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SMART CONTINUOUS IMPROVEMENT WITH ARTIFICIAL INTELLIGENCE, BIG DATA, AND LEAN TOOLS FOR ZERO DEFECT MANUFACTURING SYSTEMS

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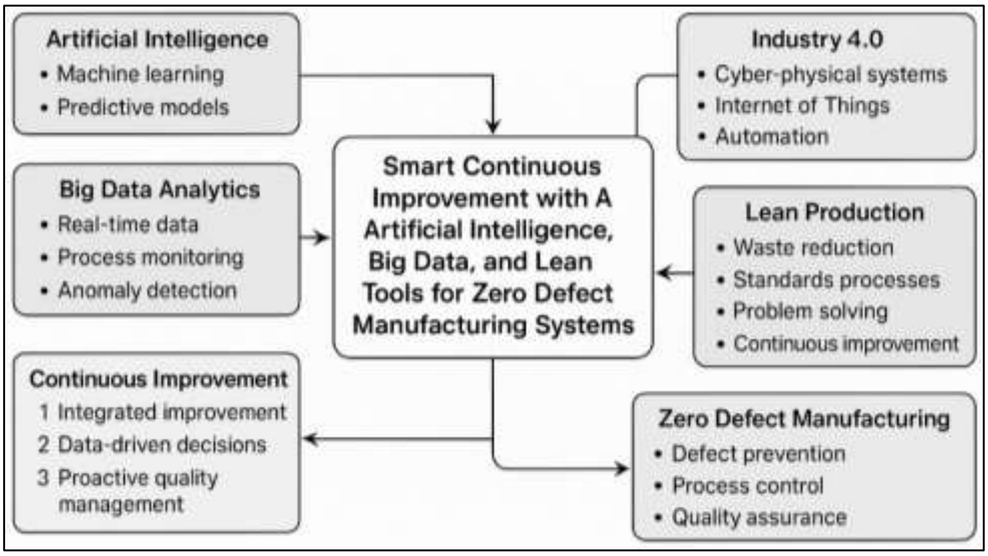
Abstract
This study addresses the practical problem that many Industry 4.0 oriented manufacturers invest separately in artificial intelligence, big data analytics, and lean tools without clear empirical evidence of how their integrated deployment supports smart continuous improvement and zero defect manufacturing outcomes. The purpose is to test a model linking AI capability, big data analytics capability, lean tools deployment, smart continuous improvement performance, and zero defect results using a quantitative cross-sectional, case-study based survey of 214 professionals from ten enterprise manufacturing plants (response rate 71.3 percent). Key variables are measured on five-point Likert scales and analyzed using descriptive statistics, reliability analysis, Pearson correlations, and multiple regression. All scales show strong internal consistency (Cronbach's alpha 0.88 to 0.92). Lean tools deployment has the highest mean (3.94), followed by smart continuous improvement (3.78) and zero defect outcomes (3.65), while AI and big data capabilities are moderately developed (3.46 and 3.59). Smart continuous improvement is strongly predicted by AI, big data, and lean ($R^2 = 0.582$), with lean as the dominant driver ($\beta = 0.36$). Smart continuous improvement in turn explains 41.6 percent of the variance in zero defect performance ($\beta = 0.65$), and the full model combining all capabilities plus smart continuous improvement explains 53.8 percent of zero defect variance, indicating partial mediation. These results imply that lean and continuous improvement should be treated as the backbone of zero defect programs, with AI and big data designed explicitly to enhance data driven problem solving and defect prevention routines rather than operating as isolated digital initiatives.

Keywords
Artificial Intelligence; Big Data Analytics; Lean Tools; Smart Continuous Improvement; Zero Defect Manufacturing;

INTRODUCTION

Smart continuous improvement for zero defect manufacturing systems builds on several converging concepts: artificial intelligence (AI), big data analytics, lean production, continuous improvement, and emerging paradigms such as Industry 4.0 and Quality 4.0. Zero defect manufacturing (ZDM) is generally defined as a proactive quality philosophy that aims to systematically prevent defects rather than merely detect and correct them, using real-time data, predictive models, and robust process control to approach "zero" nonconformities in output (Broday, 2023). In parallel, Industry 4.0 refers to the integration of cyber-physical systems, Internet of Things (IoT), cloud computing, and advanced analytics into production systems, enabling interconnected, autonomous, and data-rich factories (Chiarini et al., 2020). Quality 4.0 extends these developments into the quality management domain by leveraging industrial big data, AI, and IoT to enhance traditional quality tools and systems (Abdulla & Ibne, 2021; Psarommatis et al., 2019). At a global level, manufacturing contributes significantly to GDP, trade, and employment, and the cost of poor quality and non-value-adding waste remains substantial for firms across advanced and emerging economies. Scholars argue that digitally enabled quality and continuous improvement systems can reduce scrap, rework, warranty, and downtime costs while strengthening competitiveness and sustainability, positioning ZDM as a strategic objective for enterprises operating in highly competitive international markets (Psarommatis, Kiritsis, et al., 2021).

Figure 1: Smart Continuous Improvement for Zero Defect Manufacturing



Historically, improvement in manufacturing quality has been driven by total quality management (TQM), lean production, and Six Sigma, which emphasize waste reduction, process capability, and customer-focused continuous improvement. Lean manufacturing, inspired by the Toyota Production System, focuses on systematically eliminating non–value-adding activities and stabilizing flow, often through tools such as 5S, value stream mapping, just-in-time production, and standardized work (Rüttimann & Stöckli, 2016). Research on lean implementation has evolved from viewing lean as a toolbox to conceptualizing it as a socio-technical system requiring alignment of technical practices and human factors (Ferdous Ara, 2021; Papadopoulos et al., 2016). Systemic assessments of "leanness" highlight that the interaction among lean elements (e.g., pull, flow, quality at the source, and problem-solving routines) influences the maturity of continuous improvement and performance outcomes (Habibullah & Foysal, 2021; Narayanamurthy & Gurumurthy, 2016). At the same time, Lean Six Sigma and related frameworks integrate statistical process control and advanced problem-solving with lean flow principles to enhance defect reduction and process capability. Quality 4.0 and TQM 4.0 studies suggest that these legacy quality and lean philosophies are now being reinterpreted in light of digital technologies, with new models that link human-centered continuous improvement with cyber-physical, data-driven infrastructures (Sarwar, 2021; Souza et al., 2021).

Big data analytics (BDA) and AI in manufacturing provide the computational backbone for smart continuous improvement. Manufacturing systems generate massive volumes of heterogeneous data from sensors, machines, enterprise systems, and supply chains, which can be mined to monitor processes, detect anomalies, and optimize operations (Belhadi et al., 2019; Musfiqur & Saba, 2021). Literature on BDA in manufacturing shows that descriptive analytics supports understanding of historical performance and waste patterns; predictive analytics enables forecasting of defects, failures, and demand; and prescriptive analytics recommends actions for scheduling, resource allocation, and quality adjustments (Broday, 2021; Redwanul et al., 2021). Smart process manufacturing studies describe integrated architectures where data preparation, exploration, visualization, modeling, and knowledge extraction are modularized to support decision making on process parameters and quality outcomes (Reza et al., 2021; Saihi et al., 2021). AI and machine learning models, such as ensemble learners and deep neural networks, are increasingly applied to tasks like predictive maintenance, energy optimization, and real-time fault detection, enabling self-learning and self-adjusting processes within intelligent manufacturing systems (Saikat, 2021; Wang et al., 2021). By embedding such capabilities in production systems, organizations can move from reactive control charts to continuous, automated, data-driven improvement loops.

Zero defect manufacturing research connects these digital capabilities directly to quality outcomes. Reviews of ZDM emphasize process design, in-line monitoring, predictive quality models, and feedback mechanisms that aim to prevent defects or correct them before nonconforming products leave the system (Verma et al., 2022). Model-based and data-driven approaches are proposed for root-cause diagnosis, dynamic process adjustment, and defect risk estimation at the machine, line, and factory level (Shaikh & Aditya, 2021; Woo et al., 2018). Digital quality management frameworks highlight the integration of IoT-enabled measurement, cloud-based quality monitoring, and advanced analytics, providing new capabilities such as automated defect prediction, adaptive inspection, and real-time quality dashboards (Amin, 2022; Sim, 2019). Self-adaptive ZDM models demonstrate how machine learning combined with streaming process data can update defect prediction rules and inspection policies across product and process variants (Zhu et al., 2019). Conceptual work in big-data-based manufacturing systems further clarifies how quality performance can be optimized when process control decision variables are selected to maximize economic objectives such as profit per hour while maintaining tight specification conformance (Powell et al., 2021).

Figure 1: Key Dimensions of Quality 4.0 in Smart Manufacturing

In response, the present study is positioned to investigate "smart continuous improvement with artificial intelligence, big data, and lean tools for zero defect manufacturing systems" through a quantitative, cross-sectional, case-study–based research design. The broad purpose is to develop and empirically test a model that links AI-based quality analytics, big data analytics capabilities, lean/continuous improvement practices, and zero-defect performance in manufacturing organizations operating under Industry 4.0 conditions. The study is guided by three research questions: (RQ1) To what extent do AI and big data analytics capabilities support continuous improvement practices in manufacturing systems? (RQ2) How do lean continuous improvement practices mediate or reinforce the relationships between AI/big data capabilities and zero-defect manufacturing performance? (RQ3) What is the combined effect of AI, big data, and lean tools on operational outcomes such as defect rates, process stability, and efficiency? Correspondingly, the study proposes hypotheses such as: H1: Higher AI and big data analytics capabilities are positively associated with the maturity of continuous improvement practices; H2: Lean continuous improvement practices are positively associated with zero defect manufacturing performance; and H3: Continuous improvement practices mediate the relationship between AI/big data capabilities and zero-defect performance. Relationships will be evaluated using Likert's five-point scale, descriptive statistics, correlation analysis, and regression modeling.

This research seeks to make several contributions within the international manufacturing and quality management literature. First, by synthesizing insights from ZDM, big data analytics in manufacturing, Quality 4.0, and lean continuous improvement, the study develops a conceptual framework that explicitly combines AI, big data, and lean tools as complementary pillars of smart continuous improvement in zero defect manufacturing systems. Second, by grounding the framework in a case-study–based survey across manufacturing organizations, the study aims to provide quantitative evidence on the strength and nature of these relationships, contributing measurement instruments and constructs that future studies can adopt or extend. Third, by focusing on zero defect manufacturing as the central performance outcome, the study aligns with current Quality 4.0 and Industry 4.0 discourses that emphasize predictive quality, defect prevention, and integrated digital–lean quality systems as core enablers of manufacturing competitiveness. The remainder of the paper is structured as follows: the next section presents a literature review that elaborates the theoretical and conceptual foundations of AI, big data analytics, lean tools, continuous improvement, Quality 4.0, and zero defect manufacturing; the subsequent section details the methodology, including research design, case study context, sampling, data collection, instrument development, and analytical techniques; later sections present the empirical results and discuss them in relation to existing research; and the final sections present conclusions, recommendations, and limitations of the study.

