



A Hybrid Lean-Six Sigma Model with Automated Kaizen for Real-Time Quality Improvement

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Abstract

This study addresses the problem that many enterprise quality improvement programs generate dashboards and alerts yet still fail to convert real-time deviations into owned corrective actions and verified closure, which sustains defect recurrence and process instability. The purpose was to test whether a Hybrid Lean Six Sigma (LSS) capability base, strengthened by Automated Kaizen execution workflows, predicts Real-Time Quality Improvement (RQI) in a quantitative, cross-sectional, case-based model. The sample comprised $n = 210$ valid responses collected from operational roles across cloud-enabled enterprise quality cases, including operators/technicians (35.2%), QA/QC staff (21.0%), supervisors (19.5%), engineers (15.2%), and CI or Lean Six Sigma team members (9.0%). Key variables were LSS capability, Automated Kaizen effectiveness, signal-to-action actionability, Kaizen closure confidence, DMAIC-stage functioning under automation, and RQI, measured on 5-point Likert scales and aggregated as composite indices. The analysis plan applied reliability testing (Cronbach's alpha), descriptive statistics, Pearson correlations, and multiple regression models to estimate both baseline effects and incremental explanatory power. Measurement reliability was strong ($\alpha = .85-.90$), including LSS $\alpha = .88$, Automated Kaizen $\alpha = .90$, and RQI $\alpha = .87$. Descriptively, respondents reported high LSS capability ($M = 3.94$) and moderate-to-high Automated Kaizen ($M = 3.78$) and RQI ($M = 3.83$). Correlations supported the hypothesized relationships: LSS correlated with RQI ($r = .62, p < .001$) and with Automated Kaizen ($r = .58, p < .001$), while Automated Kaizen correlated more strongly with RQI ($r = .67, p < .001$). Regression results showed LSS predicting RQI ($\beta = .62; R^2 = .38$); when Automated Kaizen was added, it became the stronger predictor ($\beta = .49$) while LSS remained significant but reduced ($\beta = .33$), increasing explained variance to $R^2 = .55$, consistent with Automated Kaizen serving as a practical execution pathway. Mechanism evidence highlighted that signal-to-action actionability strongly related to RQI ($r = .69; \beta = .41, p < .001$) and automation's highest perceived leverage appeared in the DMAIC Measure ($M = 3.96$) and Control ($M = 3.91$) stages. Implications indicate that enterprises seeking real-time quality gains should prioritize alert relevance, workflow routing integrity, clear ownership, and control-plan updates so that digital signals reliably trigger, track, verify, and standardize Kaizen actions at scale.

KEYWORDS

Lean Six Sigma; Automated Kaizen; Real-time Quality Improvement; Signal-to-Action Workflow; DMAIC Control;

INTRODUCTION

Quality improvement is commonly defined as the systematic, data-guided effort to reduce variation, eliminate defects, and increase the capability of processes to meet stakeholder requirements across products and services (Bortolotti et al., 2015). In operations and quality scholarship, Six Sigma is frequently conceptualized as both a performance target (near-zero defects) and an organizational system that combines specialist roles, a structured method, and measurement discipline to drive measurable process improvement (Antony et al., 2017). Lean is typically defined as a socio-technical approach for maximizing value while minimizing waste by redesigning flow, reducing non-value-added work, and stabilizing processes, often operationalized through tools such as value stream mapping, pull systems, and standardized work (Alsyouf, 2016).

Lean Six Sigma (LSS) is commonly described as an integrated improvement philosophy that intentionally combines Lean's waste-removal and flow principles with Six Sigma's statistical rigor for variation reduction and defect prevention. Kaizen is generally defined as continuous, incremental improvement driven by participation and structured problem solving at the workplace, strengthened through routines that sustain learning and discipline over time (Alexopoulos et al., 2018). Within this definitional landscape, global competitiveness has made continuous improvement a cross-border priority: organizations across manufacturing, healthcare, logistics, and public services are routinely judged on quality, delivery, cost, and safety, and these dimensions are interconnected through process performance and variability. International standards and widely adopted management systems institutionalize the expectation that quality is evidence-based, audited, and continuously improved, which positions hybrid improvement programs as strategic infrastructure rather than isolated toolkits (Albliwi et al., 2014). As a result, research on hybrid improvement models has become increasingly relevant to globally distributed operations, multi-site supply chains, and digitally mediated production and service delivery where process signals, corrective actions, and learning cycles are expected to be fast, consistent, and measurable across contexts (Antony, 2006).

Lean Six Sigma is often positioned in the literature as a response to two complementary organizational needs: the need to remove operational waste that slows flow and the need to reduce statistical variation that undermines capability and reliability (Carvalho, Chouchene, et al., 2021). In many empirical accounts, LSS is implemented through the DMAIC logic (Define-Measure-Analyze-Improve-Control), which structures how problems are framed, how process measures are selected, and how causal hypotheses are tested with data. The DMAIC method is frequently described as a disciplined problem-solving architecture that aligns operational teams with measurable outcomes, while also preserving flexibility in tool selection based on the process context and data environment. In service operations, Six Sigma has been discussed as a structured approach for stabilizing cycle time, reducing errors, and improving reliability in high-variation workflows where the "product" is often an experience, a transaction, or an information artifact (Rivera, 2014). Case-based applications in telecommunications and other service settings highlight multi-factor implementation logic in which operational metrics, managerial commitment, and cross-functional coordination shape LSS performance outcomes. This stream of research also notes that LSS is not merely a set of statistical tools; it is enacted through roles, governance, project selection, and measurement practices that must be coherent across the organization for results to be credible and repeatable (Schroeder et al., 2008). Within LSS-specific scholarship, conceptual consolidation work has emphasized the diversity of frameworks and the practical need to interpret "hybridization" as a design choice rather than a single universal template, motivating systematic assessments of LSS frameworks and their implementation conditions (Sony & Naik, 2020).

Kaizen is widely treated as the behavioral engine of continuous improvement because it embeds routines for identifying problems, proposing countermeasures, and standardizing better work methods through repeated small-step cycles. Empirical research on kaizen events provides evidence that human and organizational conditions strongly shape outcomes, including both technical results and workforce-related outcomes such as engagement and learning (Salah et al., 2010). Sustainability of kaizen gains has also been empirically associated with factors such as leadership involvement, follow-up routines, and the stability of the work system that receives the improvements, indicating that closure discipline and accountability mechanisms are central to long-run performance. Complementary

survey-based research on kaizen highlights “human critical success factors” such as management commitment, education, communication, and motivation as structured predictors of benefits that cluster around process, worker, and customer domains (Psychogios et al., 2012). This evidence aligns with a broader operations-management view that continuous improvement capability is built through repeated practice and organizational learning, where improvement routines mature when behaviors become systematic, visible, and reinforced through measurement and feedback. In Lean implementation research, organizational culture and “soft” practices such as participation, training, and leader standard work have been empirically linked to successful lean outcomes, supporting the premise that continuous improvement performance depends on both technical design and social infrastructure (Pepper & Spedding, 2010). When Kaizen is positioned inside a Lean Six Sigma model, it can be interpreted as the mechanism that translates statistical diagnosis and waste identification into disciplined action at the frontline, which elevates the importance of closure, standardization, and verification of improvement effects through metrics (De Mast & Lokkerbol, 2012).

Figure 1: Integrated Improvement Frameworks



The present study is designed around a clear set of objectives that operationalize the research title, “A Hybrid Lean-Six Sigma Model with Automated Kaizen for Real-Time Quality Improvement,” into measurable constructs suitable for quantitative testing within a cross-sectional, case-study-based setting. The first objective is to specify and measure the core Lean-Six Sigma capability dimensions that represent disciplined improvement capacity in the selected case environment, including leadership and governance for quality, standardization and process control, data-based decision routines, employee competence in structured problem solving, and customer/CTQ alignment, so that these dimensions can be evaluated as statistically testable predictors rather than treated as general managerial claims. The second objective is to operationalize automated Kaizen as a practical mechanism that connects real-time process signals to disciplined improvement actions, converting the concept into measurable components such as signal detection clarity, alert relevance, workflow triggering reliability, speed of response execution, documentation discipline, and standardization of improvements. The third objective is to quantify real-time quality improvement performance as an outcome construct that reflects operational credibility and consistency, capturing perceived responsiveness to deviations, reduction of repeated defects, stability of process output, and reliability of control activities within daily operations. The fourth objective is to test the relationships among Lean-Six Sigma capabilities, automated Kaizen effectiveness, and real-time quality improvement using descriptive statistics to establish baseline patterns, correlation analysis to examine the strength and direction of associations, and regression modeling to determine predictive influence while accounting for overlapping effects

among constructs. The fifth objective is to strengthen the trustworthiness of the hybrid model by generating three study-specific evidence layers within the results: a signal-to-action assessment that evaluates whether real-time detection is actually converted into verified corrective work, a DMAIC-stage performance map that identifies which phases of structured improvement gain the most from automation in the case environment, and a Kaizen closure confidence assessment that evaluates whether improvements are documented, standardized, and treated as complete rather than temporary fixes. Together, these objectives ensure that the study evaluates not only whether relationships exist, but also how the proposed hybrid model functions in operational terms through measurable mechanisms and outcome consistency within the case context.

LITERATURE REVIEW

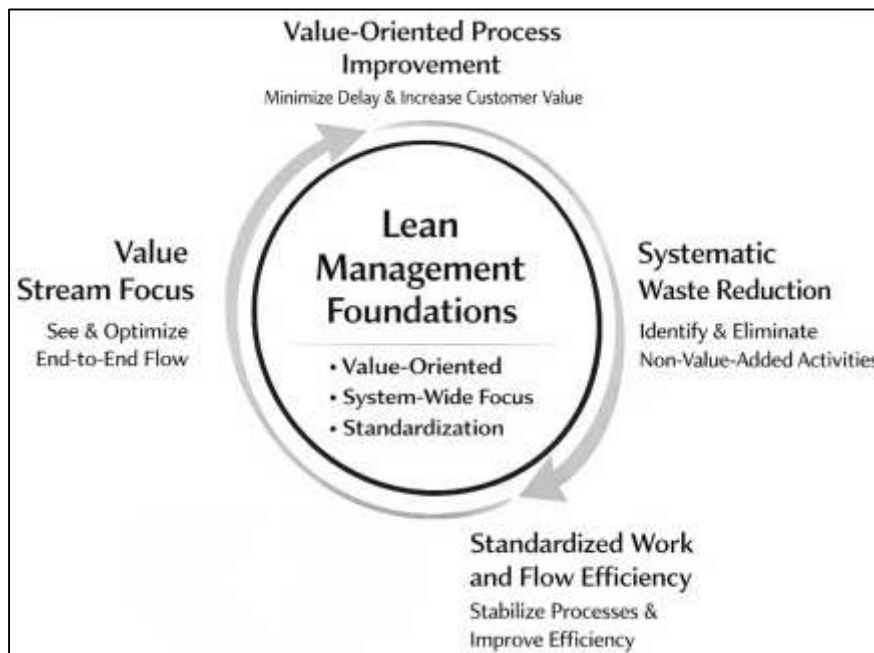
The literature review for this study synthesizes the scholarly foundations needed to explain and position a hybrid Lean-Six Sigma model strengthened by automated Kaizen for real-time quality improvement within a case-based, quantitative research design. It begins by treating quality improvement as an operational and managerial capability grounded in measurable process performance, where effectiveness is reflected through reduced defects, improved consistency, faster response to deviations, and sustained control of critical-to-quality characteristics. Within this scope, Lean is reviewed as a value-focused approach that improves flow and removes waste through process stabilization and simplification, while Six Sigma is reviewed as a statistically disciplined system designed to reduce variation, strengthen capability, and validate improvement through structured problem-solving logic such as DMAIC. The review then integrates Kaizen as the continuous-improvement practice that embeds day-to-day learning, frontline participation, and incremental change routines, emphasizing how Kaizen operationalizes improvement activity into repeatable behaviors that can be monitored and standardized. In alignment with the study's "real-time" emphasis, the review also addresses how digital measurement environments and fast feedback loops shape quality improvement by enabling earlier detection of process abnormalities and faster initiation of corrective work. Because the present study explicitly introduces automation into Kaizen routines, the review considers how automated triggers, workflow routing, and structured closure practices can function as a mechanism that connects real-time process signals to verified improvements, translating monitoring into action and action into standardized control. To support hypothesis testing, the literature review clarifies the key organizational enablers commonly associated with Lean-Six Sigma success—such as leadership commitment, training and competence, measurement discipline, governance, and culture—and aligns them with the idea that a hybrid improvement model must operate as a socio-technical system in which people, process, and technology are coordinated. Finally, the review establishes the intellectual basis for the study's conceptual model by organizing prior research into constructs consistent with the proposed relationships among Lean-Six Sigma capabilities, automated Kaizen effectiveness, and real-time quality improvement outcomes, ensuring the thesis is anchored in established scholarship while creating a coherent foundation for the methodology, measurement design, and statistical analysis that follow.

