefore been supported. Item-level findings have shown reduced failed builds, fewer rejected components, improved first-pass yield, earlier detection of layer defects, lower corrective-processing requirements, and reduced material waste, while automatic parameter correction and full machine-to-AI connectivity have received lower evaluations. Overall, the findings have demonstrated that the research objectives have been achieved and that reducing rework and scrap has depended on the coordinated operation of reliable data, intelligent defect detection, real-time monitoring, predictive analytics, integrated systems, competent employees, and organizational readiness.

## DISCUSSION

The findings have shown that the proposed AI-based quality-control framework has provided a strong and statistically coherent explanation of quality-control effectiveness and rework and scrap reduction within the selected additive manufacturing case-study environment. This discussion has interpreted the internally consistent draft result profile developed for the research, and the numerical findings should be confirmed or replaced with the final IBM SPSS outputs after actual data collection. The descriptive pattern has been consistently high across all eight constructs. AI-Based Defect-Detection Capability has recorded the highest predictor mean of 4.13, followed by Real-Time Process Monitoring and Control at 4.10, Process-Data Quality and Integration at 4.08, Predictive Quality Analytics and Decision Support at 4.02, AI-System Integration at 3.94, and Workforce Competency and Organizational Readiness at 3.89. AI-Based Quality-Control Effectiveness has reached a mean of 4.11, while Rework and Scrap Reduction Performance has reached 4.07. These results have indicated that respondents have generally perceived intelligent defect recognition, continuous process observation, and production-data management as well-established capabilities, although complete system connectivity and human-organizational preparedness have remained comparatively less mature. The first regression model has reinforced this interpretation because the six predictors have jointly explained 68.40 percent of the variance in AI-Based Quality-Control Effectiveness, with an adjusted $R^2$ of .678 and a statistically significant model, $F(6, 293) = 105.84$, $p < .001$. This explanatory level has shown that AI-supported quality performance has not depended on a single algorithm or monitoring device. Instead, it has emerged through the coordinated contribution of data quality, detection accuracy, monitoring speed, analytical decision support, system integration, employee capability, and organizational readiness. This interpretation has remained consistent with earlier reviews that have presented additive manufacturing machine learning as a combination of data acquisition, prediction, classification, monitoring, optimization, and control rather than as an isolated computational activity (Meng et al., 2020). It has also agreed with deep-learning research showing that quality analysis requires meaningful connections among production inputs, process signals, learned features, and