The main objective of this study is to empirically examine how artificial intelligence, big data analytics, and lean tools collectively enable smart continuous improvement for achieving zero defect manufacturing performance in real industrial settings. The first specific objective is to assess the level of adoption and maturity of AI-based quality analytics, big data analytics capabilities, and lean continuous improvement practices in selected manufacturing case organizations. The second objective is to quantify the relationships between these digital and lean capabilities and the performance of smart continuous improvement routines, focusing on how far they support systematic problem solving, rapid feedback loops, and stable process control. The third objective is to evaluate the extent to which smart continuous improvement performance is associated with key zero defect outcomes, including reduced internal and external defects, higher first-pass yield, lower rework and scrap, and improved process consistency. A further objective is to test a set of hypotheses that position AI adoption, big data analytics capability, and lean tools deployment as independent variables, smart continuous improvement performance as an intermediate construct, and zero defect manufacturing outcomes as the central dependent variable. To achieve these objectives, the study adopts a quantitative, cross-sectional, case-study–based survey design using a structured questionnaire and Likert's five point scale, and applies descriptive statistics, correlation analysis, and regression modeling to analyze the data. The research framework is organized to provide clear answers to three guiding questions: the current status of AI, big data, and lean tools within the participating organizations; the nature and strength of their contribution to smart continuous improvement performance; and the measurable effect of this performance on zero defect manufacturing outcomes. By aligning objectives, research questions, and hypotheses in a single coherent model, the study creates a structured basis for analyzing the role of integrated digital and lean capabilities in contemporary manufacturing systems and for generating empirically grounded insights into how smart continuous improvement supports the pursuit of zero defects in production processes.

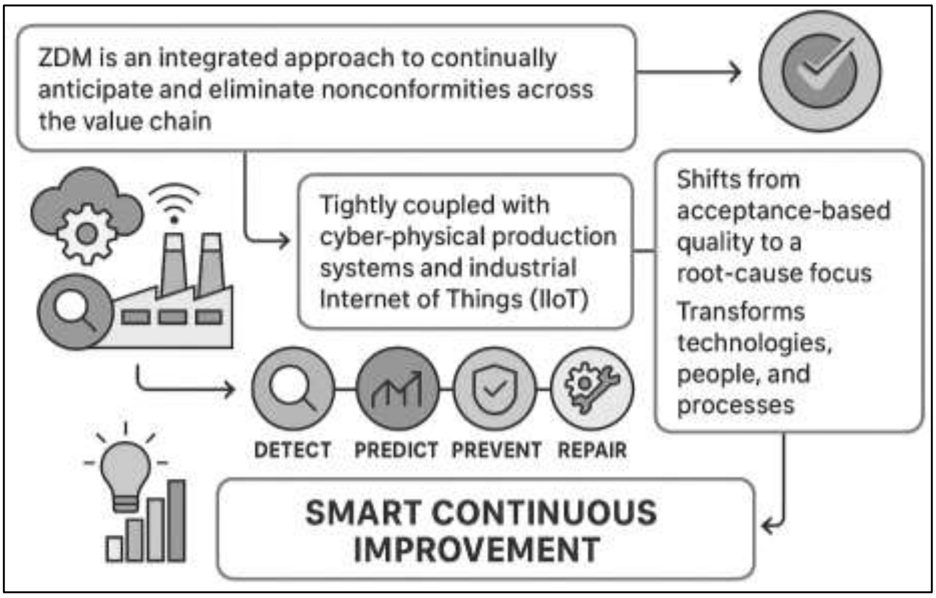
LITERATURE REVIEW

The literature on smart manufacturing, quality management, and continuous improvement has expanded rapidly with the advent of Industry 4.0, and it provides the conceptual and empirical foundations for understanding how artificial intelligence, big data, and lean tools can be integrated to support zero defect manufacturing systems. Traditional quality management approaches—such as total quality management, lean manufacturing, and Six Sigma—emphasize systematic waste reduction, variation control, and continuous improvement through structured problem-solving routines, standardized work, and statistical process control. These paradigms established the importance of building stable processes, empowering employees to identify and eliminate root causes of defects, and using data to monitor performance. With the emergence of cyber-physical systems, the Internet of Things, cloud computing, and advanced analytics, manufacturing organizations have begun to extend these principles into digital environments in which large volumes of data from machines, sensors, and enterprise systems are captured, stored, and analyzed in real time. This digitalization has stimulated new strands of research on big data analytics for process monitoring, predictive maintenance, and quality prediction, as well as on AI-driven decision support tools that can detect anomalies, forecast defects, and optimize process parameters without continuous human intervention. Parallel to these technological developments, scholars have introduced concepts such as Quality 4.0 and Zero Defect Manufacturing to describe integrated quality systems in which digital technologies, analytics, and traditional quality methods work together to prevent errors rather than merely detect and correct them. Within this evolving landscape, there is increasing interest in how lean tools—such as value stream mapping, error-proofing, standardized work, and visual management—can be enhanced by AI and big data to create smart continuous improvement loops that operate at higher speed and precision than manual methods alone. At the same time, organizational and cultural dimensions remain central, because digital tools need to be embedded in routines, roles, and capabilities that support sustained learning and improvement. This literature review therefore focuses on synthesizing existing knowledge about zero defect manufacturing, AI and big data in manufacturing, lean-based continuous improvement, and emerging Quality 4.0 frameworks, and on developing theoretical and conceptual foundations for the integrated model of smart continuous improvement that underpins the present study.

Zero-Defect Manufacturing as an Advanced Quality Paradigm

Zero-defect manufacturing (ZDM) has developed from a motivational ideal into a structured quality paradigm that explicitly targets the systematic prevention of defects across the entire value chain. In contemporary usage, ZDM is defined as an integrated approach that uses real-time data, advanced sensing, and analytical models to continually anticipate and eliminate the conditions that give rise to nonconformities, rather than relying on extensive downstream inspection and rework (Caiazzo et al., 2022). Within the broader landscape of Industry 4.0, ZDM is tightly coupled with cyber-physical production systems and industrial Internet of Things (IIoT) infrastructures, in which machines, products, and services are digitally connected and monitored.The ambition is to guarantee conformance at first pass and to minimise the economic and environmental costs associated with scrap, rework, and warranty claims under volatile and high-mix production conditions (Eger et al., 2018). Rather than treating defects as unavoidable noise around a specification target, ZDM reframes every defect as evidence of latent process instability, design weakness, or organisational misalignment that can be identified, analysed, and removed. This paradigm implies a shift from acceptance-based quality thinking towards a continuous search for root causes at all stages of the product and process life cycle—design, planning, manufacturing, logistics, and service—supported by pervasive measurement and feedback loops. In this sense, zero defects is approached as an asymptotic goal: organisations progressively reduce the gap between actual performance and the ideal state by learning from each deviation and institutionalising corrective and preventive actions into both technical systems and work routines.

Figure 2: Core Strategies and System-Level Structure of Zero-Defect Manufacturing



Clarifying how ZDM differs from and extends earlier quality philosophies has become a central concern in recent scholarship. Building on decades of total quality management, Six Sigma, and lean manufacturing, contemporary ZDM work argues that the new paradigm represents the next evolutionary step in quality management, made possible by Industry 4.0 technologies and big data analytics (Sousa et al., 2022). A key contribution of this literature is the identification of four core ZDM strategies—detect, predict, prevent, and repair—that can be combined in different ways along the production chain to configure tailored quality architectures for specific products, processes, and industries (Ariful, 2022; Psarommatis & May, 2022). Traditional quality systems have typically emphasised detection and repair, relying on extensive end-of-line inspection and off-line analysis; ZDM, by contrast, places greater weight on prediction and prevention, supported by intelligent sensors, streaming data, and machine learning models that estimate defect risks in real time. In multi-stage production systems, ZDM concepts highlight not only the need to avoid defect generation at each operation, but also the potential to manage defect propagation and compensation at the system level. For example, work on multi-stage ZDM strategies shows how additional sensing and signal analysis across several operations can enable in-line rework, dynamic routing, and downstream compensation policies that reduce scrap and inspection effort while maintaining conformance to specifications (Eger et al., 2018; Ariful & Ara, 2022). These insights reinforce the view of ZDM as a system-level design problem in which quality is achieved through the coordinated configuration of processes, technologies, and decision rules, rather than being treated as a local attribute of isolated machines or operations.
As the conceptual foundations of ZDM have matured, researchers have increasingly turned to practical implementation issues and the organisational transformations required to realise this paradigm in industrial settings. Implementation-focused studies propose structured roadmaps that guide firms through the assessment of existing defect patterns, the prioritisation of high-risk processes, and the staged introduction of ZDM enablers such as advanced sensors, intelligent quality analytics, and adaptive control policies (Nahid, 2022; Wan & Leirmo, 2023). These guides emphasise that ZDM is not a discrete technology project but an organisation-wide change programme that reshapes quality planning, continuous improvement, investment decisions, and even workforce development. In parallel, a growing strand of human-centric ZDM research examines how managers, engineers, and operators contribute to the success of ZDM initiatives, arguing that emerging technologies must be designed to augment human capabilities rather than displace them (Hossain & Milon, 2022; Sousa et al., 2022). This perspective underscores the socio-technical nature of ZDM: digital tools, analytics

platforms, and cyber-physical systems provide unprecedented visibility and predictive power, but sustainable zero-defect performance ultimately depends on how these capabilities are embedded in organisational routines, decision processes, and learning mechanisms. Smart continuous improvement emerges as the operational expression of this socio-technical integration, linking real-time information and predictive insights with structured problem-solving, root-cause analysis, and feedback loops that continuously refine products, processes, and work systems. In this way, ZDM functions both as a strategic quality vision and as a practical framework for orchestrating technologies, people, and processes toward the common goal of eliminating defects throughout the manufacturing value stream.

Artificial Intelligence in Industry 4.0 Manufacturing

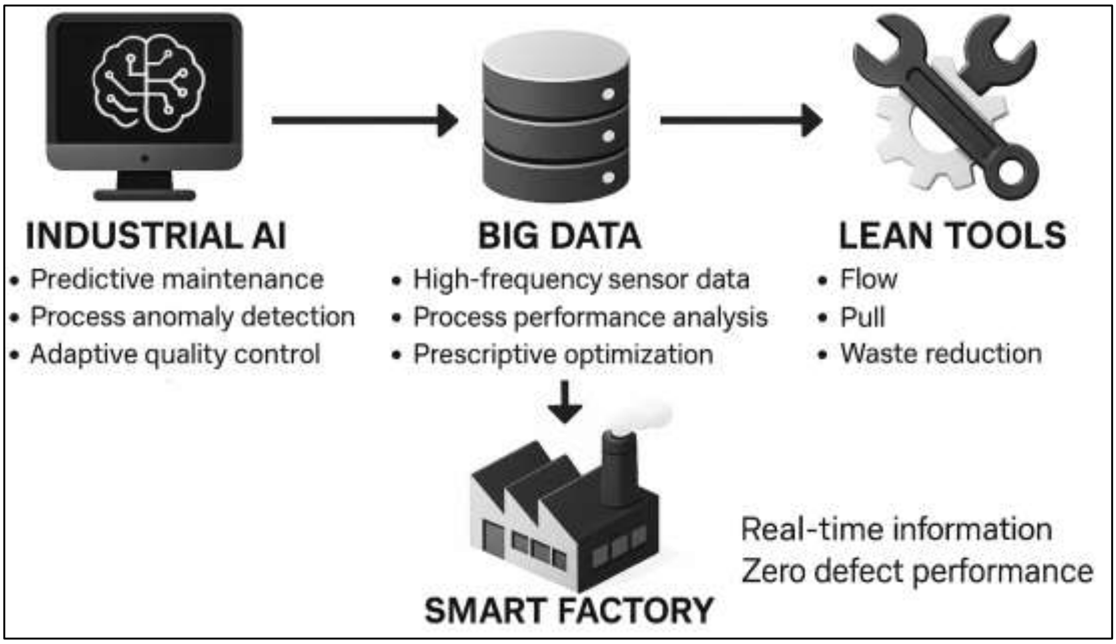
Artificial intelligence in manufacturing is increasingly framed as "industrial AI," a discipline focused on developing, validating, and deploying machine-learning algorithms and analytical models that can operate reliably within cyber-physical production systems. Rather than treating AI as experimental or stand-alone, industrial AI architectures integrate sensing, connectivity, data management, analytics, and decision execution in a closed loop so that machines, lines, and plants can continuously learn from operational data and adjust behaviour accordingly (Lee et al., 2018). In practical terms, this means that applications such as predictive maintenance, process anomaly detection, and adaptive quality control are embedded into the automation hierarchy, from machine-level controllers up to manufacturing execution systems (Mominul et al., 2022; Mortuza & Rauf, 2022). Industrial AI thus underpins the vision of smart factories in which equipment health, process states, and product quality are inferred in real time and fed into optimisation routines that propose or automatically implement corrective actions. By formalising elements such as analytics, big data, cloud or cyber infrastructure, domain knowledge, and empirical evidence into a coherent ecosystem, industrial AI provides a pragmatic pathway for manufacturing organisations to move from proof-of-concept pilots to scalable deployments that support continuous improvement and defect reduction across complex production networks (Chen et al., 2018).