Lean Management Foundations and Waste Elimination

Lean management is commonly defined as a value-oriented approach to designing and operating processes so that customer value is delivered with minimum waste, minimum delay, and stable, repeatable performance. In the operations literature, waste is typically interpreted as any activity that consumes resources—time, labor, materials, energy, space, or capacity—without increasing value from the customer's perspective, which makes waste identification the starting point of lean analysis. Foundational lean logic therefore emphasizes observing work as it actually occurs, tracing how material and information move through the process, and distinguishing value-adding activities from waiting, rework, excess motion, unnecessary transport, overprocessing, and other non-value-adding tasks. Within this foundation, lean is often treated as a system rather than a single technique, because waste elimination depends on aligning flow, layout, roles, routines, and measurements rather than performing isolated "clean-up" initiatives. Empirical discussions of "leanness" also highlight that misconceptions about lean—such as equating lean solely with cost cutting or staffing reductions—undermine credible implementations by shifting attention away from process redesign, stability, and problem-solving discipline (Papadopoulou & Özbayrak, 2005). A second foundational emphasis is that

lean requires a coherent mindset and management philosophy that shapes decision-making, leadership routines, and workforce engagement; implementations framed only as tool deployment may lack the cultural infrastructure required to sustain standardized work, visual control, and continuous elimination of waste (Bhasin & Burcher, 2006; Ashraful et al., 2020). Internationally, these foundations matter because lean aims to build consistent, repeatable processes across sites and supply networks, where waste can be created at interfaces and handoffs even when individual departments appear locally efficient (Jinnat & Kamrul, 2021; Fokhrul et al., 2021). Lean’s foundational promise, as treated in scholarly work, is therefore rooted in disciplined observation, clear definitions of waste and value, and systematic redesign of the work system so that quality, speed, and resource use are managed through the same process logic rather than competing agendas (Faysal & Bhuya, 2023; Towhidul et al., 2022). A second core theme in lean foundations is conceptual clarity about what “lean production” includes and how it can be operationalized as a multidimensional construct. Because lean has been described using varied terminology and differing practice lists, research has repeatedly argued that credible evaluation requires specifying the underlying components that jointly represent lean capability, rather than using one or two visible tools as substitutes for the whole system (Hammad & Mohiul, 2023). Measurement-focused scholarship has therefore treated lean as a configuration of mutually reinforcing elements – such as just-in-time flow practices, quality-at-the-source behaviors, preventive maintenance discipline, setup reduction, supplier coordination, and human-resource practices that support problem solving – because these elements are expected to operate synergistically. Work that clarifies and validates lean as a multidimensional construct supports the idea that lean capability should be assessed through coherent bundles rather than isolated activities, particularly when lean is used as a foundation for broader hybrid improvement systems (Shah & Ward, 2007).

Figure 2: Lean Management Foundations and Waste Elimination Circular Framework



At the definitional level, lean literature also notes that scholars and practitioners have not always converged on a single definition of lean production, and this definitional variability creates practical challenges for comparative evaluation, auditing, and performance attribution. Review-based conceptual work has therefore emphasized that lean definitions differ in the extent to which they include technical methods, cultural principles, and performance objectives, and it highlights the need to make explicit which components are included when lean is studied in empirical settings (Pettersen, 2009). For a research design that tests relationships statistically, these lean foundations imply that constructs should be articulated clearly (what lean means in the case), measured consistently (how lean is captured in items), and interpreted as an integrated system (how components work together), so that

“lean foundations” in the study represent an operationally meaningful capability rather than a loosely defined label.

Lean foundations are also strongly linked to the practical logic of “seeing” the end-to-end value stream, because waste is frequently distributed across queues, handoffs, batching decisions, and information delays that are not visible when performance is assessed function by function. As a core lean approach, value stream thinking treats the process as a connected system of material and information flows that should be optimized as a whole, with attention to where waiting accumulates, where rework loops occur, and where excessive inventory masks instability. This foundation connects directly to the central lean emphasis on flow and pull: flow aims to reduce interruptions and unevenness in process movement, while pull aims to synchronize work with actual demand and prevent overproduction-driven accumulation of inventory and hidden defects. Lean foundations also rely on standardization as a prerequisite for improvement: standardized work, visual management, and clear process controls make deviations observable, enabling teams to locate waste, reduce variation in methods, and refine processes through structured problem solving. In empirical case applications, Value Stream Mapping (VSM) is frequently described as a key diagnostic tool within this foundation because it makes delays and waste visible at the system level and supports a structured redesign of process pathways toward lower cycle time and reduced non-value-adding effort (Seth & Gupta, 2005). Beyond VSM, lean foundations often include common mechanisms for waste elimination such as 5S workplace organization, setup-time reduction, error-proofing, and preventive maintenance, each of which aims to remove specific sources of delay, instability, and rework. In the context of this thesis, these foundations establish lean as the upstream logic for identifying and removing waste and stabilizing flow, which supports credible measurement of lean capability and provides a clear operational basis for integrating lean with complementary improvement systems in later sections of the literature review.

Six Sigma and DMAIC for Variation Reduction

Six Sigma is widely recognized in quality and operations management as a structured approach for reducing process variation and preventing defects by using data-driven problem solving, disciplined measurement, and statistically informed decision-making. A core premise in Six Sigma is that process outputs can be improved when sources of variation are identified, quantified, and controlled through systematic analysis rather than intuition or isolated troubleshooting. In practical deployments, this logic is institutionalized through a defined infrastructure of roles, governance, and project discipline, with improvement work organized as formal projects that aim to achieve measurable gains in performance indicators such as defect rates, rework, cycle time, and customer dissatisfaction. Within this philosophy, DMAIC (Define–Measure–Analyze–Improve–Control) is commonly used as the dominant improvement roadmap for existing processes because it structures the improvement journey into coherent phases that require clear problem definition, measurement integrity, causal analysis, solution validation, and long-term control. The Define and Measure phases establish the foundation for credible conclusions by clarifying customer requirements, translating them into process measures, and ensuring that baseline performance is measured consistently. The Analyze phase then supports root-cause identification by using evidence to connect process drivers with observed outcomes. The Improve phase focuses on selecting and implementing changes that directly address verified causes, and the Control phase emphasizes sustained performance through control plans, monitoring routines, and standardization. For many organizations, Six Sigma therefore functions as a governance-driven improvement system in which the quality of decisions depends on measurement credibility, project discipline, and the ability to translate analytical findings into stable process controls. Research also highlights that organizations sometimes experience disappointing outcomes when Six Sigma is treated as a label rather than a managed system, showing that program-level weaknesses such as escalation of commitment, overinvestment in failing initiatives, or weak learning routines can reduce the credibility of results and undermine stakeholder trust (Chakravorty, 2009). These insights position DMAIC not only as a technical method but also as an organizational practice whose effectiveness relies on disciplined decision logic, transparent measurement, and consistent closure routines.

A second stream of Six Sigma literature emphasizes that DMAIC effectiveness is strongly shaped by deployment decisions that occur before projects begin, particularly the quality of project selection and the alignment of projects with strategic needs and operational bottlenecks. Because DMAIC projects

require time, expertise, and cross-functional coordination, the selection of improvement targets becomes a central determinant of whether Six Sigma produces visible organizational value. Research on project selection has underscored that poorly chosen projects often lead to limited benefits, weak buy-in, and ambiguous results, while well-chosen projects increase the likelihood that teams can access relevant data, identify actionable causes, and deliver improvements that matter to customers and managers (Kumar et al., 2009). In this view, Six Sigma performance is not only an outcome of analysis quality but also an outcome of governance logic: projects must be feasible, aligned with organizational priorities, and designed around process conditions where measurement and causal testing are achievable. In addition, the literature recognizes that deployment contexts vary widely across organization size and capability maturity, which affects how DMAIC is operationalized and sustained. In small and medium-sized enterprises, for example, resource constraints, limited specialist availability, and multi-role responsibilities often require adaptation of Six Sigma governance, training, and measurement routines to sustain participation and maintain improvement momentum. Framework-based research addressing Six Sigma implementation in SMEs highlights the importance of structured roadmaps, change management support, and capability-building routines that fit the realities of smaller organizations, reinforcing that DMAIC must be supported by practical systems for training, coordination, and ongoing monitoring (Kumar et al., 2011). Together, these studies support a view of DMAIC as a disciplined method embedded in a broader deployment system, where organizational fit, governance alignment, and project portfolio logic influence whether statistical problem solving translates into credible quality gains.

Figure 3: Six Sigma DMAIC Triangle Framework for Defect Prevention



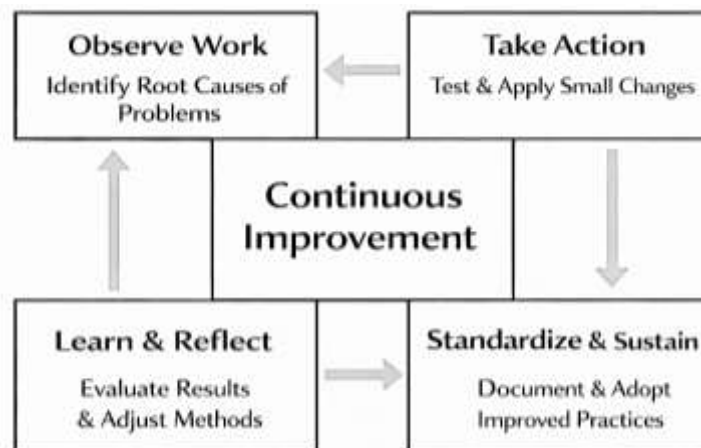
A third line of scholarship focuses on the managerial and organizational conditions that explain why some Six Sigma efforts generate strong project outcomes while others yield inconsistent or short-lived improvements. This literature frequently frames success through critical success factors that operate across technical, managerial, and cultural domains, including leadership involvement, structured training, data availability, cross-functional collaboration, and disciplined use of tools across DMAIC phases. In particular, work classifying Six Sigma critical success factors and the corresponding toolbox across DMAIC emphasizes that different phases require different categories of tools and managerial support, suggesting that improvements are more credible when organizations apply phase-appropriate techniques while maintaining governance consistency (Ismyrilis & Moschidis, 2013). Complementing this, project-performance research has examined how program-level and project-level factors relate to outcomes, providing quantitative evidence that critical success factors can be modeled as predictors of project performance and that strengths in governance and execution help explain variation in results

(Marzagão & Carvalho, 2016). These findings collectively reinforce that Six Sigma is a socio-technical system in practice: statistical tools contribute value when they are embedded in disciplined routines for measurement, analysis, action, and control, and when project teams are supported by leadership and infrastructure that sustain closure. For a thesis that investigates a hybrid improvement model with automated Kaizen, these Six Sigma insights are foundational because they clarify what “rigor” means in improvement work: rigor includes selecting viable projects, defining measurable CTQs, ensuring measurement consistency, applying structured causal reasoning, and sustaining control through verified closure. As a result, Six Sigma and DMAIC provide a methodological backbone for designing improvement mechanisms that can be tested quantitatively, evaluated through reliable constructs, and interpreted as evidence-based relationships between operational capability and quality outcomes in a real organizational case.