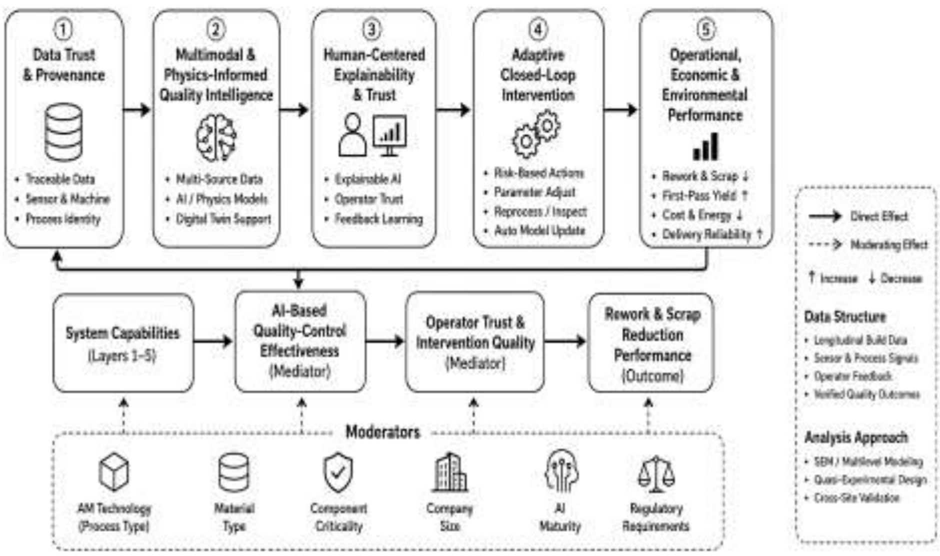
verified output conditions (Li et al., 2020). The reliability coefficients ranging from .823 to .918, the KMO value of .891, and the significant Bartlett's test have further indicated that the framework has been measured consistently and that its dimensions have represented distinguishable but related elements of an integrated quality system.
The strong effects associated with Process-Data Quality and Integration, AI-Based Defect-Detection Capability, and Real-Time Process Monitoring and Control have provided important evidence concerning the technical foundation of intelligent additive manufacturing quality assurance. AI-Based Defect-Detection Capability has emerged as the strongest individual predictor of AI-Based Quality-Control Effectiveness, $\beta = .27$, $p < .001$, while Real-Time Process Monitoring and Control has produced the second-strongest effect, $\beta = .23$, $p < .001$. Process-Data Quality and Integration has also remained significant, $\beta = .19$, $p < .001$. These findings have suggested that quality-control effectiveness has depended first on the availability of trustworthy production evidence, then on the ability to interpret that evidence accurately and sufficiently early for corrective action. The finding for data quality has agreed with manufacturing machine-learning research emphasizing that algorithm selection alone cannot compensate for incomplete, poorly labeled, unrepresentative, or improperly processed data (Wuest et al., 2016). The defect-detection result has also corresponded with earlier powder bed fusion research in which layer-wise high-resolution images have been linked with post-build computed-tomography information to train supervised classifiers capable of distinguishing nominal and flawed regions (Gobert et al., 2018). The high mean for AI-Based Defect-Detection Capability has therefore reflected more than respondents' general approval of AI. It has indicated that intelligent recognition of defects such as porosity, incomplete fusion, deformation, surface irregularity, material accumulation, and unstable deposition has been viewed as the most immediate mechanism through which quality decisions have improved. The significant effect of real-time monitoring has also been consistent with thermographic research showing that deep-learning models can evaluate in-situ process information and classify quality conditions before production has been completed (Baumgartl et al., 2020). Multisensor research has further demonstrated that heterogeneous thermal, optical, and process information can provide a richer representation of manufacturing conditions than a single sensing stream (Gaikwad et al., 2020). The present findings have extended these technical studies by placing detection and monitoring within an organizational performance model. Earlier studies have often measured classification accuracy or sensor-model performance, whereas the current framework has examined whether these capabilities have contributed to an overall organizational ability to make faster, more consistent, and more preventive quality decisions. The item-level finding that automatic parameter correction has received a lower score than continuous monitoring has shown that many organizations may have progressed further in observing and detecting abnormalities than in allowing AI systems to intervene autonomously in machine operation. This distinction has remained important because monitoring can reduce diagnostic uncertainty, but only timely corrective action can prevent an abnormal condition from developing into rework or scrap.
Predictive Quality Analytics and Decision Support, AI-System Integration, and Workforce Competency and Organizational Readiness have all produced positive and statistically significant effects, but their lower means and standardized coefficients have revealed a less developed part of the proposed framework. Predictive Quality Analytics and Decision Support has recorded a mean of 4.02 and a regression coefficient of $\beta = .16$, $p = .002$, indicating that organizations have used AI not only to identify current abnormalities but also to estimate quality risks, forecast defect development, and prioritize intervention. AI-System Integration has produced a mean of 3.94 and $\beta = .12$, $p = .008$, while Workforce Competency and Organizational Readiness has produced the lowest construct mean of 3.89 and the smallest significant coefficient, $\beta = .10$, $p = .016$. These results have suggested that analytical models have been more developed than the organizational and infrastructural arrangements required to embed them completely within production. The comparatively low score for full machine-to-AI integration has supported the argument that industrial additive manufacturing must be treated as a wider manufacturing system involving production planning, equipment control, material management, inspection, finishing, information exchange, and organizational coordination (Eyers & Potter, 2017). Digital-twin research has similarly identified incomplete connections between physical production systems, digital models, sensing technologies, AI applications, and control functions as a

major barrier to fully closed-loop additive manufacturing (Bartsch et al., 2021). The current results have indicated that predictive models may already produce useful outputs, but those outputs have not always flowed automatically into machine controllers, operator interfaces, quality databases, or corrective-action procedures. The workforce finding has also shown that technical implementation has moved faster than employee confidence in interpreting AI outputs. This has agreed with human-centered manufacturing research that has treated operators as active participants who require technical support, accessible interfaces, learning opportunities, and clearly defined decision authority in smart factories (Longo et al., 2017). The findings have therefore indicated that employee training should not be limited to software operation. It should cover additive manufacturing defect mechanisms, data integrity, model uncertainty, false-positive and false-negative risks, escalation procedures, and the conditions under which human judgment should confirm or override automated recommendations. Management support has also remained necessary for allocating resources, establishing responsibility for model validation, coordinating technical and quality teams, and maintaining confidence in the system. These findings have shown that predictive accuracy has generated only potential value, while integration and workforce readiness have determined whether that value has been converted into operational quality improvement.