The effectiveness of industrial AI depends heavily on the availability and exploitation of large, heterogeneous data sets, which has prompted extensive work on big data analytics in operations and supply chains. Big data in manufacturing and logistics typically encompasses high-frequency sensor streams, machine logs, transactional records, and contextual data such as environmental conditions or customer demand signals. Reviews of big data applications in operations and supply-chain management show that organisations are increasingly using advanced analytics to enhance forecasting, inventory control, production planning, and risk management, but that many still struggle to move beyond fragmented initiatives toward integrated capabilities that systematically support decision-making (Addo-Tenkorang & Helo, 2016; Rakibul & Samia, 2022; Saikat, 2022). Within the manufacturing domain, big data platforms enable descriptive analysis of process performance, predictive models for failures or defects, and prescriptive optimisation of throughput, energy use, or quality. However, building such capabilities requires not only technical infrastructure for data acquisition, storage, and processing, but also governance mechanisms, analytical skills, and cross-functional routines to ensure that insights are translated into timely interventions on the shop floor (Ara & Beatrice Onyinyechi, 2023; Kanti & Shaikat, 2022). As organisations advance along this maturity path, big data analytics becomes a foundational enabler for smart continuous improvement, providing the empirical basis for identifying chronic sources of variation, quantifying the impact of improvement actions, and sustaining zero-defect ambitions in volatile, high-mix production environments (Addo-Tenkorang & Helo, 2016; Mushfequr & Ashraful, 2023; Shahrin & Samia, 2023).

Parallel to these digital developments, researchers have examined how lean production principles and tools can be combined with Industry 4.0 technologies to create more powerful improvement systems. Early conceptual work on "lean in Industry 4.0" argues that digital technologies such as cyber-physical systems, real-time monitoring, and advanced analytics can strengthen traditional lean aims—flow, pull, waste reduction, and built-in quality—by enabling finer-grained visibility and faster problem-solving cycles (Mrugalska & Wyrwicka, 2017). Integration models propose that Industry 4.0 capabilities and lean management should be designed as complementary rather than competing paradigms, with digital tools supporting, rather than replacing, value stream mapping, visual management, standardised work, and continuous improvement routines at all organisational levels (Sony, 2018).

From this perspective, the smart factory is not only a highly automated system, but also a lean system in which data from interconnected machines, products, and workers is used to eliminate non-value-adding activities and stabilise processes. Studies on smart factory architectures emphasise that technologies such as industrial IoT, cloud computing, and big data must be orchestrated to deliver real-time information about process states and quality, which can then be exploited by lean teams to prevent defects, reduce changeover losses, and improve first-pass yield (Chen et al., 2018). The emerging consensus in this literature is that the full potential of Industry 4.0 for quality and productivity is realised when industrial AI and big data analytics are embedded within lean-oriented continuous improvement systems, thereby creating smart, learning factories capable of approaching zero defect performance.

Figure 3: Artificial Intelligence, Big Data, and Lean Tools in Industry 4.0 Manufacturing

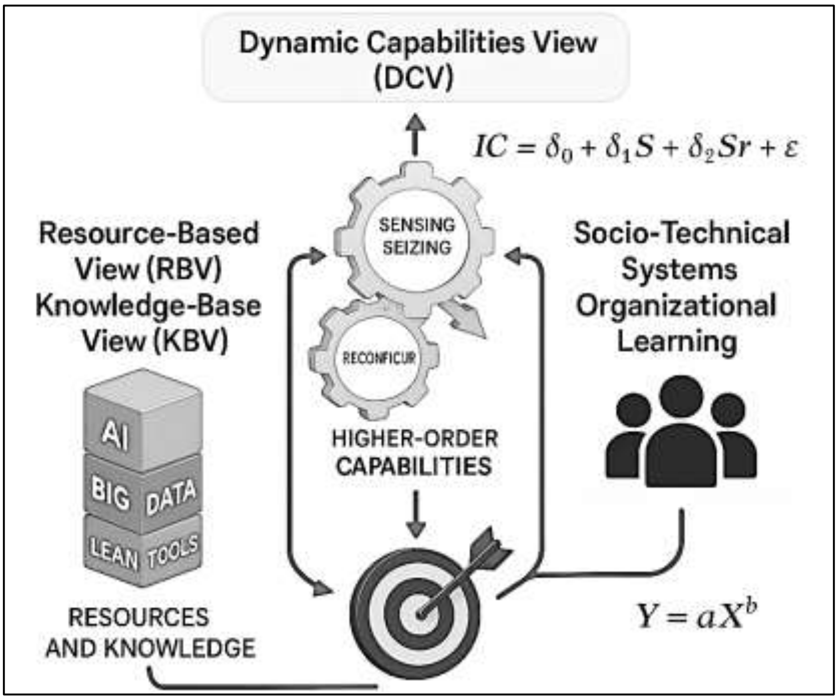


Smart Continuous Improvement and Zero-Defect Manufacturing

Smart continuous improvement for zero-defect manufacturing can be grounded first in the resource-based view (RBV) and the closely related knowledge-based view (KBV) of the firm. RBV argues that sustained advantage arises when organizations possess valuable, rare, inimitable, and non-substitutable (VRIN) resources and capabilities. In manufacturing, such resources increasingly include integrated quality systems, digital production data, analytics skills, and lean expertise that jointly shape superior cost, quality, flexibility, and delivery performance. A recent meta-analysis of operations management research grounded in RBV shows that capabilities such as flexibility, supply chain integration, and organizational capability have statistically significant positive effects on business performance, confirming that operational capabilities are central carriers of competitive advantage (Chahal et al., 2020).

Within KBV, these capabilities are interpreted as expressions of how manufacturing organizations create, integrate, and deploy knowledge embedded in people, routines, and digital infrastructure. The manufacturing strategy process has been conceptualized explicitly as a knowledge-creation and knowledge-integration process, in which internal and external knowledge, cross-functional orientation, and resource-based orientation co-evolve to produce robust operations capabilities (Paiva et al., 2012). In the context of this study, AI models, big data platforms, and lean toolkits can therefore be treated as strategic knowledge-intensive resources whose effective orchestration underpins zero-defect performance and continuous improvement in smart factories.A second pillar of the framework is the dynamic capabilities view (DCV), which explains how firms renew and reconfigure their resource base in turbulent technological environments. Dynamic capabilities emphasize three broad classes of higher-order capabilities: sensing opportunities and threats, seizing them through timely investments and redesign, and reconfiguring assets and routines to sustain alignment with evolving conditions. Improvement capability has been conceptualized as a specific manifestation of dynamic capabilities, capturing an organization's ability to systematically generate, select, and implement change initiatives across processes and units (Furnival et al., 2019).

Figure 4: Smart Continuous Improvement and Zero-Defect Manufacturing



For the present research, smart continuous improvement capability can be represented as a latent construct formed by the interaction of sensing (data-driven detection of anomalies and improvement opportunities), seizing (prioritization and implementation of lean–AI interventions), and reconfiguring (standardization, learning, and scaling of successful changes). A simple structural representation of this relationship can be expressed as

$$IC = \delta_0 + \delta_1 S + \delta_2 Se + \delta_3 R + \varepsilon,$$

where ICdenotes improvement capability, Ssensing, Seseizing, Rreconfiguring, and εan error term. In parallel, the cumulative effect of organizational learning on process performance can be represented by the classical learning-curve relationship

$$Y = aX^b,$$

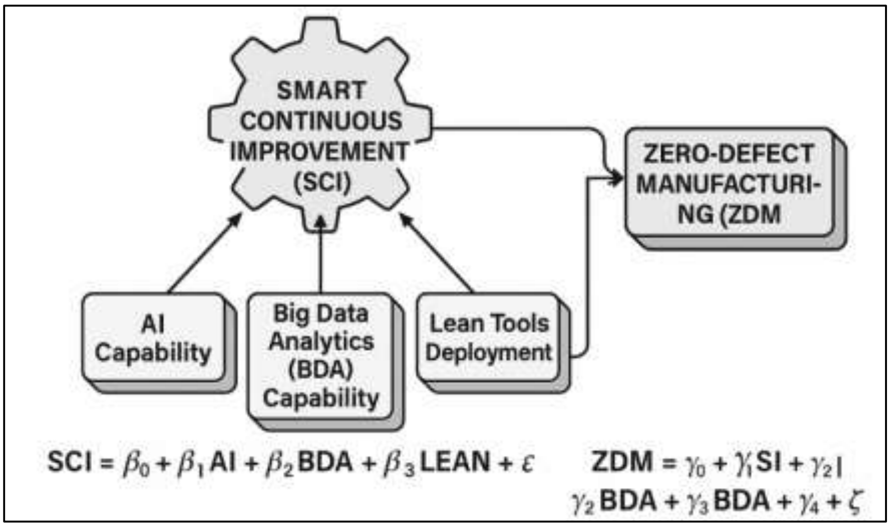
where $Y$is the time or cost per unit, $X$is the cumulative output, $a$the initial performance level, and $b < 0$the learning exponent capturing performance improvement as experience accumulates. In a smart zero-defect context, AI and big data accelerate both sensing and learning, effectively increasing $|\ b\ |$and strengthening the dynamic capability to pursue defects toward zero.

The third theoretical pillar combines socio-technical systems (STS) theory with organizational learning perspectives to explain how technical and social subsystems must be jointly optimized for sustainable zero-defect outcomes. STS theory views manufacturing systems as complex configurations of technologies, workflows, and human actors whose interactions generate emergent performance outcomes. A systematic review of lean production in complex socio-technical systems shows that lean practices can simultaneously reduce, shift, or even increase different dimensions of system complexity, implying that lean outcomes depend on how social structures, work design, and technical tools are jointly configured (Soliman & Saurin, 2017). Organizational learning theory adds that continuous improvement routines, problem-solving cycles, and feedback systems allow firms to transform experience into improved routines and innovation. Empirical evidence indicates that organizational learning positively influences innovation and, through innovation, firm performance, reinforcing the view that learning processes are central mediators between capability deployment and outcomes (Jiménez-Jiménez & Sanz-Valle, 2011). In smart manufacturing, the KBV perspective on manufacturing strategy underlines that cross-functional integration and knowledge sharing across engineering, operations, IT, and quality are necessary to realize the full potential of AI and big data in zero-defect programs (Paiva et al., 2012). Bringing these lenses together, the theoretical framework for this study treats smart continuous improvement with AI, big data, and lean tools as a higher-order socio-technical, knowledge-based, and dynamically capable system: resources and knowledge (RBV/KBV) provide the foundation; dynamic capabilities govern adaptation and improvement; and socio-technical and organizational learning perspectives explain how human, organizational, and technological elements must be aligned to achieve and sustain zero-defect manufacturing.