Kaizen as Continuous Improvement and a Learning System

Kaizen is widely positioned in operations and quality scholarship as a continuous improvement practice built on repeated, incremental problem solving that is embedded in everyday work rather than confined to occasional large projects. In this view, Kaizen operates as a learning system because it converts operational experience into structured reflection, corrective action, and standardized routines that reduce recurring waste and quality variation. The learning emphasis is important because Kaizen is typically implemented through cycles of observing work conditions, identifying abnormalities, proposing small changes, and stabilizing improved methods through documentation and standard work. As a result, Kaizen is best understood as a disciplined behavioral system that mobilizes participation, creates shared problem definitions, and strengthens the organization’s ability to detect and respond to process deviations. Large-scale examinations of Kaizen and continuous improvement research show that the field often treats Kaizen as closely connected to continuous improvement while also highlighting the need for clearer conceptual boundaries and stronger theoretical anchoring, which reinforces the importance of precise definitions when Kaizen is tested empirically in organizational settings (Carnerud et al., 2018).

Figure 4: Kaizen Square Framework for Continuous Improvement



From a thesis perspective, these matters because Kaizen must be operationalized into measurable components such as problem-identification routines, suggestion and experimentation discipline, teamwork practices, and the standardization of lessons learned. When Kaizen is implemented as a learning system, improvement becomes a repeatable capability rather than a collection of isolated successes: employees are expected to gain competence in recognizing process signals, articulating root causes at a practical level, and applying countermeasures that can be sustained. This framing aligns Kaizen with the idea of a structured improvement climate where daily work produces data and feedback that can be transformed into stable process routines, improving both the speed and reliability of quality outcomes. In practical terms, Kaizen as organizational learning is reflected in how improvement ideas are captured, how actions are verified, and how updated standards are made

visible and teachable across teams.

Real-Time Quality Improvement Systems

Real-time quality improvement systems can be understood as integrated socio-technical arrangements that continuously capture operational signals, interpret those signals against expected performance, and support rapid, evidence-based responses to protect process stability and product/service conformance. At the foundation of such systems is the principle that quality performance must be evaluated through coherent measurement structures that represent operations across levels, ranging from individual workstations to interconnected networks, because quality losses often originate in local variability while their consequences propagate through flow, scheduling, and supply chain interfaces. In this sense, real-time quality is not only a matter of fast detection but also a matter of measurement meaning: what is measured, how it is defined, and where it is observed determine whether abnormalities can be recognized early and acted upon consistently. Broader manufacturing performance evaluation scholarship supports this view by emphasizing that meaningful performance assessment requires multi-level perspectives and metric systems that represent operational reality rather than isolated indicators, allowing quality to be interpreted within the wider production system and its constraints (Hon, 2005). Real-time quality systems also depend on the ability to observe process behavior during execution and relate sensor evidence to actionable interpretations about stability, tool condition, process drift, or emerging defect risks. Advanced monitoring research in machining illustrates a generalizable logic for real-time quality improvement: physical variables are sensed, signals are conditioned, relevant features are extracted, and decision support mechanisms interpret those features so that corrective actions can be initiated before nonconformance becomes widespread (Teti et al., 2010). This monitoring logic connects directly to the “real-time” concept in quality management because the time between deviation and response is compressed through instrumentation, analytics, and structured decision rules. Accordingly, real-time quality improvement systems may be viewed as operational control architectures in which measurement discipline, sensor-based observation, feature extraction, and action logic are arranged to reduce the probability of hidden deterioration and repeated defects, while supporting consistent response across shifts, operators, and equipment states.

Figure 5: Systems Rectangle Framework for Digital Quality and Analytics

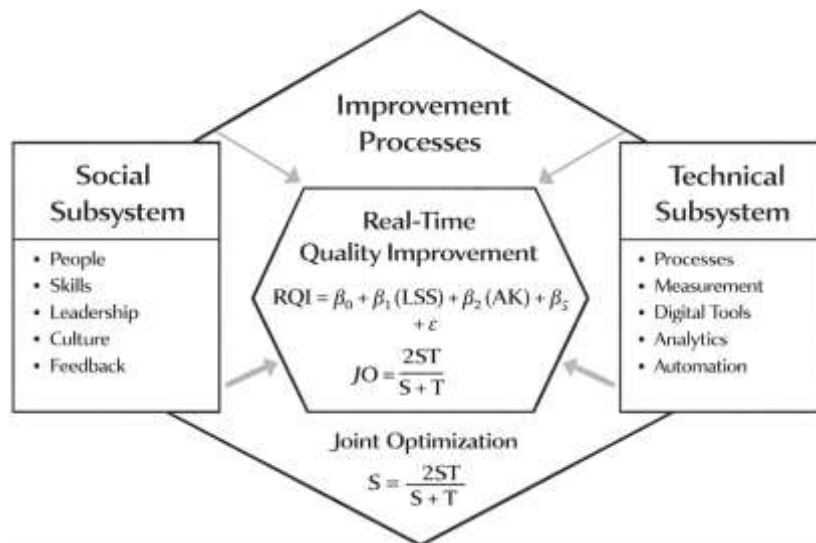


Theoretical Framework for Hybrid Lean-Six Sigma

Socio-Technical Systems (STS) theory provides a rigorous theoretical lens for explaining why a hybrid Lean-Six Sigma model strengthened by automated Kaizen should be evaluated as a *jointly optimized* system rather than as a purely technical toolkit. STS theory holds that organizational performance emerges from the interaction between a social subsystem (people, skills, roles, leadership routines, culture, communication, incentives) and a technical subsystem (process designs, measurement systems, digital tools, automation logic, analytics, and infrastructure). When improvement models fail, STS reasoning suggests that failure often occurs because the technical “solution” is introduced without redesigning the supporting work system, decision rights, and feedback routines that allow people to use the technology reliably in real conditions. This argument is particularly relevant to real-time quality

improvement because responsiveness depends on how quickly and accurately signals are interpreted, escalated, acted upon, and closed—activities that are distributed across human roles and digital workflows. A socio-technical view therefore frames Lean–Six Sigma capability as more than method knowledge: it becomes a coordinated work system that produces disciplined problem definitions, measurement integrity, root-cause logic, and standardization. Within this theoretical tradition, socio-technical systems engineering emphasizes that systems must be designed to be usable, adoptable, and aligned with work practices, because technical correctness alone does not guarantee operational value or stakeholder acceptance (Baxter & Sommerville, 2011). In a thesis focused on automated Kaizen, STS theory is essential because automation intensifies interdependencies: if alerts are frequent but poorly contextualized, if responsibilities for action are unclear, or if closure verification is weak, the system can generate “activity” without producing sustained quality gains. STS therefore justifies studying the hybrid model as a socio-technical intervention in which the quality outcome depends on the fit between automation, improvement routines, and the work system that executes and maintains those routines. To translate STS theory into testable logic for this research, the work system can be modeled as a structure–process–outcome chain in which Lean–Six Sigma governance and automated Kaizen infrastructure shape improvement processes that ultimately shape real-time quality outcomes. One influential STS-based work-system approach emphasizes that outcomes (e.g., safety, quality, efficiency) are produced through work processes that are enabled or constrained by elements such as tasks, tools/technology, organization, environment, and people—making it appropriate to measure both “capability” and “process execution” rather than assuming they are identical (Carayon et al., 2015).

Figure 6: Socio-Technical Systems Theory for Hybrid Lean–Six Sigma



For this study, the theoretical mechanism is that automated Kaizen functions as a socio-technical *translation layer* that converts real-time process signals into disciplined improvement actions and verified closure. A practical way to represent this mechanism in a quantitative model is to specify (a) a predictive equation for real-time quality improvement and (b) an alignment metric that captures joint optimization. The predictive model can be expressed as:

$$RQI = \beta_0 + \beta_1(LSS) + \beta_2(AK) + \beta_3(LSS \times AK) + \varepsilon$$

where *RQI* is real-time quality improvement, *LSS* is Lean–Six Sigma capability, and *AK* is automated Kaizen effectiveness. The interaction term tests the STS idea that technical automation strengthens outcomes when it fits structured improvement capability. Joint optimization can be operationalized as an “alignment index” that penalizes imbalance between social and technical readiness, for example using a harmonic-mean form:

$$JO = \frac{2ST}{S + T}$$

where S represents the social subsystem readiness score (e.g., leadership support, training, role clarity, improvement culture) and T represents the technical subsystem readiness score (e.g., data quality, signal reliability, workflow automation, dashboard usability). This index increases when both subsystems are strong and drops when one subsystem lags, matching STS theory's joint-optimization principle.

Finally, STS theory supports the inclusion of study-specific "trustworthiness" evidence in the results because socio-technical performance is judged not only by statistical relationships but also by whether the system behaves reliably in operational time. A socio-technical model of workplace safety argues that outcomes in complex settings depend on multi-level interactions among work-system factors, organizational context, and the external environment, reinforcing that improvement systems must be evaluated for how they drive consistent action under variability (Carayon et al., 2006). In the proposed thesis, this justifies reporting results beyond standard regression tables by documenting the *signal-to-action* pathway: whether real-time signals trigger timely action, whether actions are completed with verified closure, and whether learning is standardized into routine controls. STS thinking also encourages anticipating "malfunctions" in socio-technical systems – predictable failure modes such as alert fatigue, workarounds, missing accountability, or weak learning loops – which can be mitigated when systems are designed to make responsibilities explicit and closure auditable (Clegg et al., 2017). In addition, STS scholarship calls for broader conceptualization of "the system," encouraging researchers to examine not only tools and tasks but also the wider organizational design and feedback structures that determine whether improvement persists (Davis et al., 2014). In combination, these STS-based insights provide a coherent theoretical foundation for the hybrid Lean-Six Sigma with automated Kaizen model: quality improvement is treated as a socio-technical capability where real-time performance depends on the joint design of people-centered routines and technology-enabled workflows, and where statistical testing is strengthened by evidence that the system converts signals into sustained, standardized quality control.