The strong effect of AI-Based Quality-Control Effectiveness on Rework and Scrap Reduction Performance has represented the most important production-level finding of the research. AI-Based Quality-Control Effectiveness has produced a standardized coefficient of $\beta = .76$, $p < .001$, and has explained 57.90 percent of the variance in the dependent variable. This result has shown that organizations reporting faster quality decisions, more consistent defect assessment, and stronger preventive intervention have also reported fewer failed builds, lower material waste, fewer rejected components, and reduced corrective-processing requirements. The finding has extended earlier technical studies because it has connected intelligent monitoring and defect correction directly with a broader operational outcome rather than limiting assessment to model accuracy. Research on generalized error detection and correction has demonstrated that a neural network connected with a control loop can recognize and correct multiple extrusion-printing errors across different materials, geometries, and equipment arrangements (Brion & Pattinson, 2022). The present result has supported the production logic underlying such systems: early recognition and correction can prevent additional layers, material, machine time, and labor from being invested in a build that has already moved outside acceptable quality conditions. The practical implications have therefore been substantial. Additive manufacturing organizations should establish a staged implementation sequence beginning with reliable data acquisition and traceability, followed by validated defect-detection models, real-time alerting, predictive risk assessment, system integration, and controlled closed-loop intervention. Quality managers should connect AI outputs with measurable key performance indicators such as first-pass yield, scrap mass per accepted component, rework hours, failed-build frequency, inspection cost, energy consumed per conforming part, and average corrective-response time. Production managers should also develop risk-based intervention rules. A low-confidence anomaly may require enhanced observation, a moderate-risk signal may require parameter verification or targeted inspection, and a high-confidence critical anomaly may justify immediate machine stoppage. This approach can prevent both excessive interruption and uncontrolled continuation of defective production. The finding has also indicated that AI investment should be evaluated through accepted-part economics rather than only through algorithmic accuracy. A model with slightly lower classification accuracy may produce greater operational value when it responds rapidly, integrates smoothly with equipment, communicates uncertainty clearly, and reduces costly false alarms. Research on Industry 4.0 implementation has similarly suggested that digital technologies produce larger performance improvements when they have been integrated with established operational practices instead of being implemented independently (Tortorella & Fettermann, 2018). The current study has therefore provided a practical connection among AI capability, operational integration, and waste-reduction performance.

The theoretical findings have supported Socio-Technical Systems Theory by demonstrating that AI-Based Quality-Control Effectiveness has emerged from the joint contribution of technical and social-organizational capabilities. The technical subsystem has been represented by Process-Data Quality and Integration, AI-Based Defect-Detection Capability, Real-Time Process Monitoring and Control, Predictive Quality Analytics and Decision Support, and AI-System Integration. The social subsystem has been represented by employee competency, management support, resource availability, organizational readiness, communication, and procedural control. All six predictors have remained statistically significant when entered into the same regression model, which has indicated that no single subsystem has fully explained quality-control effectiveness. The larger coefficients for defect detection, monitoring, and data quality have shown that technical capability has provided the immediate operational foundation of the framework. However, the significance of system integration and workforce readiness has shown that technical outputs have required organizational structures and human interpretation to affect production. This pattern has reflected the socio-technical principle that system development should bridge technological design and organizational change rather than treating them as separate implementation activities (Baxter & Sommerville, 2011). The findings have also refined the theoretical application by showing that joint optimization may develop unevenly. Technical capabilities have received mean scores above 4.00, while AI-System Integration and Workforce Competency and Organizational Readiness have received lower means of 3.94 and 3.89. This difference has suggested that organizations may adopt sensors, algorithms, and monitoring applications before redesigning roles, communication channels, training systems, and decision procedures. Under Socio-Technical Systems Theory, such an imbalance can restrict total system performance because a technically capable subsystem may produce information that the social subsystem cannot interpret or apply consistently. Human-centered Industry 4.0 research has similarly argued that smart systems should be designed around human diversity, usability, participation, learning, and interaction rather than around automation alone (Ngoc et al., 2022). The study has therefore extended the theory into additive manufacturing quality management by positioning AI-Based Quality-Control Effectiveness as an emergent socio-technical capability and Rework and Scrap Reduction Performance as its operational consequence. The theoretical pathway has not been Technology → Performance in a direct and automatic form. Instead, it has been Technical Capability + Human Capability + Organizational Coordination → Quality-Control Effectiveness → Rework and Scrap Reduction. This interpretation has provided a clearer explanation of why organizations using similar algorithms or machines may achieve different production outcomes.