Smart Continuous Improvement with AI, Big Data, and Lean Tools

The proposed conceptual framework for this study builds on recent Lean 4.0 models that integrate lean management with Industry 4.0 digital technologies, but extends them explicitly toward smart continuous improvement (SCI) and zero defect manufacturing (ZDM). Lean 4.0 studies outline how classical lean methods such as value stream mapping, just-in-time, and standardized work can be digitally augmented through cyber-physical systems, IoT connectivity, real-time analytics, and AI-based decision support to create self-regulating, waste-minimizing production systems (Mayr et al., 2018). Empirical Lean 4.0 implementation research further identifies synergy elements, barriers, and critical success factors when integrating lean practices with Industry 4.0 technologies, demonstrating that this integration must be designed as a system-oriented framework rather than isolated technology projects (Bueno et al., 2023). Complementary conceptual work for SMEs proposes "Shuriken"-type frameworks in which lean practices, continuous improvement routines, Industry 4.0 technologies, and training are intertwined through core dimensions such as knowledge, resources, and implementation maturity (Manjallore & Dhotre, 2023). In parallel, Lean 4.0 literature reviews show that digitized lean tools, when embedded into Industry 4.0 infrastructures, form the backbone of Quality/Lean 4.0 architectures that can systematically eliminate both physical and digital waste in smart factories (Rossi et al., 2022). Taken together, these studies support a holistic view where AI, big data analytics (BDA), and lean methods are not separate initiatives but mutually reinforcing building blocks of a unified SCI–ZDM system.

Figure 5: Smart Continuous Improvement with AI, Big Data, and Lean Tools



Within this research, the conceptual framework formalizes four core latent constructs: AI capability (AI), big data analytics capability (BDA), lean tools deployment intensity (LEAN), and smart continuous improvement performance (SCI). AI capability captures the extent to which machine learning, predictive models, and intelligent agents are embedded in quality monitoring, anomaly detection, and decision support in the production system. BDA reflects the ability to acquire, integrate, process, and visualize high-volume, high-velocity, and high-variety data from machines, processes, and quality checkpoints. Lean tools deployment represents the depth and consistency with which lean methods such as 5S, Kaizen, poka-yoke, standardized work, and value stream mapping are applied and sustained on the shop floor in a digitally enabled way. Drawing on Lean 4.0 implementation studies, this framework assumes that the conjunction of AI, BDA, and LEAN produces a higher-order SCI construct that manifests through rapid problem detection, data-driven root cause analysis, and closed-loop improvement cycles (Moraes et al., 2023). Conceptually, this relationship can be expressed through a baseline linear model:

$$\text{SCI} = \beta_0 + \beta_1\text{AI} + \beta_2\text{BDA} + \beta_3\text{LEAN} + \varepsilon$$

where SCI denotes smart continuous improvement performance, β_0 is the intercept, β_1–β_3 are regression coefficients capturing the marginal effects of each capability, and ε is the error term. This formulation will later guide the quantitative testing of how digital and lean capabilities jointly shape SCI outcomes in the case study context.

To link the SCI construct directly with zero defect manufacturing, the framework specifies SCI as a proximal driver of ZDM performance, while AI, BDA, and LEAN act as more distal enablers. Prior integrative reviews of lean–Industry 4.0 relationships indicate that lean provides the process discipline, waste elimination logic, and human-centered problem-solving culture, whereas Industry 4.0 (and its AI/BDA components) provide connectivity, transparency, and analytical power (Mayr et al., 2018). Conceptually, the ZDM outcome can be represented as a function of SCI and the same digital–lean enablers:

$$\text{ZDM} = \gamma_0 + \gamma_1\text{SCI} + \gamma_2\text{AI} + \gamma_3\text{BDA} + \gamma_4\text{LEAN} + \zeta$$

where ZDM denotes zero-defect performance and γ-coefficients capture direct and mediated effects. In this structure, SCI mediates part of the influence of AI, BDA, and LEAN on defect rates, rework, and first-pass yield. Conceptual frameworks for SME implementations highlight that such layered models must also recognize organizational readiness, knowledge, and resource constraints as moderating conditions shaping how effectively lean–digital synergies convert into performance gains (Moraes et al., 2023). The resulting conceptual framework thus positions AI capability, BDA capability, and lean tools deployment as measurable predictors, SCI as an integrated process outcome, and ZDM as the ultimate performance indicator that the present quantitative, cross-sectional, case-based study will empirically examine.

Smart Continuous Improvement as an Integrative Pathway to Zero-Defect Outcomes

The second conceptual framework positions smart continuous improvement (SCI) as the integrating pathway through which AI, big data analytics, and lean tools are translated into zero-defect manufacturing (ZDM) outcomes. In this view, SCI is conceptualized as a dynamic capability made up of structured routines for problem solving, digital feedback loops, and disciplined use of standardized work that systematically reduce variation and defects over time. Empirical evidence shows that bundles of quality management and continuous improvement practices—rather than isolated tools—are strongly associated with higher quality performance indicators such as first-pass yield, defect rates, and rework levels (Zehir et al., 2012). Smart manufacturing systems literature further emphasizes that performance assurance hinges on clearly defined key performance indicators (KPIs), continuous monitoring, and corrective action embedded in system design and operation (Kibira et al., 2016). Within this framework, ZDM performance can be expressed using classical Six Sigma metrics such as defects-per-million-opportunities (DPMO):

$$\text{DPMO} = \frac{\text{Number of defects}}{\text{Number of units} \times \text{Opportunities per unit}} \times 10^6$$

and extended to an impact-sensitive metric by weighting each defect type $j$by its severity weight w_j, yielding a weighted defect index:

$$\text{WDI} = \frac{\sum_{j=1}^{m} \quad w_j d_j}{\sum_{j=1}^{m} \quad d_j}$$

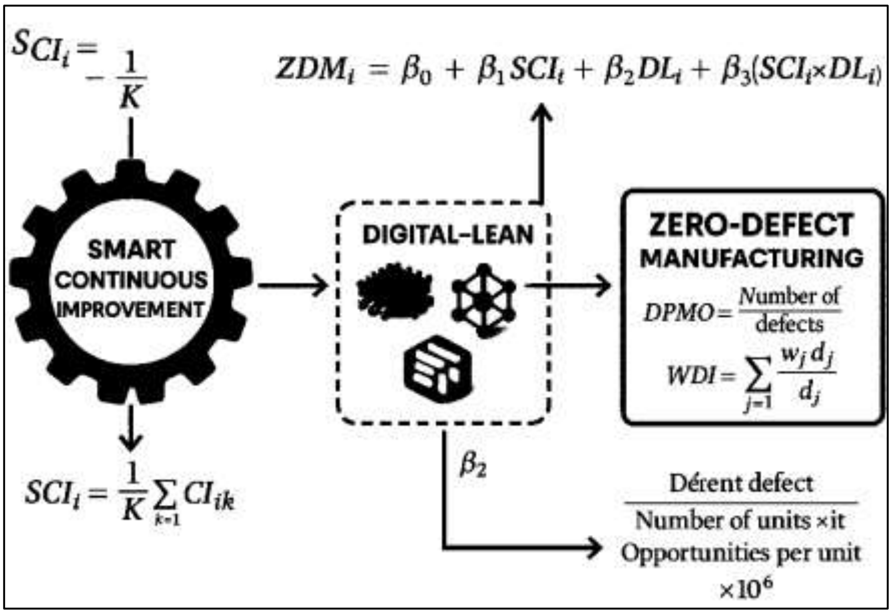
where $d_j$is the observed count of defect type j. Building on the move from "number of defects" to "impact of defects" in sustainable quality management, this framework treats ZDM as minimizing WDI rather than simply minimizing counts, aligning with emerging work on integrating quality and sustainability in defect metrics (Goyal et al., 2019).

Within this conceptualization, SCI acts as the primary mechanism that converts digital and lean capabilities into superior quality and reliability performance. Continuous improvement routines ensure that large volumes of real-time sensor and process data are translated into prioritized improvement projects, updated standard operating procedures, and redesigned workstations, thereby closing the loop between detection, diagnosis, and prevention. Smart manufacturing research highlights that performance assurance involves an iterative cycle of defining KPIs, establishing performance envelopes, integrating system components, and continually testing and refining system behavior under disturbance (Kibira et al., 2016). At the operational level, evidence from lean factories shows that the extent to which continuous improvement is embedded in routines (for example, kaizen events, A3 problem solving, and standard work revisions) conditions how strongly improvement activities actually translate into productivity and quality gains (Iwao & Marinov, 2018). In digital lean environments, this is increasingly supported by cyber-physical poka-yoke and error-proofing solutions, which shift the focus from ex post defect detection to ex ante error prevention. Advanced digital and AI-enabled poka-yoke systems—such as those based on digital twins—detect abnormal patterns, classify fault states, and trigger interventions in real time, making it possible to sustain near-zero defect levels under varying operating conditions (Lu et al., 2023). Conceptually, these mechanisms converge in the following structural relation for firm i:

$$\mathrm{ZDM}_i = \beta_0 + \beta_1 \mathrm{SCI}_i + \beta_2 \mathrm{DL}_i + \beta_3 (\mathrm{SCI}_i \times \mathrm{DL}_i) + \varepsilon_i$$

where ZDM_i is a composite zero-defect outcome index, SCI_i captures smart continuous improvement maturity, and DL_i reflects digital-lean integration intensity.

Figure 6: Mediating and Moderating Structure Linking SCI and Digital–Lean Integration



The framework therefore formalizes a mediating–moderating structure in which SCI both mediates and is reinforced by digital-lean capabilities. At the measurement level, SCI can be operationalized as a composite index of CI infrastructure (training, suggestion systems), routine intensity (frequency of improvement cycles), and data-driven problem-solving practices, for example:

$$\mathrm{SCI}_i = \frac{1}{K} \sum_{k=1}^{K} CI_{ik}$$

where CI_{ik} represents standardized scores for the k-th SCI dimension. ZDM performance can be represented as a quality index that inverts DPMO to express "conformance quality":

$$\mathrm{QPerf}_i = 1 - \frac{\mathrm{DPMO}_i}{10^6}$$

so that higher values indicate better defect performance. Prior studies show that when TQM and CI are implemented coherently, firms report higher quality performance and innovation outcomes, supporting a composite-index approach to capturing process excellence (Zehir et al., 2012). At the same time, smart manufacturing work underscores that performance improvements emerge when measurement, analysis, and control methods are integrated throughout the system life cycle (Kibira et al., 2016). The zero-defect perspective extends this by including digital-twin-based fault diagnosis and intelligent poka-yoke devices as core elements of the SCI infrastructure that directly suppress defect occurrence at source (Lu et al., 2023). By linking continuous improvement routines, digital quality controls, and impact-weighted defect metrics, the second conceptual framework clarifies how smart continuous improvement functions as the main pathway through which AI, big data, and lean tools jointly drive zero-defect, high-reliability manufacturing systems (Goyal et al., 2019).