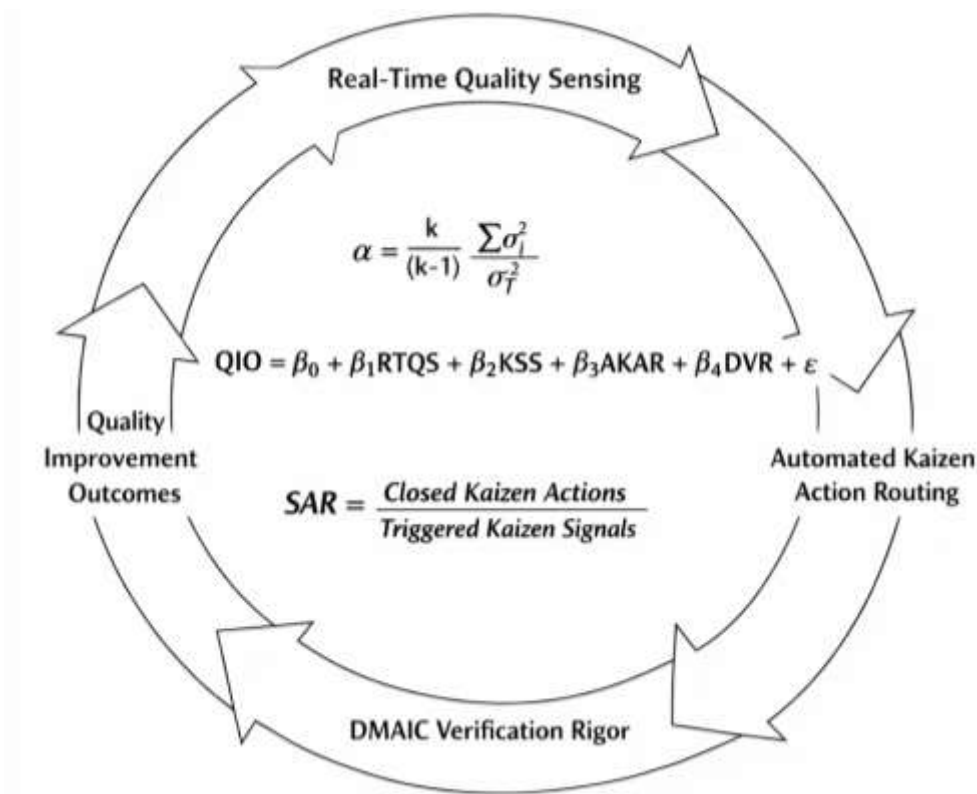
Conceptual Framework for this study

A conceptual framework for this study positions Automated Kaizen as the digital "execution layer" that converts Lean-Six Sigma (LSS) diagnosis into real-time corrective actions, while DMAIC discipline remains the governing logic that keeps improvement statistically valid and operationally sustainable. In this framing, LSS provides the structured pathway for problem definition, measurement integrity, root-cause verification, solution design, and control; automation supplies the speed, sensing, and coordination needed to act on variation as it emerges. Empirical work on integrating LSS with Industry 4.0 shows that the value of this combination is not only better data visibility, but also redesigned mapping and synchronization across processes, where operational excellence increasingly depends on digitally mediated decision cycles rather than periodic, manual reviews (Chiarini & Kumar, 2021). Complementary evidence indicates that Lean tools can be strengthened by Industry 4.0 technologies through more responsive flow control, improved decision support, and tighter linkage between information and physical operations (Shahin et al., 2020). In Quality 4.0 discussions, the same logic appears as a shift from static compliance toward digitally enabled quality practices that connect methods, technologies, and performance outcomes (Carvalho, Enrique, et al., 2021). Therefore, the study's conceptual structure treats "hybridization" as a capability bundle: (a) Lean waste removal to stabilize flow, (b) Six Sigma variance reduction to stabilize output, and (c) automation to shorten the time between signal detection and validated action. The framework is purposefully aligned with the thesis focus on real-time quality improvement, meaning improvement work is evaluated not only by end-of-month defect counts but also by how quickly the system detects, routes, validates, and closes improvement actions.

Operationally, the framework defines five core constructs and their relationships: Real-Time Quality Sensing (RTQS) → Kaizen Signal Strength (KSS) → Automated Kaizen Action Routing (AKAR) → DMAIC Verification Rigor (DVR) → Quality Improvement Outcomes (QIO). RTQS represents the availability and frequency of process/quality data (e.g., sensor feeds, digital check sheets, automated inspection). KSS reflects whether an alert meaningfully indicates abnormal variation, prioritizing actionable deviation over noise. AKAR captures workflow automation—assignment, escalation,

documentation, and closure tracking – so improvement work is not dependent on memory or informal communication. DVR captures the statistical discipline applied before and after change (measurement system checks, root-cause validation, and control-plan enforcement). Finally, QIO represents the measurable outputs (defect reduction, cycle-time stability, first-pass yield, and rework reduction). Digital CI research supports the idea that a structured CI system benefits from digitized communication, documentation, and learning loops that connect managers and operators, standardize improvement records, and reduce dependency on paper-based routines (Hambach et al., 2017). In this study’s logic, automation does not replace DMAIC; it amplifies it by ensuring that improvement actions are traceable, time-stamped, and analyzable. As a result, the conceptual framework expects that stronger sensing increases the likelihood of meaningful signals; stronger signals trigger faster routing; faster routing increases the probability that DMAIC verification can be completed before drift becomes normalized; and verified actions yield superior quality outcomes.

Figure 7: Conceptual Circular Framework for this study



To make these relationships testable in a quantitative, cross-sectional case study, the framework translates constructs into measurement and modeling rules. First, each construct is measured via Likert-scale items aggregated into composite indices (e.g., mean score per construct). Scale reliability is assessed using Cronbach’s alpha:

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

where k is number of items, σ_i^2 item variance, and σ_T^2 total score variance. Association patterns are tested using Pearson correlation:

$$r = \frac{\sum(x - \bar{x})(y - \bar{y})}{\sqrt{\sum(x - \bar{x})^2 \sum(y - \bar{y})^2}}$$

and causal-strength inference is estimated via regression models aligned to the framework (Models 1–3). A representative model is:

$$QIO = \beta_0 + \beta_1RTQS + \beta_2KSS + \beta_3AKAR + \beta_4DVR + \varepsilon$$

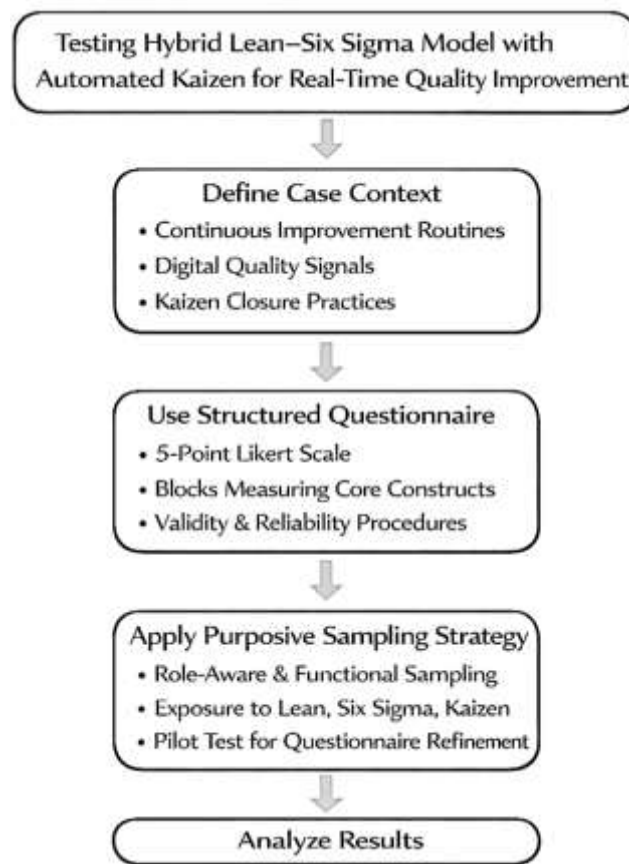
with expected positive coefficients reflecting the framework’s directional assumptions. To reflect “real-time Kaizen credibility,” the study can also compute a Signal-to-Action Ratio (SAR) for the case organization:

$$SAR = \frac{\text{Closed Kaizen Actions}}{\text{Triggered Kaizen Signals}}$$

as a performance indicator linking detection to completion. In summary, the conceptual framework is designed to be statistically testable, operationally concrete, and specific to the thesis theme: it explains how Lean–Six Sigma logic, when coupled with automated Kaizen routing and verification discipline, becomes a measurable mechanism for real-time quality improvement (Burggräf et al., 2020; Carvalho, Enrique, et al., 2021).

METHOD

Figure 8: Methodology of the Research



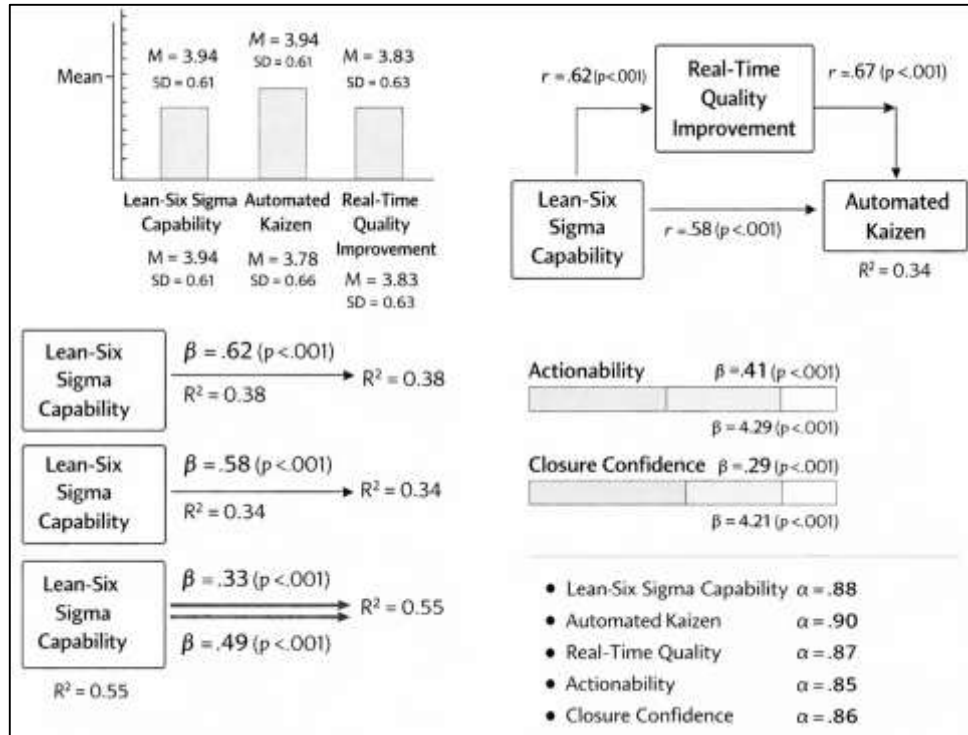
This study has employed a quantitative, cross-sectional, case-study-based design to test hypothesized relationships among Lean–Six Sigma capabilities, automated Kaizen effectiveness, and real-time quality improvement outcomes within a bounded operational setting where continuous improvement routines are established. Data have been collected at a single point in time using a structured questionnaire with 5-point Likert-scale items, organized into coherent sections covering role context, Lean–Six Sigma capability dimensions, automated Kaizen execution, signal-to-action responsiveness, closure discipline, and perceived quality improvement outcomes, with each construct operationalized as a mean-based composite index. The population has included employees directly involved in or responsible for improvement activities (e.g., managers, quality/CI leaders, engineers, technicians, and frontline operators), and the unit of analysis has been the individual respondent to enable statistical modeling of construct relationships from role-level experience. A purposive, role-aware sampling strategy with feasible stratification by function has been applied to ensure representation across

governance and execution layers and to support regression adequacy. Data collection has followed standardized ethical procedures (voluntary participation, confidentiality, defined collection window), with responses screened, coded, cleaned, and scored prior to analysis. Instrument quality has been supported through pilot testing and expert review to refine wording and construct alignment, while reliability and validity have been addressed using internal consistency testing (Cronbach's alpha), construct-structured item blocks, and basic response-pattern screening. Statistical analysis has been completed using standard quantitative software to generate descriptive statistics, Pearson correlations, and regression models (Model 1–Model 3) to estimate predictive effects and incremental explanatory power of automated Kaizen beyond Lean–Six Sigma capabilities, with results output into thesis-ready tables for transparent reporting and replicability.