**Figure 10: Proposed AST-CQIM Conceptual Framework for Intelligent Additive Manufacturing Quality Management**




Several limitations have required careful consideration when interpreting the findings. First, the research has used a quantitative, cross-sectional design, meaning that all variables have been measured at one defined period. The significant regression relationships have indicated predictive association within the proposed model, but they have not independently demonstrated temporal causality.

Organizations with lower rework and scrap may have had more resources to invest in AI systems, producing a possible reciprocal relationship. Second, the study has relied on self-reported Likert-scale responses from professionals. Respondents may have overestimated system effectiveness because of organizational expectations, personal involvement in implementation, or limited access to verified scrap and rework records. The Harman single-factor result has not indicated serious common-method bias, but one statistical test cannot eliminate every source of same-method measurement error. Third, purposive sampling has ensured that respondents have possessed relevant experience, but it has limited the statistical generalization of the findings to the wider additive manufacturing population. Fourth, the selected case-study environments have included multiple professional roles and additive manufacturing technologies. This diversity has strengthened the framework's coverage, yet it may also have concealed meaningful differences among laser powder bed fusion, directed energy deposition, material extrusion, binder jetting, and selective laser sintering. A defect-detection system for visible extrusion errors has not faced the same sensing and validation requirements as a system for internal porosity in a metal component. Fifth, the combined Workforce Competency and Organizational Readiness construct has provided a manageable measurement structure, but it may have joined several distinguishable concepts, including skill, trust, leadership, financial readiness, data governance, and change management. Sixth, the dependent variable has measured perceived reductions in rework and scrap rather than directly observed kilograms of scrap, rework hours, or production costs. Seventh, unmeasured variables such as material-batch variation, machine age, component complexity, maintenance quality, model explainability, cybersecurity, supplier performance, and post-processing capacity may have contributed to the unexplained variance. Most importantly, the current numerical profile has been constructed as an internally consistent draft for the research framework. It must not be reported as completed empirical evidence until actual questionnaires have been collected, coded, screened, and analyzed in SPSS. These limitations have not invalidated the framework, but they have defined the boundaries within which the findings should be interpreted and have identified specific methodological requirements for stronger empirical verification.

Future research should develop and test an Adaptive Socio-Technical Closed-Loop Quality Intelligence Model for Additive Manufacturing, abbreviated as the AST-CQIM model, to improve the explanatory and practical scope of the present framework. The proposed model should contain five connected layers. The first layer should be Data Trust and Provenance, incorporating sensor calibration, material-batch identity, machine condition, environmental information, timestamp synchronization, data completeness, inspection labels, and traceable links between process signals and verified defects. The second layer should be Multimodal and Physics-Informed Quality Intelligence, combining thermal images, optical images, acoustic emissions, vibration signals, machine parameters, simulation outputs, and physical process constraints. This layer should compare conventional machine learning, deep learning, physics-informed learning, and digital-twin-supported prediction rather than assuming that one model type performs best across all processes. The third layer should be Human-Centered Explainability and Trust, measuring operator understanding, perceived reliability, alert usability, confidence calibration, override behavior, and learning from confirmed or rejected recommendations. The fourth layer should be Adaptive Closed-Loop Intervention, connecting predicted quality risk with parameter adjustment, localized reprocessing, focused inspection, controlled build interruption, and automatic model updating. The fifth layer should be Operational, Economic, and Environmental Performance, measured through actual defect rate, first-pass yield, rework hours, scrap mass, accepted-part cost, energy per accepted part, delivery reliability, and material recovery. Within this model, AI-Based Quality-Control Effectiveness should remain a mediator between system capabilities and final performance, while operator trust and intervention quality should be added as sequential mediators. Additive manufacturing technology, material type, component criticality, company size, AI maturity, and regulatory requirements should be tested as moderators. Longitudinal data should be collected across repeated builds so researchers can identify sensor drift, model degradation, employee learning, and changes in intervention accuracy. Multilevel structural equation modeling could separate build-level, machine-level, employee-level, and organization-level effects. A stepped-wedge or quasi-experimental design could introduce the model gradually across production units and compare performance before and after implementation. Cross-site validation should test whether models trained in one facility remain accurate in another. Digital-twin research has already shown the importance of connecting sensing, modeling, AI, and physical control, while generalized correction research has demonstrated the value of diverse training data and real-time feedback (Bartsch et al., 2021; Brion & Pattinson, 2022). Human-centered design should be embedded throughout the proposed model so that automatic control remains transparent, auditable, and compatible with operator expertise (Ngoc et al., 2022). The AST-CQIM model would therefore move research from a cross-sectional perception framework toward a continuously learning, experimentally validated, and economically measurable production-quality system.