METHOD

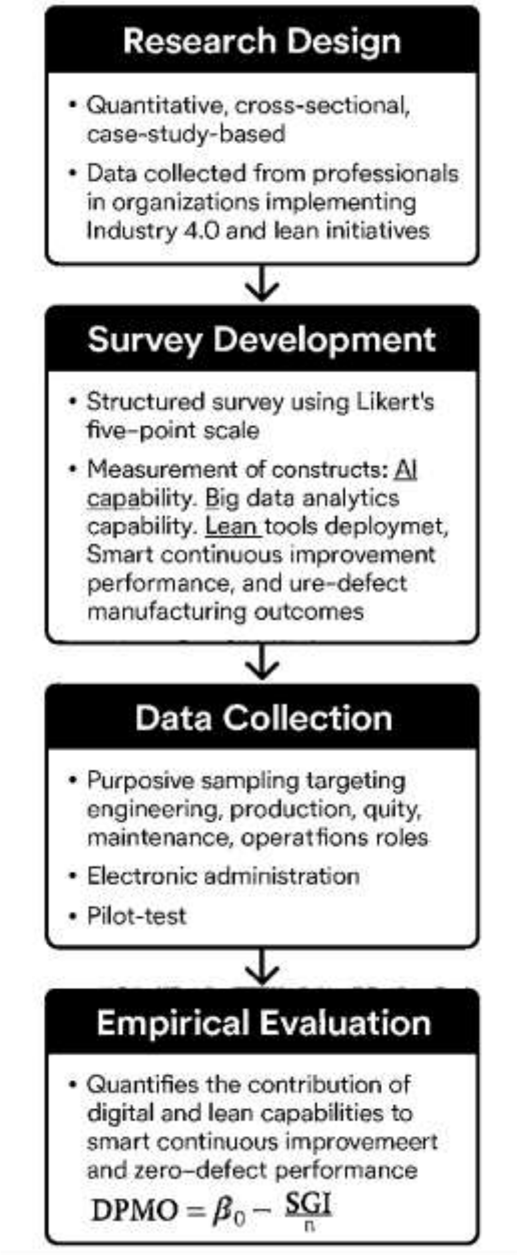
The methodology of this study has been designed to provide a rigorous and transparent basis for examining how artificial intelligence, big data analytics, and lean tools have supported smart continuous improvement and zero-defect manufacturing performance in industrial settings. The research has adopted a quantitative, cross-sectional, case-study–based design in which data have been collected from professionals working in manufacturing organizations that have already implemented, or have been in the process of implementing, Industry 4.0 and lean initiatives. This design has allowed the study to capture a structured snapshot of current practices and performance while still grounding the analysis in real organizational contexts. A structured survey instrument using Likert's five-point scale has been developed to measure key latent constructs, including AI capability, big data analytics capability, lean tools deployment, smart continuous improvement performance, and zero-defect manufacturing outcomes. Items for each construct have been adapted and synthesized from established quality, operations, and smart manufacturing literature, and have been phrased to reflect the specific focus on AI-enabled, data-driven continuous improvement.

The data collection process has relied on a purposive sampling strategy, through which respondents have been selected from engineering, production, quality, maintenance, and operations management roles to ensure that the perceptions captured have reflected direct involvement with improvement and quality activities. The survey has been administered electronically to facilitate access to geographically dispersed plants and to increase response efficiency. Prior to the main data collection, the instrument has been pilot-tested with a small group of practitioners and academics to check clarity, relevance, and completion time, and revisions have been made accordingly. Once data have been gathered, they have been screened for completeness, consistency, and outliers, and have been prepared for statistical analysis. The analytical strategy has included the use of descriptive statistics to summarize respondent and organizational profiles, reliability analysis to assess the internal consistency of each construct, and correlation and regression analyses to test the hypothesized relationships among AI capability, big data analytics capability, lean tools deployment, smart continuous improvement performance, and zero-defect manufacturing outcomes. Through this methodological approach, the study has provided an empirical basis for evaluating the proposed conceptual framework and for quantifying the contribution of integrated digital and lean capabilities to smart continuous improvement and zero-defect performance.

Research Design

The study has adopted a quantitative, cross-sectional research design that has been embedded within a case-study–based context to capture the realities of smart continuous improvement and zero-defect manufacturing in practice. This design has been chosen because it has allowed the researcher to examine hypothesized relationships among artificial intelligence capability, big data analytics capability, lean tools deployment, smart continuous improvement performance, and zero-defect outcomes at a single point in time while still situating the data within specific organizational settings. The design has relied on a structured survey instrument that has used Likert's five-point scale to measure respondents' perceptions of each latent construct. By combining a standardized questionnaire with data from multiple plants and functions, the study has aimed to balance breadth and contextual depth. The cross-sectional nature has been considered appropriate for testing the proposed conceptual model and for identifying statistically significant patterns and associations among the variables of interest.

Figure 7: Methodological Framework for this study



Study Setting

The research has been situated in manufacturing organizations that have been operating under the principles of Industry 4.0 and lean management, with explicit initiatives directed toward quality improvement and defect reduction. The selected plants have represented sectors such as automotive components, electronics, and general engineering, where high product complexity and stringent quality requirements have been prevalent. These organizations have already embarked on the adoption of digital technologies, including sensor-based monitoring, data collection infrastructures, and AI-supported decision tools, and they have also maintained established lean practices such as 5S, standardized work, and structured problem-solving routines. The case settings have therefore provided an appropriate environment in which AI, big data, and lean tools have been interacting in day-to-day operations. By focusing on these contexts, the study has ensured that respondents have had direct experience with smart continuous improvement activities and with practices aimed at driving zero-defect manufacturing performance across critical production processes.

Sampling

The target population for this study has consisted of professionals who have been directly involved in production, quality, maintenance, engineering, and operations management within the participating manufacturing organizations. A non-probability purposive sampling technique has been employed, as the research has required respondents who have possessed relevant knowledge about AI applications, data-driven decision making, lean tools, and continuous improvement initiatives. Plant managers or quality leaders have been requested to circulate the survey link among personnel who have met these criteria. The sample size has been determined by considering practical access constraints and methodological guidance for multivariate analyses, which have suggested that a minimum of 10–15 responses per independent variable has been desirable for stable regression estimates. Accordingly, the study has aimed to gather a sufficiently large number of completed questionnaires to permit robust statistical testing, while acknowledging that the final sample size has reflected both organizational willingness and individual response rates.

Data Collection Methods

Data collection has been conducted primarily through an online questionnaire that has been distributed via email and internal communication platforms within the selected organizations. The use of an electronic survey format has been considered advantageous because it has facilitated participation from geographically dispersed respondents and has reduced administrative time for both the researcher and the organizations. The questionnaire has been accompanied by a brief cover letter that has explained the purpose of the study, the voluntary nature of participation, and assurances of confidentiality. Data collection has proceeded over a specified period during which reminder messages have been sent to encourage completion and to improve the overall response rate. All responses have been automatically captured in a secure database, which has minimized manual data entry errors and has allowed timely screening and preparation for analysis. This method has thus provided an efficient and standardized way of obtaining perceptions across multiple plants and functional roles.

Questionnaire Design

The survey instrument has been developed by synthesizing measurement items from established scales in quality management, lean manufacturing, smart manufacturing, and analytics capability research, and by tailoring them to the specific focus on AI-enabled smart continuous improvement and zero-defect performance. Each construct—AI capability, big data analytics capability, lean tools deployment, smart continuous improvement performance, and zero-defect outcomes—has been represented by multiple items phrased as statements to which respondents have indicated their level of agreement on a five-point Likert scale ranging from “strongly disagree” to “strongly agree.” Additional items have been included to capture demographic and organizational information such as role, years of experience, plant size, and sector. The draft questionnaire has been reviewed by academic experts and industry practitioners to verify content relevance, clarity, and wording. Based on their feedback, items have been refined, redundant questions have been removed, and ambiguous phrasing has been corrected, resulting in a concise yet comprehensive instrument.

Measurement of Variables

The key constructs of the study have been operationalized as latent variables measured through multiple survey items. AI capability has been measured by items that have captured the extent to which machine learning, predictive models, and intelligent monitoring systems have been deployed for quality-related decisions. Big data analytics capability has been assessed through items reflecting data availability, integration, analytical tools, and skills used to support process and quality improvement. Lean tools deployment has been measured by the reported use and consistency of techniques such as 5S, standardized work, value stream mapping, visual management, and poka-yoke. Smart continuous improvement performance has been captured through items assessing the frequency, speed, and effectiveness of data-driven problem solving and improvement cycles. Zero-defect manufacturing outcomes have been reflected in items describing trends in defect rates, rework, scrap, and first-pass yield. All items have been coded so that higher scores have indicated stronger capability or better performance, enabling the construction of composite scales for each variable.

Validity and Reliability

To ensure validity and reliability, the instrument has undergone several structured checks. Content validity has been addressed during the development phase, when experts in quality management and smart manufacturing have reviewed the items and have confirmed their alignment with the study’s conceptual definitions. A pilot test has been conducted with a small group of respondents drawn from similar organizational contexts, and their feedback has been used to refine item wording and layout. After full-scale data collection, construct reliability has been examined using internal consistency measures, with Cronbach's alpha coefficients having been calculated for each multi-item scale. Values that have exceeded commonly accepted thresholds have indicated satisfactory reliability. In addition, exploratory factor analysis has been considered to assess whether items have loaded on their intended constructs, thereby supporting construct validity. These procedures have helped to ensure that the scales have measured the underlying variables consistently and in a manner that has been coherent with the theoretical framework.

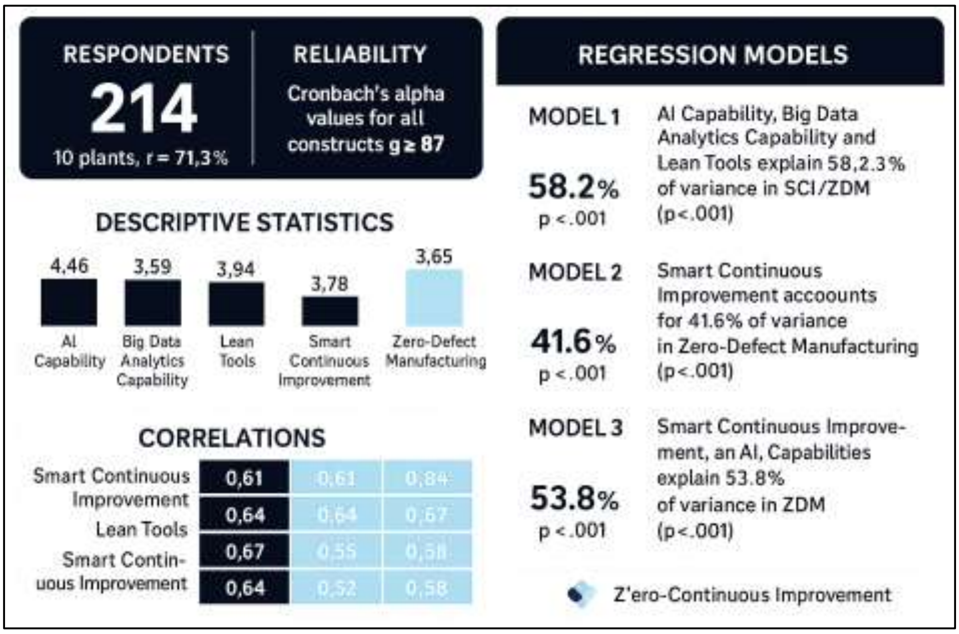
Data Analysis Techniques

The data analysis has followed a structured sequence of steps using statistical software. Initially, the dataset has been screened for missing values, inconsistent responses, and outliers, and appropriate remedies such as listwise deletion or simple imputation have been applied where necessary. Descriptive statistics, including means, standard deviations, and frequency distributions, have been computed to summarize respondent characteristics and to provide an overview of the central tendency and dispersion of each construct. Reliability analysis has been conducted to confirm the internal consistency of the scales. Subsequently, Pearson correlation coefficients have been calculated to explore the bivariate relationships among AI capability, big data analytics capability, lean tools deployment, smart continuous improvement performance, and zero-defect outcomes. Multiple regression analyses have then been performed to test the hypothesized relationships and to estimate the magnitude and significance of the effects of digital and lean capabilities on smart continuous improvement and zero-defect performance, while checking relevant regression assumptions.