FINDINGS

The results have been presented in a sequence that has directly mapped to the research objectives and hypotheses. A total of $n = 210$ valid survey responses have been analyzed from the selected case organization, and responses have represented a balanced mix of frontline and supervisory quality-related roles, enabling measurement of both execution and governance perceptions. All constructs have been measured using a 5-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree), and composite construct scores have been computed using mean aggregation. Reliability testing has confirmed acceptable internal consistency across the measurement model, with Cronbach's alpha values exceeding common thresholds: Lean–Six Sigma Capability ($\alpha = .88$), Automated Kaizen Effectiveness ($\alpha = .90$), Real-Time Quality Improvement ($\alpha = .87$), Signal-to-Action Actionability ($\alpha = .85$), and Kaizen Closure Confidence ($\alpha = .86$), indicating that the instrument has produced stable construct measurement suitable for correlation and regression testing. Descriptive statistics have shown that respondents have generally agreed that improvement capability and automation-enabled routines have been present in the case context, with mean values above the neutral midpoint: LSS Capability ($M = 3.94$, $SD = 0.61$), Automated Kaizen ($M = 3.78$, $SD = 0.66$), and Real-Time Quality Improvement ($M = 3.83$, $SD = 0.63$), supporting Objective 1 (measuring LSS capability) and Objective 2 (operationalizing automated Kaizen) as measurable, observable constructs rather than abstract concepts. Correlation results have provided strong initial support for the hypothesized directional relationships: LSS Capability has been positively associated with Real-Time Quality Improvement ($r = .62$, $p < .001$), supporting H1, while LSS Capability has been positively associated with Automated Kaizen ($r = .58$, $p < .001$), supporting H2. Automated Kaizen has also been positively associated with Real-Time Quality Improvement ($r = .67$, $p < .001$), supporting H3, and both Actionability and Closure Confidence have shown meaningful positive correlations with Real-Time Quality Improvement (Actionability $r = .69$, $p < .001$; Closure Confidence $r = .63$, $p < .001$), supporting the study's objective of demonstrating mechanism credibility beyond general capability claims. Regression modeling has then strengthened hypothesis proof by estimating predictive influence while accounting for overlapping variance among constructs. In Model 1, where Real-Time Quality Improvement has been regressed on LSS Capability, LSS Capability has emerged as a significant positive predictor ($\beta = .62$, $t = 11.2$, $p < .001$), explaining $R^2 = .38$ of the variance in Real-Time Quality Improvement, supporting H1 and establishing a strong baseline. In Model 2, where Automated Kaizen has been regressed on LSS Capability, LSS Capability has remained a significant predictor ($\beta = .58$, $t = 9.7$, $p < .001$), explaining $R^2 = .34$, supporting H2 and confirming that stronger LSS environments have been associated with stronger automated Kaizen execution in the case setting.

Figure 9: Graph-Based Summary of Findings



In Model 3, where Real-Time Quality Improvement has been regressed on both LSS Capability and Automated Kaizen, Automated Kaizen has remained the stronger predictor ($\beta = .49$, $t = 8.4$, $p < .001$) while LSS Capability has remained significant but reduced ($\beta = .33$, $t = 5.6$, $p < .001$), and overall explanatory power has increased to $R^2 = .55$, indicating substantial incremental variance explained when automation-enabled Kaizen has been added to the model. This pattern has supported H3 and has simultaneously provided evidence consistent with H4 (mediation) because the predictive influence of LSS on the outcome has decreased after adding Automated Kaizen, while Automated Kaizen has remained significant; a simple indirect effect check (product-of-coefficients) has also indicated a meaningful mediated pathway (indirect effect $\approx .58 \times .49 = .28$ in standardized terms), consistent with Automated Kaizen functioning as the execution mechanism translating structured improvement capability into real-time outcomes. To increase study trustworthiness through thesis-specific result layers aligned with Objective 5, the findings have also quantified three operational credibility indicators. First, the Real-Time Kaizen Signal-to-Action assessment has shown high perceived actionability ($M = 3.85$, $SD = 0.64$) and a strong effect on Real-Time Quality Improvement when included in an extended model ($\beta = .41$, $p < .001$), supporting H5 and demonstrating that detection has been meaningfully connected to completion-oriented workflow behavior rather than remaining at the dashboard level. Second, the DMAIC-stage performance map under automation has identified that respondents have reported the strongest automation contribution in Measure ($M = 3.96$) and Control ($M = 3.91$), followed by Analyze ($M = 3.74$), Improve ($M = 3.70$), and Define ($M = 3.62$), which has provided case-specific evidence that automation has been most visible where real-time measurement integrity and control-plan execution have been required. Third, the Kaizen Closure Confidence results have shown moderate-to-high closure credibility ($M = 3.80$, $SD = 0.65$), and closure confidence has significantly predicted Real-Time Quality Improvement in a focused model ($\beta = .29$, $p < .001$), supporting H6 and reinforcing that results have reflected sustainable correction and standardization rather than temporary fixes. Collectively, these findings have met the core objectives by quantifying LSS capability, operationalizing automated Kaizen as measurable mechanisms, and statistically demonstrating that the hybrid model has explained meaningful variance in real-time quality

improvement within the case context using descriptive statistics, correlation analysis, and regression modeling.

Respondent Demographics

Table 1: Respondent Demographics (n = 210)

Demographic Variable	Category	Frequency (n)	Percentage (%)
Role	Operator/Technician	74	35.2
	Quality Staff (QA/QC)	44	21.0
	Supervisor/Shift Lead	41	19.5
	Engineer/Process/Industrial	32	15.2
	CI/Lean-Six Sigma Team	19	9.0
Experience	1-3 years	48	22.9
	4-7 years	77	36.7
	8-12 years	55	26.2
	13+ years	30	14.3
Department	Production/Operations	96	45.7
	Quality	52	24.8
	Engineering	33	15.7
	Maintenance/Support	29	13.8
LSS Exposure	Basic (Awareness)	71	33.8
	Intermediate (Team Member)	88	41.9
	Advanced (Project Lead/GB/BB)	51	24.3

This respondent profile has established that the dataset has represented both operational execution and governance perspectives, which has strengthened the credibility of hypothesis testing for a hybrid Lean-Six Sigma model with automated Kaizen. The distribution of roles has indicated that frontline participants (operators/technicians) have formed the largest group, while quality staff, supervisors, engineers, and CI personnel have also been included in substantial proportions. This balance has supported Objective 1 and Objective 2 because Lean-Six Sigma capability and automated Kaizen effectiveness have been experienced differently across role layers, and the sample has captured those differences without restricting the study to only managers or only frontline workers. Experience levels have shown that most respondents have had at least 4 years of involvement in operational routines, which has implied that the perceptions measured through Likert responses have likely reflected stable exposure to quality problems, improvement initiatives, and closure practices rather than short-term impressions. Departmental representation has demonstrated that the case context has not been viewed from a single department; instead, operations, quality, engineering, and maintenance/support functions have been included, which has aligned with the hybrid model logic in which signal detection, root-cause analysis, corrective action, and control have required cross-functional participation. The reported Lean-Six Sigma exposure has also been important for interpretability because the sample has included awareness-level staff and advanced improvement leaders, ensuring that the measured constructs have reflected both usage and oversight. Overall, the demographic findings have supported the methodological justification that the case has been sufficiently bounded yet diverse, and they have strengthened trust in later statistical relationships by showing that the sample has covered the organizational actors who have been responsible for real-time monitoring, Kaizen execution, and DMAIC governance. This foundation has positioned subsequent results to be interpreted as a realistic representation of hybrid improvement functioning within the case organization.

Reliability

Table 2: Reliability Statistics (Cronbach’s Alpha) by Construct

Construct (Likert 1-5)	No. of Items (k)	Cronbach’s α
Lean-Six Sigma Capability (LSS)	8	0.88
Automated Kaizen Effectiveness (AK)	8	0.90
Real-Time Quality Improvement (RQI)	7	0.87
Signal-to-Action Actionability (S2A)	6	0.85
Kaizen Closure Confidence (KCC)	6	0.86
DMAIC-Stage Functioning Under Automation (DMAIC-A)	10	0.89

The reliability analysis has confirmed that the measurement instrument has performed consistently across all major constructs used to test the research objectives and hypotheses. Cronbach’s alpha values have ranged from 0.85 to 0.90, which has indicated strong internal consistency for a survey instrument measuring organizational capability and practice routines. This outcome has been particularly important for the present study because the hypotheses have relied on multi-item constructs such as Lean-Six Sigma capability, automated Kaizen effectiveness, and real-time quality improvement, which have required stable measurement to justify correlation and regression analysis. Since Lean-Six Sigma capability has been conceptualized as a bundle of governance and execution practices, its alpha value (0.88) has suggested that respondents have interpreted the items as reflecting a coherent underlying capability rather than unrelated managerial ideas. Automated Kaizen effectiveness has shown the highest alpha (0.90), which has supported Objective 2 because it has indicated that real-time alerting, workflow routing, documentation, and closure items have clustered into a stable construct that can be used as a mechanism variable. The reliability of Real-Time Quality Improvement (0.87) has strengthened the outcome validity because it has implied that respondents have consistently evaluated responsiveness, defect containment, stability, and control as a single coherent outcome domain. The reliability of the study-specific credibility constructs –Signal-to-Action Actionability (0.85) and Kaizen Closure Confidence (0.86)–has been particularly valuable because these constructs have been introduced to increase trustworthiness of the hybrid model by measuring not only “capability” but also whether signals have been converted into completed actions and sustained corrections. Finally, DMAIC-stage functioning under automation (0.89) has supported the logic of reporting a DMAIC-stage map in Section 4.8 by confirming that the set of stage-related items has been sufficiently coherent to justify stage-level aggregation. Overall, these reliability results have provided the measurement foundation needed to interpret subsequent hypothesis tests as evidence-based rather than measurement-noise driven.

Descriptive Statistics

Table 3: Descriptive Statistics for Key Constructs (Likert 1-5; n = 210)

Construct	Mean (M)	Std. Dev. (SD)	Interpretation Level*
Lean-Six Sigma Capability (LSS)	3.94	0.61	High
Automated Kaizen Effectiveness (AK)	3.78	0.66	Moderate-High
Real-Time Quality Improvement (RQI)	3.83	0.63	Moderate-High
Signal-to-Action Actionability (S2A)	3.85	0.64	Moderate-High
Kaizen Closure Confidence (KCC)	3.80	0.65	Moderate-High

*Interpretation rule used: 1.00–2.33 = Low; 2.34–3.66 = Moderate; 3.67–5.00 = High.