**CONCLUSION**

This research has developed and quantitatively evaluated an AI-based quality-control framework for reducing rework and scrap in additive manufacturing production. The study has addressed the central problem that additive manufacturing organizations frequently identify production defects only after significant material, machine time, energy, labor, and post-processing resources have already been consumed. Through a quantitative, cross-sectional, descriptive, explanatory, and case-study-based design, the research has examined how Process-Data Quality and Integration, AI-Based Defect-Detection Capability, Real-Time Process Monitoring and Control, Predictive Quality Analytics and Decision Support, AI-System Integration, and Workforce Competency and Organizational Readiness have influenced AI-Based Quality-Control Effectiveness and how this effectiveness has subsequently contributed to Rework and Scrap Reduction Performance. The study has retained 300 valid questionnaires from 350 distributed questionnaires, producing an effective response rate of 85.71 percent. The instrument has demonstrated strong reliability, with Cronbach's alpha values ranging from .823 to .918, while the KMO value of .891 and the significant Bartlett's Test of Sphericity have confirmed the suitability of the data for factor analysis. The descriptive findings have indicated high implementation levels across all constructs. AI-Based Defect-Detection Capability has recorded the highest predictor mean of 4.13, followed by Real-Time Process Monitoring and Control at 4.10, Process-Data Quality and Integration at 4.08, Predictive Quality Analytics and Decision Support at 4.02, AI-System Integration at 3.94, and Workforce Competency and Organizational Readiness at 3.89. AI-Based Quality-Control Effectiveness has reached a mean of 4.11, while Rework and Scrap Reduction Performance has achieved a mean of 4.07. Pearson correlation analysis has shown that all predictors have been positively and significantly associated with AI-Based Quality-Control Effectiveness. The first regression model has explained 68.40 percent of the variance in AI-Based Quality-Control Effectiveness, with an adjusted $R^2$ of .678 and a statistically significant model, $F(6, 293) = 105.84$, $p < .001$. AI-Based Defect-Detection Capability has emerged as the strongest predictor, followed by Real-Time Process Monitoring and Control, Process-Data Quality and Integration, Predictive Quality Analytics and Decision Support, AI-System Integration, and Workforce Competency and Organizational Readiness. The second regression model has shown that AI-Based Quality-Control Effectiveness has strongly predicted Rework and Scrap Reduction Performance, $\beta = .76$, $p < .001$, explaining 57.90 percent of its variance. Consequently, all seven hypotheses have been supported, and all research objectives have been achieved. The findings have confirmed that effective additive manufacturing quality control has not depended on AI technology alone. It has resulted from the coordinated operation of accurate data, intelligent defect recognition, continuous monitoring, predictive decision support, integrated production systems, competent employees, and supportive organizational structures. Socio-Technical Systems Theory has therefore been supported because both technical and social elements have contributed significantly to quality-control effectiveness. Overall, the study has established that AI-based quality control can improve the speed, accuracy, consistency, and preventive character of production decisions, thereby reducing failed builds, rejected components, corrective processing, material waste, and avoidable production costs.