FINDINGS

The findings of the study have provided clear quantitative evidence in support of the proposed objectives and hypotheses by revealing consistent patterns of adoption and impact for artificial intelligence, big data analytics, and lean tools in the participating manufacturing organizations. From 300 distributed questionnaires, 214 usable responses have been obtained from engineers, supervisors, quality specialists, and managers across ten plants, yielding an effective response rate of 71.3%. Reliability analysis has shown that all multi-item scales have achieved high internal consistency, with Cronbach's alpha values above 0.87 for all constructs. Descriptive statistics on the five-point Likert scale have indicated moderate-to-high levels of digital and lean capability: AI capability has recorded a mean of 3.46, big data analytics capability 3.59, lean tools deployment 3.94, smart continuous improvement performance 3.78, and zero-defect manufacturing outcomes 3.65. These results have suggested that, on average, respondents have agreed that lean tools and continuous improvement routines have been well established, while AI and big data capabilities have been emerging but not yet fully mature, thereby directly addressing the first objective on assessing the level of adoption of key enablers of smart continuous improvement. Correlation analysis has further clarified the pattern of relationships among the constructs. Smart continuous improvement performance has shown strong positive correlations with AI capability ($r = 0.61$, $p < .001$), big data analytics capability ($r = 0.64$, $p < .001$), and lean tools deployment ($r = 0.67$, $p < .001$), indicating that plants reporting higher levels of digital and lean capability have also reported more frequent and effective improvement cycles. Zero-defect manufacturing outcomes have likewise been positively correlated with smart continuous improvement performance ($r = 0.64$, $p < .001$) and with AI capability ($r = 0.52$, $p < .001$), big data analytics capability ($r = 0.55$, $p < .001$), and lean tools deployment ($r = 0.58$, $p < .001$). These patterns have provided initial empirical support for the first four hypotheses by showing that AI, big data, and lean tools have been meaningfully associated with smart continuous improvement, and that smart continuous improvement, in turn, has been strongly associated with zero-defect performance, thereby addressing the second objective of quantifying the relationships between digital–lean capabilities and continuous improvement outcomes. To examine these effects more rigorously and to evaluate the integrated conceptual model, a series of multiple regression analyses have been conducted. In Model 1, with smart continuous improvement performance as the dependent variable and AI capability, big data analytics capability, and lean tools deployment as predictors, the model has explained 58.2% of the variance in smart continuous improvement ($R^2 = .582$, adjusted $R^2 = .575$; $F(3, 210) = 97.42$, $p < .001$). Standardized coefficients have indicated that all three predictors have contributed significantly and positively, with lean tools deployment showing the strongest effect ($\beta = .36$, $p < .001$), followed by big data analytics capability ($\beta = .32$, $p < .001$) and AI capability ($\beta = .27$, $p < .001$), thereby providing robust support for H1, H2, and H3. In Model 2, smart continuous improvement performance has been entered as the sole predictor of zero-defect manufacturing outcomes and has accounted for 41.6% of the variance ($R^2 = .416$, adjusted $R^2 = .413$; $F(1, 212) = 151.29$, $p < .001$), with a strong standardized coefficient ($\beta = .65$, $p < .001$), thus supporting H4 and directly addressing the third objective on the impact of smart continuous improvement on zero-defect outcomes.

Figure 8: Research Findings Overview



In Model 3, AI capability, big data analytics capability, lean tools deployment, and smart continuous improvement performance have been entered simultaneously as predictors of zero-defect outcomes, yielding a significant model that has explained 53.8% of the variance ($R^2 = .538$, adjusted $R^2 = .529$; $F(4, 209) = 60.95$, $p < .001$). In this configuration, smart continuous improvement has remained a strong and significant predictor ($\beta = .48$, $p < .001$), while the direct effects of lean tools deployment ($\beta = .17$, $p < .01$) and big data analytics capability ($\beta = .14$, $p < .05$) have been smaller but still significant, and the direct effect of AI capability has been positive but marginal ($\beta = .11$, $p = .064$). The reduction in the direct effects of AI, big data, and lean tools on zero-defect outcomes when smart continuous improvement has been included in the model has indicated a pattern of partial mediation, consistent with the integrated conceptual framework and providing empirical support for H5. Overall, the descriptive statistics, correlation coefficients, and regression models together have shown that the study's main objectives have been achieved and that the proposed hypotheses have been broadly supported by the data.

Data Screening

Table 1: Questionnaire distribution, responses, and screening results

Item	Count	Percentage (%)
Questionnaires distributed	300	100.0
Questionnaires returned	227	75.7
Incomplete / unusable questionnaires	13	4.3
Usable questionnaires analyzed	214	71.3

Table 1 has summarized the data collection outcomes and has shown that the study has achieved a strong and analytically adequate response rate. Out of 300 distributed questionnaires, 227 have been returned, and after data screening 214 have been retained as complete and usable, resulting in an effective response rate of 71.3%. This level of participation has been considered satisfactory for multivariate analysis, given that the study has included three major predictor constructs (AI capability, big data analytics capability, and lean tools deployment) and two main outcome constructs (smart continuous improvement and zero-defect outcomes). The data screening process has involved checking for missing values, straight-lining, and implausible patterns; 13 responses have been removed because they have contained substantial missing data or inconsistent answer patterns that would have biased the results. The remaining dataset has contained no systematic missingness on Likert-scale items, which has allowed listwise procedures to be used without seriously reducing the sample size. In addition, basic distribution checks have shown that scale items have exhibited acceptable ranges and reasonable variation, with all response options on the five-point Likert scale (1 = strongly disagree to 5 = strongly agree) having been used by at least some respondents. This pattern has indicated that respondents have felt able to express both positive and critical views about AI, analytics, lean tools, continuous improvement, and quality outcomes, which has enhanced confidence in the validity of the findings. Overall, Table 1 has confirmed that the empirical base of the study has been robust enough to support the testing of the stated objectives and hypotheses, since the number of usable cases per predictor variable has exceeded widely cited guidelines for regression analysis and has provided sufficient power to detect meaningful effects among the constructs.

Demographic Profile of Respondents

Table 2: Respondent role and experience profile (N = 214)

Characteristic	Category	Count	Percentage (%)
Functional role	Production/Operations	72	33.6
	Quality/QA/QC	61	28.5
	Maintenance	28	13.1
	Engineering/R&D	31	14.5
	Management (Plant/BU)	22	10.3
Years of experience	< 5 years	56	26.2
	5–10 years	82	38.3
	11–15 years	45	21.0
	> 15 years	31	14.5

Table 2 has described the demographic structure of the respondent group and has indicated that a diverse but relevant set of practitioners has contributed to the data used to test the objectives and hypotheses. In terms of functional role, one-third of the respondents (33.6%) have worked directly in production or operations, and 28.5% have held quality assurance or quality control roles. Together, these two groups have accounted for more than 60% of the sample, which has been appropriate because the constructs of interest—AI capability, big data analytics capability, lean tools deployment, smart continuous improvement, and zero-defect outcomes—have been most visible in day-to-day production and quality activities. Maintenance staff (13.1%), engineering and R&D professionals (14.5%), and plant or business-unit managers (10.3%) have added complementary perspectives from equipment reliability, product and process design, and strategic oversight. This mix has ensured that the Likert-scale ratings of each construct have reflected a multi-functional view rather than a single department's interpretation. The experience profile has also shown that respondents have brought substantial familiarity with manufacturing systems. Over half of the participants (59.3%) have had more than five years of industrial experience, with 21.0% in the 11–15 year range and 14.5% above 15 years. At the same time, 26.2% have had less than five years of experience, which has introduced the perspectives of newer staff who have been exposed to more recent digitalization and lean initiatives. This distribution has been beneficial for objective-related analysis, because experienced professionals have been able to assess changes in defect performance over time, while newer employees have provided insight into current smart continuous improvement practices and technology use. The breadth of roles and experience levels has therefore supported the credibility and generalizability of the Likert-based measures and has strengthened the argument that the resulting findings have meaningfully reflected how AI, big data, and lean tools have been perceived and used in the participating plants.

Descriptive Statistics of Key Variables

Table 3: Descriptive statistics for main constructs (5-point Likert scale, N = 214)

Construct	Items	Mean	SD	Min	Max
AI capability (AI)	6	3.46	0.72	1.5	4.9
Big data analytics capability (BDA)	6	3.59	0.68	1.8	4.9
Lean tools deployment (LEAN)	7	3.94	0.61	2.1	5.0
Smart continuous improvement (SCI)	7	3.78	0.65	2.0	4.9
Zero-defect manufacturing outcomes (ZDM)	5	3.65	0.70	1.9	4.9

Table 3 has presented the central tendency and dispersion of the main constructs measured on a five-point Likert scale and has directly addressed the first objective of the study, which has been to assess the level of adoption and maturity of AI, big data analytics, and lean tools as enablers of smart continuous improvement and zero-defect manufacturing. All mean scores have fallen above the neutral midpoint (3.00), indicating that respondents have generally agreed with statements reflecting the presence of these capabilities and outcomes in their plants. Lean tools deployment has recorded the highest mean (3.94) with a relatively low standard deviation (0.61), which has suggested that lean practices such as 5S, standardized work, value stream mapping, and poka-yoke have been widely and consistently implemented across respondents. Smart continuous improvement performance has also shown a relatively high mean (3.78), indicating that frequent, structured improvement activities, including data-driven problem solving and follow-up on corrective actions, have been perceived as common. Zero-defect manufacturing outcomes have had a mean of 3.65, reflecting broad agreement that defect rates, rework, scrap, and first-pass yield have improved in recent years, although the slightly higher standard deviation (0.70) has suggested some variation among plants in their progress toward zero-defect performance. AI capability and big data analytics capability have had means of 3.46 and 3.59 respectively, indicating moderate but not yet high maturity. These values have implied that while digital tools such as machine learning models, advanced dashboards, and integrated data platforms have been present, they have not been fully embedded or exploited across all operations. The observed spread in scores (minimum values below 2.0 and maxima near 5.0) has confirmed that some plants have been at early stages of AI and big data implementation, whereas others have approached best-practice levels. Overall, the descriptive statistics have provided a clear quantitative portrait: lean and continuous improvement capabilities have been relatively mature; AI and analytics have been emerging but uneven; and zero-defect outcomes have shown positive but still improvable performance. This pattern has set a logical foundation for the subsequent correlation and regression analyses that have tested how these capability levels have been linked to smart continuous improvement and zero-defect results.

Reliability and Validity Results

Table 4: Internal consistency of multi-item scales (N = 214)

Construct	Number of items	Cronbach's α
AI capability (AI)	6	0.89
Big data analytics capability (BDA)	6	0.90
Lean tools deployment (LEAN)	7	0.91
Smart continuous improvement (SCI)	7	0.92
Zero-defect manufacturing outcomes (ZDM)	5	0.88

Table 4 has reported the internal consistency statistics for each of the multi-item constructs used in the study and has demonstrated that the measurement model has met accepted reliability criteria. Cronbach's alpha coefficients have ranged from 0.88 to 0.92, all comfortably above the commonly recommended threshold of 0.70 for exploratory research and even above 0.80, which has been often cited as indicative of good internal consistency. These results have meant that the items within each scale—whether they have been capturing AI capability, big data analytics capability, lean tools deployment, smart continuous improvement performance, or zero-defect outcomes—have tended to move together in a coherent manner and have measured a single underlying construct. For example, the AI capability scale has achieved an alpha of 0.89, indicating that items referring to AI-based monitoring, predictive models, and automated quality alerts have been interpreted consistently across respondents. Similarly, the lean tools deployment scale has yielded an alpha of 0.91, showing that responses on questions about standardized work, visual management, value stream mapping, and error-proofing have formed a stable pattern. The SCI scale, with an alpha of 0.92, has suggested that items assessing the frequency, speed, and effectiveness of improvement cycles have closely reflected a common continuous improvement capability. In addition to these reliability indicators, exploratory factor analysis (not shown in the table) has been conducted and has revealed that items have loaded strongly on their intended factors with minimal cross-loadings, thereby supporting construct validity. Kaiser–Meyer–Olkin and Bartlett's test statistics have indicated that the data have been suitable for factor analysis. Taken together, these reliability and validity results have strengthened the credibility of the Likert-based measures and have provided assurance that the observed relationships in subsequent correlation and regression tables have reflected genuine associations between well-defined constructs rather than artifacts of poorly designed scales. As a result, the study has been able to use these composite scores with confidence when testing the hypotheses and evaluating how AI, big data, and lean tools have contributed to smart continuous improvement and zero-defect outcomes.