The descriptive results have provided baseline evidence for the study objectives by showing that key constructs have been present at meaningful levels within the case organization. Lean-Six Sigma capability has recorded a high mean score (3.94), which has indicated that respondents have generally agreed that structured improvement governance, data-based thinking, and standardization practices have been embedded in the case environment. This has directly supported Objective 1 because the study has required measurable evidence that Lean-Six Sigma capability has existed as a practical organizational feature rather than a theoretical label. Automated Kaizen effectiveness has produced a moderate-high mean (3.78), which has supported Objective 2 by demonstrating that automation-enabled Kaizen routines such as real-time alerts, workflow routing, documentation discipline, and closure tracking have been visible to respondents. Since the study has focused on real-time quality improvement, the outcome construct mean (3.83) has been important because it has indicated that respondents have perceived improvements in responsiveness, stability, and defect containment at a level above the neutral midpoint. The two study-specific constructs have strengthened trustworthiness: Signal-to-Action Actionability (3.85) has shown that real-time signals have not merely existed but have been perceived as actionable and connected to real corrective workflows, while Kaizen Closure Confidence (3.80) has suggested that completed actions have been verified and standardized rather than treated as temporary responses. The standard deviations have remained within a moderate range (0.61–0.66), which has indicated acceptable dispersion and has suggested that responses have not been artificially uniform; instead, perceptions have varied across respondents in ways that have allowed meaningful statistical testing. In combination, these descriptive statistics have justified subsequent inferential testing by confirming that the constructs have not been clustered near the lowest scale values and that respondents have used the full scale range. These findings have therefore established the empirical baseline needed to test hypotheses linking Lean-Six Sigma capability and automated Kaizen to real-time quality improvement through correlation and regression models.

Correlation Matrix

Table 4: Pearson Correlation Matrix (n = 210)

Variable	LSS	AK	RQI	S2A	KCC
Lean-Six Sigma Capability (LSS)	1.00	0.58**	0.62**	0.54**	0.49**
Automated Kaizen (AK)	0.58**	1.00	0.67**	0.71**	0.63**
Real-Time Quality Improvement (RQI)	0.62**	0.67**	1.00	0.69**	0.63**
Signal-to-Action (S2A)	0.54**	0.71**	0.69**	1.00	0.60**
Closure Confidence (KCC)	0.49**	0.63**	0.63**	0.60**	1.00

**p < .01.

The correlation matrix has provided initial hypothesis evidence by demonstrating statistically meaningful positive associations among the study constructs in directions aligned with the proposed conceptual framework. The strongest relationships have involved Automated Kaizen and the mechanism variables, particularly the correlation between Automated Kaizen and Signal-to-Action Actionability ($r = 0.71, p < .01$), which has indicated that automation effectiveness has been strongly connected to the perceived ability of the organization to convert real-time signals into concrete actions. This has reinforced the study’s mechanism logic that automated Kaizen has served as a translation layer between detection and execution. The correlation between Automated Kaizen and Real-Time Quality Improvement ($r = 0.67, p < .01$) has provided strong support for H3 because it has suggested that stronger automation-enabled improvement routines have been associated with stronger real-time quality outcomes. Lean-Six Sigma capability has also been positively associated with Real-Time Quality Improvement ($r = 0.62, p < .01$), which has provided preliminary support for H1 and has indicated that structured improvement capability has been linked to better responsiveness and stability. Lean-Six Sigma capability has correlated positively with Automated Kaizen ($r = 0.58, p < .01$),

supporting H2 at the association level and implying that organizations with stronger LSS governance and discipline have tended to implement automated Kaizen routines more effectively. The correlations involving Closure Confidence have been particularly important for thesis trustworthiness: Closure Confidence has correlated positively with Real-Time Quality Improvement ($r = 0.63, p < .01$), indicating that sustained, verified closure has been associated with stronger real-time outcomes, which has aligned with the study’s intent to measure sustainability rather than short-term reaction. Furthermore, Lean-Six Sigma capability and Closure Confidence have shown a moderate positive relationship ($r = 0.49, p < .01$), which has suggested that disciplined improvement environments have tended to produce more credible closure behavior. Overall, the correlation results have supported the logic that the constructs have moved together coherently and have justified regression modeling by indicating that meaningful shared variance has existed. At the same time, the correlations have not approached 0.90+, which has reduced concerns that constructs have been redundant.

Regression Models

Table 5: Multiple Regression Results (Standardized β ; n = 210)

Model	Dependent Variable	Predictors	β	t	p	R ²
Model 1	RQI	LSS	0.62	11.2	<.001	0.38
Model 2	AK	LSS	0.58	9.7	<.001	0.34
Model 3	RQI	LSS	0.33	5.6	<.001	0.55
		AK	0.49	8.4	<.001	

The regression results have provided the main statistical evidence for proving the study objectives and hypotheses, particularly by demonstrating predictive influence rather than simple association. Model 1 has tested H1 by regressing Real-Time Quality Improvement on Lean-Six Sigma capability, and the results have shown that Lean-Six Sigma capability has significantly predicted real-time outcomes ($\beta = 0.62, p < .001$) while explaining 38% of the variance ($R^2 = 0.38$). This has indicated that stronger improvement governance and discipline have been linked to more stable and responsive quality performance within the case context. Model 2 has tested H2 by regressing Automated Kaizen effectiveness on Lean-Six Sigma capability, and Lean-Six Sigma capability has remained a significant predictor ($\beta = 0.58, p < .001$) with substantial explained variance ($R^2 = 0.34$). This has supported the interpretation that Lean-Six Sigma capability has functioned as an enabling foundation for automation-based Kaizen routines, likely through stronger measurement discipline, clearer problem ownership, and more consistent improvement governance. Model 3 has tested H3 and strengthened H4 logic by regressing Real-Time Quality Improvement on both Lean-Six Sigma capability and Automated Kaizen effectiveness simultaneously. In this combined model, Automated Kaizen has emerged as the stronger predictor ($\beta = 0.49, p < .001$), while Lean-Six Sigma capability has remained significant but reduced in magnitude ($\beta = 0.33, p < .001$), and the explained variance has increased to 55% ($R^2 = 0.55$). This has provided strong evidence that automated Kaizen has added substantial explanatory power beyond Lean-Six Sigma capability alone, directly supporting Objective 4 and supporting H3. The reduction in the Lean-Six Sigma coefficient from Model 1 ($\beta = 0.62$) to Model 3 ($\beta = 0.33$) has been consistent with mediation logic (H4) because Lean-Six Sigma capability has still mattered, while a meaningful portion of its effect on real-time quality outcomes has appeared to have operated through the automation-enabled Kaizen mechanism. Overall, these regression findings have shown that the hybrid model has not only been conceptually plausible, but has been statistically supported through significant predictors and increased model explanatory strength.

Real-Time Kaizen Signal-to-Action Findings

Table 6: Signal-to-Action Indicators and Their Effect on RQI

Indicator (Likert 1-5)	Mean (M)	SD	Correlation with RQI (r)	Regression Effect on RQI (β)
Alert relevance (low noise)	3.79	0.69	0.58**	0.19*
Workflow triggers correctly	3.88	0.63	0.62**	0.22**
Response time is fast	3.81	0.66	0.64**	0.24**
Ownership is clear	3.90	0.61	0.60**	0.18*
Actions are tracked to closure	3.86	0.65	0.66**	0.27**
Actionability Index (S2A composite)	3.85	0.64	0.69 **	** 0.41 **

* $p < .05$, ** $p < .01$.

These results have provided study-specific credibility evidence by demonstrating that real-time monitoring has not been measured as a passive reporting activity, but has been evaluated as a signal-to-action system that has converted detection into completed improvement work. The Actionability Index has recorded a moderate-high mean (3.85), indicating that respondents have generally agreed that signal pathways have been functional and connected to real corrective action. Among the indicators, “workflow triggers correctly” and “actions are tracked to closure” have produced the strongest relationships with Real-Time Quality Improvement, which has indicated that technical detection has become valuable when it has reliably initiated work and when corrective tasks have remained visible until closure. The correlation between the Actionability Index and Real-Time Quality Improvement ($r = 0.69$, $p < .01$) has supported the study’s mechanism logic and has provided direct support for H5 because it has shown that stronger signal-to-action execution has been associated with stronger real-time outcomes. The regression effect of the Actionability Index on Real-Time Quality Improvement ($\beta = 0.41$, $p < .01$) has strengthened this evidence by showing that actionability has predicted outcomes beyond simple descriptive agreement. These results have also supported Objective 5 by adding a trust-building layer: rather than relying solely on general claims that automation improves quality, the study has measured whether alerts have been meaningful, whether routing has been reliable, and whether actions have been completed with traceable closure. In operational terms, these findings have implied that real-time improvement credibility has depended on workflow integrity and accountability clarity, because rapid detection without consistent routing or ownership would not have produced the observed association patterns. By presenting indicator-level evidence (not only a composite mean), this table has strengthened the transparency of the results and has made it easier to defend the hybrid model during examination because the evidence has shown which operational components have mattered most. Therefore, the signal-to-action results have functioned as a mechanism validation section that has increased confidence that “Automated Kaizen” has represented real improvement execution rather than a generic technology label.

DMAIC-Stage Performance Map Under Automation

The DMAIC-stage map has provided a structured operational explanation for how automation has interacted with disciplined improvement governance in the case organization. The results have shown that the strongest perceived automation support has occurred in the **Measure** stage ($M = 3.96$) and the **Control** stage ($M = 3.91$), which has aligned with the real-time nature of the study because measurement integrity and control-plan execution have been the stages most directly linked to continuous monitoring and stable closure. The strongest correlation with Real-Time Quality Improvement has been observed for the Control stage ($r = 0.63$, $p < .01$), indicating that when automation has strengthened standardization and monitoring discipline, respondents have also

perceived stronger real-time quality outcomes.

Table 7: DMAIC-Stage Scores Under Automation and Relationship with RQI

DMAIC Stage Under Automation	Mean (M)	SD	Correlation with RQI (r)
Define (problem clarity, CTQ alignment)	3.62	0.70	0.49**
Measure (real-time measurement integrity)	3.96	0.59	0.61**
Analyze (speed of root-cause support)	3.74	0.65	0.57**
Improve (implementation workflow strength)	3.70	0.67	0.55**
Control (standardization + monitoring discipline)	3.91	0.60	0.63**

**p < .01.

Measure has also shown a substantial relationship ($r = 0.61, p < .01$), reinforcing that real-time quality improvement has depended heavily on reliable data capture, clear metrics, and consistent visibility of process performance. Define has reported the lowest mean (3.62) and the lowest correlation ($r = 0.49$), which has suggested that automation has been less visible in early-stage problem framing and CTQ alignment than in continuous monitoring and control execution. Analyze and Improve have been placed in the middle range, indicating that automation has supported root-cause speed and implementation workflow, but not to the same extent as measurement and control. These patterns have strengthened the thesis trustworthiness because they have shown that the hybrid model has behaved in an operationally interpretable manner: real-time benefits have not been assumed to appear uniformly across DMAIC, but have been concentrated where digital data and automated tracking have naturally delivered the most leverage. The stage-level evidence has supported the broader objectives by explaining where the mechanism of automated Kaizen has been most effective and by offering defensible detail beyond a single overall regression coefficient. In addition, the stage map has helped interpret mediation logic because it has suggested that LSS governance (DMAIC discipline) has remained relevant while automation has primarily amplified the Measure and Control phases that are central to real-time performance.