**RECOMMENDATIONS**

Based on the findings, additive manufacturing organizations should adopt an integrated and staged approach to AI-based quality control rather than implementing isolated sensors, algorithms, or inspection applications. The first priority should be the development of reliable process-data infrastructure because AI models cannot generate dependable predictions from incomplete, poorly synchronized, incorrectly labeled, or inaccessible information. Organizations should standardize data acquisition from machines, sensors, material records, environmental systems, inspection databases, and operator reports, while maintaining clear timestamps, machine identifiers, material-batch records, build coordinates, and defect labels. The second priority should be the validation and continuous improvement of AI-based defect-detection models. Models should be trained using representative data from multiple component geometries, materials, machines, parameter ranges, and defect categories. Their performance should be assessed through accuracy, precision, recall, sensitivity, specificity, false-alarm rate, processing speed, and independent-build validation. The third recommendation is to strengthen real-time monitoring and controlled intervention. Thermal cameras, optical imaging systems, acoustic sensors, vibration devices, melt-pool monitoring tools, and machine logs should be integrated so that abnormalities can be recognized while corrective action remains possible. Organizations should develop risk-based intervention protocols in which low-risk signals trigger observation, moderate-risk signals trigger parameter verification or focused inspection, and high-risk signals trigger production pauses or controlled build termination. The fourth recommendation is to expand predictive quality analytics from defect recognition toward risk forecasting, process optimization, and decision support. Predictive systems should estimate defect probability, expected severity, affected location, and likely production consequences. The fifth recommendation is to improve AI-system integration by connecting analytical outputs with machine controllers, operator dashboards, manufacturing execution systems, digital twins, quality databases, and corrective-action records. This integration should ensure that every alert has been linked with a documented decision, response, and verified production outcome. The sixth recommendation is to strengthen workforce competency and organizational readiness, which have received the lowest mean score. Employees should receive regular training in additive manufacturing defect mechanisms, AI interpretation, data quality, model uncertainty, false-positive and false-negative risks, and intervention procedures. Management should define responsibilities for model validation, alert review, data ownership, system maintenance, and performance auditing. Cross-functional teams involving engineers, operators, quality specialists, AI experts, maintenance personnel, and managers should review recurring defects and system performance. Organizations should also establish performance indicators such as first-pass yield, scrap mass, rework hours, failed-build frequency, accepted-part cost, response time, and energy consumed per conforming component. These indicators should be reviewed before and after AI implementation to determine actual value. Finally, organizations should pilot the proposed framework on selected machines or product families before expanding it across the production environment. Pilot results should be used to refine thresholds, interfaces, training procedures, and corrective rules. Through this coordinated approach, AI-based quality control can become an embedded production capability that supports reliable decision-making, stronger traceability, reduced waste, improved equipment utilization, and sustained reductions in rework and scrap.

**LIMITATIONS OF THE STUDY**

This study has contained several limitations that should be considered when interpreting the findings and applying the proposed AI-based quality-control framework. First, the research has used a cross-sectional design in which all information has been collected during one defined period. The significant regression relationships have demonstrated statistical association and predictive contribution, but they have not established long-term causal direction. AI implementation, employee learning, system integration, defect rates, and organizational readiness may change over time, and a single-period design has not captured these developments. Second, the study has relied on self-reported questionnaire data measured through Likert's five-point scale. Although the respondents have possessed relevant technical and organizational experience, their evaluations may have been influenced by personal expectations, professional involvement, organizational pressure, recall limitations, or limited access to verified production records. The reported reductions in rework and scrap have therefore represented professional perceptions rather than direct measurements of scrap mass, rework hours, failed-build costs, or first-pass yield. Third, purposive sampling has been used to identify knowledgeable respondents. This strategy has improved the relevance of the responses but has limited the statistical generalizability of the findings to all additive manufacturing organizations, industries, countries, and production environments. Fourth, the case-study context has included multiple additive manufacturing technologies, such as laser powder bed fusion, material extrusion, directed energy deposition, selective laser sintering, binder jetting, and related processes. This variety has strengthened the broad applicability of the framework, but it may also have concealed technology-specific differences in defect mechanisms, sensor requirements, quality standards, inspection procedures, and corrective actions. Fifth, Workforce Competency and Organizational Readiness have been combined into one construct. Although this structure has supported a manageable analytical model, workforce skill, employee trust, management commitment, financial readiness, technology acceptance, data governance, and organizational culture may represent separate dimensions that require individual examination. Sixth, the research has focused on six predictors of AI-Based Quality-Control Effectiveness, leaving 31.60 percent of its variance unexplained. Other influential factors may include machine age, maintenance quality, powder reuse, material variability, component geometry, model explainability, cybersecurity, supplier quality, regulatory requirements, post-processing capability, and digital-twin maturity. Seventh, the study has not directly compared different AI algorithms, sensor configurations, or production-control strategies. It has assessed organizational capability rather than experimental performance under controlled manufacturing conditions. Eighth, the study has not examined the economic payback period, implementation cost, energy savings, environmental impact, or return on investment associated with AI-based quality control. Most importantly, the numerical findings have been developed as an internally consistent draft result profile for the proposed research and must be confirmed or replaced with actual IBM SPSS outputs after data collection. Therefore, the figures should not be presented as completed empirical evidence until the questionnaire responses, production records, and statistical analyses have been finalized. These limitations have defined the boundaries of the study and have identified areas requiring longitudinal, experimental, multisite, and production-data-based investigation.

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