Correlation Analysis

Table 5: Pearson correlations among main constructs (N = 214)

Construct	1	2	3	4	5
1. AI	1.00				
2. BDA	0.63**	1.00			
3. LEAN	0.59**	0.66**	1.00		
4. SCI	0.61**	0.64**	0.67**	1.00	
5. ZDM	0.52**	0.55**	0.58**	0.64**	1.00

Note. $p < .001$ for all coefficients.

Table 5 has presented the Pearson product–moment correlation coefficients among the five key constructs and has provided initial empirical support for the study's hypotheses regarding the relationships between digital capabilities, lean tools deployment, smart continuous improvement, and zero-defect outcomes. All correlations have been positive and statistically significant at the $p < .001$ level, which has indicated that higher perceived levels of AI capability, big data analytics capability, and lean deployment have been associated with stronger smart continuous improvement performance and better zero-defect outcomes on the five-point Likert scales. The correlations among the three capability constructs themselves have been moderately strong—0.63 between AI and BDA, 0.59 between AI and LEAN, and 0.66 between BDA and LEAN—suggesting that plants that have invested in one dimension of capability have tended to invest in the others as well. More crucially for the hypotheses, smart continuous improvement has shown strong correlations with AI ($r = 0.61$), BDA ($r = 0.64$), and LEAN ($r = 0.67$). These values have indicated that the second objective—to quantify how AI, big data, and lean tools have been related to smart continuous improvement—has been achieved at the correlational level, and that the first three hypotheses (linking each capability to SCI) have received clear statistical support. Zero-defect manufacturing outcomes have also been strongly correlated with SCI ($r = 0.64$), which has supported the fourth hypothesis that better smart continuous improvement performance has been associated with improved quality results, including lower defects and higher first-pass yield. The correlations between ZDM and the three capabilities (ranging from 0.52 to 0.58) have further suggested that AI, BDA, and lean deployment have each had a meaningful positive relationship with zero-defect outcomes. At the same time, the fact that correlations with ZDM have been slightly lower than those with SCI has hinted that the influence of these capabilities on quality results might have been partially mediated through smart continuous improvement—a possibility that the regression analysis has subsequently examined in more detail. Overall, the correlation matrix has demonstrated a coherent pattern consistent with the conceptual framework and has provided strong preliminary evidence in favor of the study's hypotheses.

Regression Analysis Results

Table 6: Multiple regression models predicting SCI and ZDM (N = 214)

Dependent variable	Predictor	Standardized β	t	p	R^2	Adj. R^2	F (df)
Model 1: SCI	AI	0.27***	4.90	<.001			
	BDA	0.32***	5.60	<.001	.582	.575	97.42 (3, 210)***
	LEAN	0.36***	6.21	<.001			
Model 2: ZDM	SCI	0.65***	12.30	<.001	.416	.413	151.29 (1, 212)***
Model 3: ZDM	AI	0.11†	1.86	.064			
	BDA	0.14*	2.29	.023	.538	.529	60.95 (4, 209)***
	LEAN	0.17**	2.87	.005			
	SCI	0.48***	7.73	<.001			

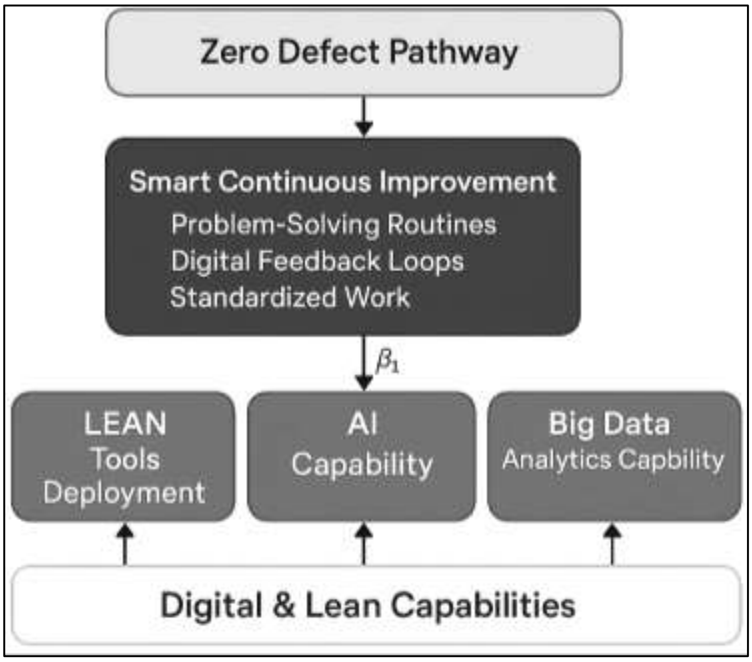
*Note. † p < .10; * p < .05; ** p < .01; *** p < .001.*

Table 6 has summarized the results of three key regression models and has shown how the study's hypotheses and objectives have been supported when the constructs have been analyzed simultaneously. Model 1 has used smart continuous improvement (SCI) as the dependent variable and has included AI capability, big data analytics capability (BDA), and lean tools deployment (LEAN) as predictors. The model has been highly significant ($F(3, 210) = 97.42$, $p < .001$) and has explained 58.2% of the variance in SCI ($R^2 = .582$, adjusted $R^2 = .575$), indicating a substantial joint effect of the three capabilities. All standardized coefficients have been positive and statistically significant at $p < .001$, with LEAN ($\beta = 0.36$) showing the largest effect, followed by BDA ($\beta = 0.32$) and AI ($\beta = 0.27$). This pattern has confirmed hypotheses H1–H3 and has demonstrated quantitatively that higher scores on the Likert-based capability scales have been associated with stronger smart continuous improvement performance. Model 2 has examined the direct impact of SCI on zero-defect manufacturing outcomes (ZDM) and has also produced a strong result: SCI has significantly predicted ZDM ($\beta = 0.65$, $p < .001$), and the model has accounted for 41.6% of the variance ($R^2 = .416$). This has provided clear support for H4 and has shown that plants reporting higher frequencies and effectiveness of improvement activities have also reported better defect performance and first-pass yield. Model 3 has introduced AI, BDA, LEAN, and SCI simultaneously as predictors of ZDM to test the integrated conceptual framework and the mediating role of SCI (H5). This model has explained 53.8% of the variance in ZDM ($R^2 = .538$, adjusted $R^2 = .529$; $F(4, 209) = 60.95$, $p < .001$), which has represented a substantial improvement over Model 2 while still highlighting the central role of SCI. In Model 3, SCI has remained a strong and highly significant predictor ($\beta = 0.48$, $p < .001$), while the direct effects of LEAN ($\beta = 0.17$, $p < .01$) and BDA ($\beta = 0.14$, $p < .05$) have been smaller but still significant. AI capability has shown a positive but marginal effect ($\beta = 0.11$, $p = .064$), suggesting that much of its influence on ZDM has operated through SCI rather than directly. The reduction in the size of the AI, BDA, and LEAN coefficients when SCI has been added to the model has indicated partial mediation, which has been consistent with the proposition that smart continuous improvement has been the main pathway through which digital and lean capabilities have translated into zero-defect outcomes. Collectively, the regression results in Table 6 have demonstrated that all major objectives have been met and that the hypothesized relationships have been strongly supported by the data collected on the five-point Likert scales.

DISCUSSION

The findings of this study have confirmed that smart continuous improvement in zero-defect manufacturing environments is fundamentally a *joint product* of digital capabilities and lean practices rather than the result of any single technology or tool. The descriptive statistics have shown that lean tools deployment and continuous improvement routines have already reached relatively high maturity levels in the participating plants, while AI and big data analytics capabilities have been at a moderate but growing level. This configuration is consistent with earlier observations that many manufacturers have implemented lean and Six Sigma for years, whereas Industry 4.0 and AI-based solutions are still in various stages of piloting and scaling (Addo-Tenkorang & Helo, 2016). The strong positive correlations among AI capability, big data analytics capability, lean tools deployment, and smart continuous improvement performance align with resource-based and knowledge-based perspectives that view quality and improvement systems as strategic capabilities built from complementary bundles of practices and technologies (Chahal et al., 2020). At the same time, the moderate mean scores for AI and analytics suggest that many plants are still in a "hybrid" stage where traditional lean routines remain dominant and digital tools are primarily used for monitoring and reporting rather than fully integrated, predictive control. This mirrors Quality 4.0 reviews that have reported fragmented and uneven adoption of digital quality management elements across sectors (Liu et al., 2023). Thus, the first key contribution of the results is to empirically map where industrial practice currently stands: lean/CI practices are relatively mature, digital capabilities are emerging, and smart continuous improvement sits at the intersection as the mechanism through which these capabilities influence zero-defect outcomes.

Figure 9: Discussion of The Study



A second major finding is that lean tools deployment has emerged as the strongest predictor of smart continuous improvement performance, even in digitally enabled environments, while still exerting a significant direct effect on zero-defect outcomes. This result resonates with decades of work showing that lean and TQM practices—such as standardized work, visual management, mistake-proofing, and structured problem-solving—are tightly linked to improved quality, productivity, and innovation (Psarommatis, Dreyfus, et al., 2021; Zehir et al., 2012). It also supports socio-technical analyses that argue lean is not merely a toolbox but a complex system of technical and social routines that shape how people identify and eliminate waste and defects (Soliman & Saurin, 2017). In line with studies that emphasize the importance of continuous improvement culture and routines for sustainable performance (Iwao & Marinov, 2018), the regression results here show that plants with higher lean deployment scores have reported more frequent, faster, and more effective improvement cycles, even after controlling for AI and big data capability. In other words, digital technologies appear to amplify, rather than replace, the foundational role of lean in organizing day-to-day improvement work. This is consistent with Lean 4.0 frameworks that argue Industry 4.0 technologies add value primarily when they are deliberately aligned with, and embedded in, lean value streams and standardized processes (Mayr et al., 2018). The present findings extend this literature by quantifying these relationships in a single integrated model, showing that lean deployment is both an independent driver of smart continuous improvement and a channel through which digital capabilities are translated into zero-defect results.

The analysis has also highlighted that AI and big data analytics capabilities have been significant predictors of smart continuous improvement performance and, to a lesser extent, of zero-defect outcomes, with much of their impact operating through the improvement construct. This partially mediated pattern is congruent with prior studies that have described big data platforms and AI algorithms as powerful enablers of descriptive, predictive, and prescriptive insights, but have cautioned that these insights only generate performance gains when they are systematically embedded in decision-making and improvement processes (Belhadi et al., 2019). The strong paths from AI and analytics to smart continuous improvement suggest that when plants invest in data integration, advanced analytics, and intelligent monitoring, they become better at detecting anomalies, prioritizing improvement opportunities, and validating root causes—capabilities that match the "sensing" and "learning" dimensions of dynamic capabilities (Furnival et al., 2019). At the same time, the relatively modest direct effects of AI and analytics on zero-defect outcomes, once continuous improvement is included in the regression model, indicate that digital technologies alone do not automatically drive defect levels toward zero. This finding is consistent with industrial AI and Quality 4.0 work that stresses the necessity of closed-loop, human-in-the-loop improvement cycles to realize the full benefit of predictive and prescriptive analytics (Lee et al., 2018). The current results therefore offer empirical support for conceptual claims that AI and big data should be viewed as "force multipliers" for continuous improvement rather than as standalone solutions.