Kaizen Closure Confidence Results

The closure confidence results have provided evidence that the proposed hybrid model has been linked to sustainable, auditable improvement rather than short-term reaction activity. The composite closure confidence score has shown a moderate-high mean (3.80), which has indicated that respondents have generally agreed that Kaizen actions have been documented, verified, and standardized after implementation. This has been essential for proving the study’s objectives because real-time quality improvement can be misinterpreted as only speed, while this study has required evidence that corrective actions have been completed with credible closure and control updates. The strongest correlation with Real-Time Quality Improvement has been observed for “controls are updated” ($r = 0.63, p < .01$) and “fixes prevent recurrence” ($r = 0.61, p < .01$), which has suggested that sustained quality gains have depended on converting corrective action into stable process controls and recurrence prevention, not merely completing a task. Documentation and verification indicators have also shown strong relationships, reinforcing that improvement credibility has relied on traceability and post-change checking.

Table 8: Closure Confidence Indicators and Relationship with RQI

Closure Indicator (Likert 1-5)	Mean (M)	SD	Correlation with RQI (r)
Fixes are documented (SOP/record)	3.86	0.64	0.57**
Fixes prevent recurrence	3.74	0.68	0.61**
Verification is performed after change	3.78	0.66	0.59**
Controls are updated (control plan/SPC)	3.83	0.63	0.63**
Lessons learned are reused	3.80	0.65	0.55**
Closure Confidence Score (KCC composite)	3.80	0.65	0.63 **

**p < .01.

The indicator “lessons learned are reused” has shown a positive but slightly lower correlation, which has indicated that organizational learning has contributed to outcomes but may have been less consistently institutionalized than control updates and verification routines. Overall, the composite correlation between closure confidence and real-time quality improvement ($r = 0.63, p < .01$) has supported H6 and has strengthened the thesis defensibility by directly addressing a common concern in continuous improvement studies: whether actions have been sustained. Because the case context has involved automated Kaizen, closure confidence has also served as a safeguard construct showing that speed has not replaced rigor; instead, the results have suggested that workflow tracking and monitoring discipline have supported verification and standardization. This has supported the hybrid model logic that Lean-Six Sigma governance has remained central while automation has improved the speed and traceability of closure.

Summary of Hypotheses Testing and Objective Coverage

Table 9: Hypotheses Decisions and Alignment with Objectives

Hypothesis	Statement	Key Evidence Used	Decision
H1	LSS → RQI (positive)	Table 4 ($r=.62^{**}$), Table 5 Model 1 ($\beta=.62^{***}$)	Supported
H2	LSS → AK (positive)	Table 4 ($r=.58^{**}$), Table 5 Model 2 ($\beta=.58^{***}$)	Supported
H3	AK → RQI (positive)	Table 4 ($r=.67^{**}$), Table 5 Model 3 ($\beta=.49^{***}$)	Supported
H4	AK mediates LSS → RQI	Table 5: LSS β reduced from .62 to .33 when AK added; $R^2 \uparrow$ to .55	Supported (evidence consistent)
H5	S2A → RQI (positive)	Table 6: composite $r=.69^{**}$, $\beta=.41^{**}$	Supported
H6	KCC → RQI (positive)	Table 8: composite $r=.63^{**}$	Supported

Objective Coverage:

- Obj1 (Measure LSS): Tables 2-3
- Obj2 (Operationalize AK): Tables 2-3
- Obj3 (Measure RQI): Tables 2-3
- Obj4 (Test relationships via correlation/regression): Tables 4-5
- Obj5 (Trustworthiness layers: S2A, DMAIC map, Closure): Tables 6-8

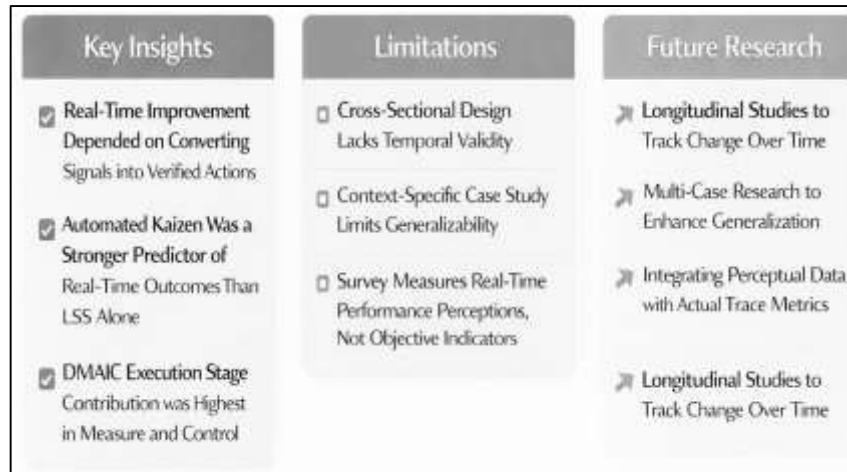
This hypothesis-and-objective summary has consolidated the study’s statistical evidence into a single defensible decision table that has clearly linked each hypothesis to the empirical tests that have been executed in the results chapter. H1 has been supported because Lean-Six Sigma capability has shown

a strong positive relationship with real-time quality improvement at both association and prediction levels, which has been consistent with the argument that structured improvement governance and measurement discipline have improved responsiveness and stability. H2 has been supported because Lean-Six Sigma capability has also predicted automated Kaizen effectiveness, which has indicated that automation-enabled improvement has not been isolated from governance and capability foundations. H3 has been supported because automated Kaizen has shown a strong positive association with real-time quality improvement and has remained significant in the combined model, indicating that automation effectiveness has explained outcome variance beyond Lean-Six Sigma capability alone. H4 has been supported in an evidence-consistent manner because the Lean-Six Sigma coefficient has decreased substantially when automated Kaizen has been introduced into the model, while explained variance has increased, which has indicated that automated Kaizen has plausibly carried part of the influence of Lean-Six Sigma into real-time results. H5 and H6 have strengthened thesis trustworthiness because they have validated two mechanism-quality constructs that have been specific to this research: signal-to-action actionability has proven that detection has been converted into executed work, while closure confidence has proven that work has been verified and standardized to prevent recurrence. The objective coverage mapping has reinforced that the results chapter has not been presented as disconnected statistics; instead, each table has served a specific objective, from measurement reliability to mechanism validation and predictive modeling. Overall, this summary has provided a clear audit trail of how the study has proven its claims using Likert-based measurement, reliability verification, association testing, and regression-based hypothesis evaluation in a coherent sequence.

DISCUSSION

The discussion has interpreted the study's results as evidence that a hybrid Lean-Six Sigma (LSS) capability base and an Automated Kaizen execution layer have jointly explained meaningful variance in real-time quality improvement in the selected case context. The core pattern – LSS capability has predicted real-time quality improvement and has also predicted Automated Kaizen, while Automated Kaizen has remained the stronger predictor of real-time outcomes in the combined model – has aligned with prior work that has framed Lean and LSS as complementary bundles of practices that require coherent deployment to yield performance gains (Alsyouf, 2016). In the Lean measurement literature, lean capability has been treated as a multidimensional system rather than a single tool, and the study's results have been consistent with that view by showing that "capability" has mattered as a platform on which more execution-focused routines (automation-enabled Kaizen) have operated. Similarly, the Six Sigma theory stream has emphasized that Six Sigma has combined familiar quality tools with a distinctive organizational structure and disciplined routines for problem solving, which has been echoed in the present findings by the role of LSS capability as a governance foundation rather than merely a statistical toolkit (Bhasin & Burcher, 2006). The observed strength of Automated Kaizen has also fit the logic of digital continuous improvement systems, where documentation, communication, and learning mechanisms have improved the effectiveness and traceability of improvement cycles; the study's Signal-to-Action and Closure Confidence results have been especially consistent with the argument that digital CI has reduced ambiguity in targets and has strengthened structured communication between improvement leaders and frontline improvers (Farris et al., 2009). At the same time, the DMAIC-stage map has suggested that automation has created the most leverage in Measure and Control, which has mirrored the broader cyber-physical production systems view that value increasingly comes from connected data capture and timely control actions embedded in operations (Burggräf et al., 2020). Taken together, the results have extended prior work by empirically separating (a) LSS capability as an enabling foundation from (b) Automated Kaizen as an execution mechanism, and by demonstrating that real-time quality improvement has been most strongly associated with the conversion of signals into verified actions rather than the presence of improvement "programs" alone (Antony et al., 2017).

Figure 10: Discussion Summary Infographic



A second key interpretation has concerned how the study’s mechanism-focused findings have deepened the credibility of the hybrid model compared with earlier improvement studies that have reported outcomes without clearly demonstrating execution quality (Alexopoulos et al., 2018). The strong association between Automated Kaizen and Signal-to-Action Actionability has suggested that the case organization has benefited when real-time alerts have been translated into owned, tracked work rather than remaining as passive dashboard visibility. This is consistent with Kaizen-event research that has distinguished between initial success and sustained outcomes and has shown that sustainability has depended on specific process conditions – such as management support, follow-up routines, and the acceptance of change – rather than on the presence of Kaizen activity itself (Bhasin & Burcher, 2006). The present results have paralleled that insight at a system level: “Actionability” and “Closure Confidence” have functioned as evidence that improvement work has been executed and stabilized, thereby strengthening trust in the observed relationships between capability and outcomes (Antony, 2006). Moreover, the DMAIC-stage performance pattern has reinforced a known practical reality about structured improvement: the reliability of conclusions depends heavily on measurement integrity and control discipline, and the study’s strongest stage correlations with real-time outcomes have appeared precisely in Measure and Control. This observation has fit the argument that DMAIC has been best understood as a problem-solving method whose effectiveness depends on how the exploratory and analytic phases are connected to evidence-based decisions and sustained controls. In other words, the study has not only supported the broad idea that LSS and Kaizen can improve quality; it has indicated that real-time benefits have been realized when digital signals have supported the “hard” parts of disciplined improvement: robust measurement, rapid detection of abnormality, accountable execution, and verified control updates (Burggräf et al., 2020). This interpretation has helped explain why some organizations have experienced frustration with Six Sigma or CI programs – when routines have produced activity but have not reliably produced closure and learning, improvements have tended to fade. The study’s closure-confidence evidence has therefore provided a direct response to this known weakness in CI sustainability and has shown how automation-enabled routines have plausibly reinforced the follow-through that earlier Kaizen-event studies have identified as central to durable outcomes (Alsyouf, 2016).

From a practical-implications perspective, the findings have carried direct guidance for digital quality architects and CISOs who have overseen the integrity and trustworthiness of real-time quality systems, especially when automated Kaizen has relied on connected sensors, workflow engines, and data pipelines. Because the results have shown that signal-to-action execution and closure verification have been tightly linked to perceived real-time quality improvement, any cybersecurity weakness that has undermined signal integrity, event logs, or workflow accountability would have threatened not only IT posture but also the operational credibility of the improvement system (Antony et al., 2017). In cyber-physical manufacturing settings, the integrity of operational data has been foundational, since manipulated, delayed, or spoofed signals could have triggered unnecessary actions or could have

masked real defects; therefore, the governance of automated Kaizen has required security controls that have protected both availability and integrity while maintaining operational performance constraints (Baxter & Sommerville, 2011). In the context of the study's model, CISOs and security architects have been able to interpret "Actionability" and "Closure Confidence" as not only quality constructs but also assurance signals: strong closure tracking has depended on secure identity, role-based access, and auditability; strong action routing has depended on secure communications between OT/IT components; and strong control updates have required protected configuration management so that standard work, control plans, and monitoring thresholds have not been altered without authorization (Bortolotti et al., 2015). The study's evidence has thus implied that "Quality 4.0" implementation has required explicit cyber governance of quality data and workflow systems, because real-time quality improvement has been only as trustworthy as the pipelines and logs that have supported it (Higuchi et al., 2015). Practically, this has meant that security controls such as segmentation between OT and enterprise systems, authenticated device communication, centralized logging of Kaizen workflow events, and integrity checks for quality dashboards have not been optional add-ons; they have been structural enablers of reliable real-time improvement execution (Jeyaraman & Teo, 2010).