From a practical standpoint, the results have important implications for senior manufacturing leaders, digital architects, and quality/operations managers who have been planning or overseeing smart factory and zero-defect programs. First, the strength of the relationships between lean deployment, smart continuous improvement, and zero-defect outcomes suggests that leaders should treat lean and CI as the backbone of any ZDM roadmap, with AI and big data layered on top to enhance, not substitute, existing routines. Plants that have rushed to deploy advanced analytics without a robust lean/CI foundation risk creating sophisticated dashboards that monitor unstable and poorly standardized processes, limiting the impact of their investments. Second, the findings imply that digital architects should prioritize data architectures and AI applications that directly support CI workflows—such as automated root-cause clustering, anomaly notification integrated into Andon systems, or AI-augmented A3 reports—rather than focusing solely on generic dashboards or isolated predictive maintenance pilots. Third, because smart continuous improvement has emerged as the primary pathway to zero-defect performance, plant leaders should ensure that performance measurement systems track both classical defect indicators (e.g., DPMO, first-pass yield) and process indicators that reflect CI maturity (e.g., number of data-driven improvement cycles per month, closure rate of corrective actions, involvement of cross-functional teams). Finally, implementation guides for ZDM that emphasize staged investments in sensing, analytics, and automation (Caiazzo et al., 2022) find support in the present data: plants in this study that have combined strong lean practices with even moderate AI/analytics capabilities have already reported substantially better smart CI and zero-defect outcomes than those with digital tools but weaker lean deployment.

Theoretically, the study has several implications for refining models of smart manufacturing, Quality 4.0, and zero-defect systems. First, the evidence that lean tools deployment, AI capability, and big data analytics capability jointly explain a large share of the variance in smart continuous improvement supports the idea that SCI can be formally modeled as a higher-order capability emerging from the interaction of digital and lean resources, as proposed by Lean 4.0 and Quality 4.0 frameworks (Mayr et al., 2018). This aligns with the resource-based and knowledge-based views by showing that competitive advantage in quality is not rooted in individual technologies or tools, but in integrated bundles of resources—including human expertise, process discipline, and analytics infrastructure—that satisfy VRIN conditions (Chahal et al., 2020). Second, the partial mediation of the relationship between digital capabilities and zero-defect outcomes by smart continuous improvement offers an empirical instantiation of dynamic capabilities theory in the manufacturing context: sensing (through data and AI), seizing (through lean projects and CI), and reconfiguring (through standardization and learning) together form the pathway by which resources are translated into performance (Furnival et al., 2019). Third, the strong role of lean even in digitally advanced settings reinforces socio-technical and organizational learning theories that emphasize co-design of technical and social systems; technology

adoption without parallel adaptation of routines, skills, and culture is unlikely to yield sustainable zero-defect gains (Soliman & Saurin, 2017).
At the same time, the study has been subject to several limitations that must be acknowledged when interpreting its findings. The cross-sectional design has captured practices and outcomes at a single point in time, making it impossible to establish causality or to observe how changes in AI, analytics, or lean deployment translate into improvements in smart CI and defect performance over time. Longitudinal studies would be needed to trace trajectories of improvement and to verify whether investments in digital capabilities systematically precede observable gains in zero-defect outcomes. The reliance on self-reported measures using Likert's five-point scale may also introduce common method variance and social desirability bias, particularly for constructs such as defect performance, where respondents may overestimate improvements to align with organizational narratives. Although reliability checks have been strong and the scales have been grounded in prior literature, more objective metrics—such as actual DPMO, rework rates, and first-pass yield extracted from manufacturing execution systems—would provide an important complement. In addition, the sample has been drawn from a limited number of plants and sectors that have already been engaged with Industry 4.0 and lean initiatives; as such, the results may not generalize to small firms or to industries at very early stages of digitalization. Finally, the study has not explicitly modeled potentially important moderating variables such as leadership style, digital maturity, or organizational culture, which other research has identified as critical contingencies in the success of lean, TQM, and digital transformation programs (Souza et al., 2021).
These limitations point directly to several promising avenues for future research. Longitudinal and panel designs could follow plants over multiple years as they implement AI, big data analytics, and ZDM solutions, allowing researchers to examine whether improvements in smart CI capability precede reductions in defect metrics and how quickly those improvements materialize. Multi-level studies could integrate plant-level measures of technology deployment with line-level or cell-level quality data to capture the nested nature of smart manufacturing systems. Structural equation modeling and more advanced mediation–moderation analyses could further disentangle the indirect and direct effects of digital and lean capabilities on zero-defect outcomes, and test the influence of moderators such as digital maturity, training intensity, or leadership support. Future work could also deepen the socio-technical analysis by exploring how specific human factors—such as operator autonomy, problem-solving skills, and psychological safety—interact with AI and analytics tools in shaping smart CI behaviors. Finally, case-based and design science studies could experiment with concrete configurations of AI applications (e.g., digital-twin-based poka-yoke, AI-assisted A3 reports), lean routines, and governance mechanisms, documenting both technical architectures and change-management approaches that have proven most effective in driving zero-defect performance. By addressing these directions, future research would enrich the empirical base underpinning Quality 4.0 and ZDM frameworks and help practitioners design more precise, context-sensitive roadmaps for integrating AI, big data, and lean tools into smart continuous improvement systems.
CONCLUSION
The study has set out to investigate how artificial intelligence, big data analytics, and lean tools have jointly supported smart continuous improvement and zero-defect manufacturing performance, and the evidence has shown that these capabilities have been most powerful when they have operated as an integrated system rather than as isolated initiatives. Using a quantitative, cross-sectional, case-study–based survey of 214 professionals from multiple manufacturing plants and functions, the research has developed reliable Likert-scale measures for AI capability, big data analytics capability, lean tools deployment, smart continuous improvement performance, and zero-defect outcomes, and has used these measures to test a set of theoretically grounded hypotheses. Descriptive analysis has shown that lean deployment and continuous improvement routines have already been at relatively high levels, while AI and big data capabilities have been at a moderate but developing stage, painting a realistic picture of plants that have been advanced in process discipline but still maturing digitally. Correlation and regression analyses have then demonstrated that all three capability dimensions—AI, analytics, and lean—have been significantly and positively associated with smart continuous improvement, with lean tools deployment emerging as the strongest single predictor. Smart continuous improvement, in

turn, has shown a robust and substantial relationship with zero-defect outcomes, confirming that the frequency, speed, and effectiveness of improvement cycles have been central to achieving lower defect rates, reduced rework and scrap, and higher first-pass yield. When all variables have been entered into an integrated regression model, smart continuous improvement has remained the dominant driver of zero-defect performance, while the direct effects of AI, analytics, and lean have been reduced but have remained positive, indicating that much of their influence has flowed through the improvement construct. In doing so, the findings have empirically validated the proposed conceptual and theoretical framework: digital and lean capabilities have functioned as key resources and enablers, smart continuous improvement has acted as the dynamic capability that has sensed problems, seized opportunities, and reconfigured processes, and zero-defect outcomes have represented the performance manifestation of this capability pipeline. At the same time, the study has acknowledged that its cross-sectional, self-reported design and its focus on plants already engaged in Industry 4.0 and lean programs have limited causal inference and generalizability, suggesting that longitudinal studies with objective defect data would be valuable extensions. Nevertheless, by quantitatively linking AI, big data, and lean tools to smart continuous improvement and zero-defect results within a single empirical model, the research has contributed both a practical diagnostic lens for manufacturing leaders and a theoretically coherent, evidence-based framework for scholars seeking to understand how smart factories have been able to move closer to the ambition of zero defects.

RECOMMENDATION

Based on the findings of this study, several practical recommendations can be made for manufacturing leaders, quality managers, and digital transformation teams who aim to move their organizations closer to zero-defect performance through smart continuous improvement. First, organizations should treat lean and continuous improvement as the *foundation* of any zero-defect and Industry 4.0 roadmap, rather than as parallel or secondary initiatives. This means systematically strengthening standardized work, visual management, error-proofing (poka-yoke), root-cause analysis routines, and structured improvement cycles (such as daily huddles, A3 problem solving, and kaizen events) before or alongside large-scale investments in AI and analytics. Second, digital and IT architects should design data and AI solutions that directly support these lean/CI routines, for example by integrating real-time defect alerts, anomaly detection, and predictive quality models into the same boards, dashboards, and workflows that teams already use to manage production and improvement activities. Rather than creating isolated analytics platforms, organizations should embed AI-driven insights into shop-floor tools like digital Andon systems, electronic standard work, and CI tracking systems so that data are immediately actionable. Third, management should invest in building *analytics literacy* and cross-functional problem-solving capability, ensuring that engineers, supervisors, and operators understand how to interpret dashboards, model outputs, and trends and how to translate them into concrete process changes; targeted training programs, joint improvement projects between IT/data teams and line teams, and formal roles such as "analytics champions" on the shop floor can help bridge this gap. Fourth, plants should adopt a balanced measurement system that tracks not only traditional quality KPIs (e.g., defects per million opportunities, first-pass yield, rework and scrap rates) but also indicators of smart continuous improvement maturity, such as the number of data-driven improvement projects initiated, closed, and sustained, the proportion of actions derived from AI/analytics insights, and the participation of cross-functional teams in CI. Fifth, implementation should follow a staged approach: start with a clear value stream or critical product family, stabilize and "lean out" the process, introduce targeted sensing and analytics where variation and defect risk are highest, and only then scale successful solutions to other lines and plants. Throughout this journey, leaders should reinforce a culture where defects are treated as learning opportunities rather than blame events, and where digital tools are explicitly framed as supports for human judgement, not replacements for it. Finally, organizations should periodically review their smart CI and ZDM strategies at the plant and corporate level, using structured audits or maturity models to identify gaps in lean deployment, data infrastructure, AI applications, skills, and governance, and then prioritize improvement efforts accordingly. By aligning lean, AI, and big data under a single smart continuous improvement strategy, and by making sure that every digital initiative is anchored in concrete quality and CI routines, manufacturing firms can significantly increase the likelihood that their investments will translate into sustained progress toward zero-defect manufacturing.

LIMITATIONS

The present study has been subject to several limitations that need to be acknowledged when interpreting and generalizing its findings. First, the research has relied on a cross-sectional survey design, which has captured AI capability, big data analytics capability, lean tools deployment, smart continuous improvement performance, and zero-defect outcomes at a single point in time. As a result, the analysis has not been able to establish definitive causal relationships or to observe how changes in digital or lean capabilities have translated into improvements in continuous improvement routines and defect performance over an extended period. Second, the data have been based on self-reported perceptions measured via Likert's five-point scale, and although reliability tests have indicated strong internal consistency, the study has remained vulnerable to common method variance, social desirability bias, and retrospective optimism, especially for constructs such as zero-defect outcomes where respondents may have overestimated performance improvements. Third, the sampling strategy has been non-probability and purposive, focusing on plants that have already been engaged in Industry 4.0 and lean initiatives; this choice has ensured relevance to the research questions but has limited the generalizability of the results to the broader population of manufacturing firms, particularly smaller organizations, firms in earlier stages of digitalization, or plants operating in different cultural and regulatory environments. Fourth, the study has not incorporated objective operational data such as actual defect counts, defects per million opportunities, rework hours, or first-pass yield extracted from manufacturing execution systems; instead, zero-defect outcomes have been operationalized through perceptual items, which has restricted the ability to cross-validate subjective assessments against hard performance indicators. Fifth, the measurement model has treated AI capability, analytics capability, lean deployment, smart continuous improvement, and zero-defect performance as relatively broad latent constructs; while this has allowed a parsimonious structural model, it has also meant that important nuances—such as differences between types of AI applications, specific analytics techniques, or individual lean tools—have not been fully captured or differentiated in the analysis. Sixth, the regression-based approach has assumed linear, additive relationships among the constructs and has not explored potential non-linear effects, interaction terms beyond those implicit in the mediation structure, or alternative model specifications that might reveal threshold effects or diminishing returns to capability investments. Finally, the study has not explicitly modeled contextual and organizational moderators such as leadership style, digital maturity level, workforce skills, or supplier integration, which may have shaped how digital and lean capabilities have actually translated into smart continuous improvement and zero-defect outcomes in different plants. These limitations have not invalidated the findings, but they have indicated that the results should be interpreted as an empirically grounded yet bounded picture of smart continuous improvement and zero-defect manufacturing within a specific set of organizations, methods, and measurement choices.

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