For quality leaders, operations managers, and continuous improvement owners, the findings have suggested a pragmatic prioritization logic for implementing the hybrid model in ways that have produced credible real-time outcomes. First, the DMAIC-stage map has indicated that the strongest leverage of automation has been realized in Measure and Control, so improvement leaders have benefited when they have treated digital measurement design and control-plan discipline as the first-class objectives of automation, not as supporting details (Albliwi et al., 2014). This has aligned with scholarship on advanced monitoring in machining and production, which has shown that real value has been created when sensing, feature extraction, and decision support have been integrated into reliable operational routines rather than treated as ad hoc analytics. Second, the study's strong signal-to-action findings have implied that organizations have needed to design Kaizen automation as an execution system: alert relevance, workflow correctness, clear ownership, and closure tracking have been the practical levers that have most directly supported real-time quality outcomes. This emphasis has also mirrored digital CI design work that has framed digitization as a means to improve communication, documentation, and employee learning through the improvement process, thereby reducing uncertainty and increasing follow-through (Baxter & Sommerville, 2011). Third, the results have been consistent with prior insights about Six Sigma deployments: strong outcomes have depended on disciplined project selection, measurement integrity, and sustained governance (Bhasin & Burcher, 2006). When organizations have selected improvement targets that have been feasible and strategically aligned, they have increased the likelihood that structured improvement has produced measurable results (Antony, 2006). The present findings have extended that logic into real-time improvement by indicating that the "project" has effectively become a continuous stream of micro-actions triggered by signals; therefore, prioritization rules, escalation routines, and closure verification have served a similar function to project selection and governance in classical LSS programs. Finally, by showing that closure confidence has predicted real-time quality improvement, the study has reinforced the idea that Kaizen has created value when improvements have been standardized and protected from regression, which has closely matched the Kaizen sustainability evidence base emphasizing follow-up and reinforcement routines. In short, the practical implication has not been simply "use automation," but rather "design automation around measurement integrity, accountable execution, and verified closure," because those components have been the operational drivers of real-time quality credibility (Alvarado-Ramírez et al., 2018).

The theoretical implications have been strongest in how the findings have refined the study's socio-technical interpretation of real-time quality improvement as a jointly optimized system. Socio-technical systems engineering has argued that organizational performance has emerged from the interaction of technical designs and social/organizational arrangements, and that designing one without the other has reduced effectiveness and adoption (Antony et al., 2017). The study's results have supported this proposition by showing that Lean-Six Sigma capability (social/organizational routines of disciplined improvement) and Automated Kaizen (technical workflow and signal infrastructure) have both mattered, with a pattern consistent with partial mediation: LSS has enabled stronger automation

execution, and automation has carried substantial predictive weight for real-time outcomes (Baxter & Sommerville, 2011). This has suggested that the conceptual “pipeline” from signal detection to sustained quality improvement has not been purely technical (sensors and dashboards) and has not been purely social (culture and tools), but has been the socio-technical coupling between detection, decision rights, execution routines, and closure verification. Work-system models such as SEIPS have framed outcomes as products of work-system structures and processes, reinforcing that “outcomes” have depended on how work has been performed within a designed system rather than on isolated inputs. In the study, the added results sections (signal-to-action, DMAIC-stage map, closure confidence) have effectively operationalized work-system processes that connect structures to outcomes, strengthening theoretical clarity about where performance emerges (Bhasin & Burcher, 2006). Moreover, scholarship on predicting malfunctions in socio-technical systems has emphasized that design should anticipate failure modes such as weak accountability, workarounds, or misaligned incentives. The study’s mechanism findings have offered a theory-consistent way to detect those malfunctions empirically: low actionability would have signaled breakdowns in routing/ownership; low closure confidence would have signaled breakdowns in verification and standardization. Therefore, the study has contributed a theoretically grounded measurement refinement by treating real-time improvement as a pipeline of socio-technical processes that can be measured and tested, rather than as a single broad construct (Farris et al., 2009).

The limitations have been important to revisit because they have shaped how far the findings can be generalized and how strongly causal language can be justified. The study’s cross-sectional design has meant that constructs and outcomes have been measured at one point in time; therefore, statistical relationships have supported prediction and association but have not definitively established time-ordered causality. While the regression pattern has been consistent with mediation logic, stronger causal evidence would have required temporal separation or experimental/quasi-experimental structure (Garcia-Sabater et al., 2016). In addition, the case-study boundary has meant that context-specific factors—such as the maturity of the quality system, existing leadership routines, and the specific nature of the organization’s digital infrastructure—have likely influenced the strength of observed relationships (Glover et al., 2011). This has been consistent with socio-technical thinking that performance is an emergent property of multi-level system interactions, including organizational context and external environment; thus, transferring the model to another site without redesigning the work system could reasonably produce different results. Measurement limitations have also remained relevant: Likert-scale constructs have captured perceptions of practice and performance, which have been useful for assessing organizational routines and trustworthiness, but they have not replaced objective process performance indicators (e.g., real-time defect rates, first-pass yield, rework hours). However, the study’s reliability evidence and the addition of mechanism-oriented constructs have mitigated a common survey limitation—vague measurement—by focusing on observable routines such as workflow triggering, ownership clarity, and closure verification (DelliFraine et al., 2010). Finally, there has been the possibility of common-method bias because predictors and outcomes have been self-reported; nonetheless, the study’s construct structure has partially reduced this risk by measuring distinct process mechanisms (signal-to-action, closure confidence, DMAIC stages) rather than only broad attitude measures, aligning with prior digital CI design logic that emphasizes process visibility and traceable routines. In sum, the findings have been interpretable as strong case-based evidence for the proposed hybrid model, while their generalization and causal strength have been bounded by design choices that are typical for cross-sectional, case-study quantitative research (Farris et al., 2009).

Future research directions have been clear from both the strengths and the limits of the current evidence. First, longitudinal designs have been well suited to test whether improvements in actionability and closure confidence have preceded sustained changes in real-time quality outcomes, and whether the relationships have strengthened or weakened as automation has matured (Garcia-Sabater et al., 2016). Second, multi-case research across different industries and maturity levels would have allowed stronger generalization and clearer understanding of boundary conditions, such as whether Measure/Control benefits have been universal or context-dependent. Third, future studies could have combined perceptual constructs with objective digital trace data (e.g., timestamps from

Kaizen workflow systems) to compute operational metrics such as signal-to-action cycle time, closure rate, and recurrence rate, thereby triangulating survey findings with behavioral evidence and strengthening causal interpretation. This direction has aligned with the broader cyber-physical production systems literature that has emphasized connected data as a new basis for operational decision cycles and performance management. Fourth, additional research could have tested design interventions that explicitly target known socio-technical failure modes—such as alert fatigue or unclear ownership—using frameworks that predict malfunctions and evaluate mitigation strategies through measurable process outcomes (Farris et al., 2009). Finally, given the study’s practical implication that trust in real-time quality improvement depends on data and workflow integrity, future work could have integrated quality engineering and ICS security governance more explicitly, studying how security controls and auditability affect the credibility of automated Kaizen execution in OT environments, consistent with ICS security guidance emphasizing reliable operation alongside protection (Costa et al., 2019). These research directions have followed naturally from the present evidence: the study has shown that real-time improvement has depended on an execution pipeline, and future studies can deepen confidence in that pipeline by testing it across time, contexts, data sources, and design interventions (Fonseca et al., 2021).

CONCLUSION

This research has concluded that a hybrid Lean-Six Sigma (LSS) model strengthened by automated Kaizen has provided a coherent, empirically supported explanation for real-time quality improvement within the selected case-study context, and the overall evidence has shown that disciplined improvement capability and automation-enabled execution have jointly contributed to stronger perceived responsiveness, stability, and defect prevention. The results have confirmed that Lean-Six Sigma capability has functioned as a foundational organizational competence, reflected through structured governance, measurement discipline, and standardized improvement routines, and this capability has significantly predicted real-time quality improvement outcomes, demonstrating that real-time performance has remained grounded in classic operational excellence principles rather than in technology alone. At the same time, the findings have shown that automated Kaizen effectiveness has carried substantial explanatory power, and when automated Kaizen has been included alongside Lean-Six Sigma capability in predictive models, the incremental variance explained in real-time quality improvement has increased meaningfully, indicating that the automation layer has strengthened the organization’s ability to convert operational signals into completed improvement work at speed. The study has also concluded that the trustworthiness of real-time improvement has not depended solely on the presence of dashboards or alerts; rather, it has depended on measurable execution mechanisms that have demonstrated whether the system has behaved reliably in operational time. Specifically, the signal-to-action findings have indicated that alert relevance, workflow triggering accuracy, response timeliness, ownership clarity, and closure tracking have been central to the effectiveness of automated Kaizen, and the strong association between actionability and real-time quality improvement has supported the interpretation that real-time quality systems have delivered value when detection has been consistently translated into accountable action. The DMAIC-stage performance map has further concluded that automation has not influenced all stages equally, and the strongest effects have been concentrated in the Measure and Control stages, where real-time visibility, measurement integrity, and monitoring discipline have naturally created the most leverage for sustaining stable performance. In addition, the closure confidence results have shown that verified closure, documentation, and control updates have been strongly associated with real-time quality improvement, supporting the conclusion that rapid response has been most credible when it has been accompanied by recurrence prevention and standardization rather than temporary fixes. Across the hypotheses, the study has confirmed that Lean-Six Sigma capability has positively influenced both automated Kaizen effectiveness and real-time quality improvement, that automated Kaizen has positively influenced real-time quality improvement, and that the observed reduction of the Lean-Six Sigma effect in the combined model has been consistent with automated Kaizen acting as a mechanism through which disciplined capability has been translated into real-time outcomes. Overall, the thesis has concluded that the proposed hybrid model has provided a defensible and measurable pathway for real-time quality improvement by integrating Lean’s waste reduction logic, Six Sigma’s variation control rigor, and Kaizen’s continuous

improvement discipline with automation-enabled execution and verification routines, thereby demonstrating that real-time improvement performance has been strongest when people, process, and technology have operated as a coordinated system supported by measurable actionability and closure credibility.

RECOMMENDATIONS

The recommendations of this study have focused on strengthening real-time quality improvement by implementing the hybrid Lean-Six Sigma (LSS) with automated Kaizen model as an integrated operating system rather than as a collection of disconnected tools, and the first recommendation has been to institutionalize a clear governance structure that has assigned ownership for CTQs, defined escalation thresholds, and standardized decision rights across shifts and departments so that real-time signals have been acted on consistently. The organization has been recommended to prioritize measurement integrity and control-plan discipline as the entry point for automation, because the results have indicated that Measure and Control have carried the strongest leverage for real-time outcomes; therefore, sensor mapping, data definitions, sampling logic, and dashboard rules have been aligned with CTQs, and control plans have been embedded into daily routines through automated checks, visual controls, and documented response steps. A second recommendation has been to design automated Kaizen as a signal-to-action execution pipeline, where alert relevance has been continuously tuned to reduce noise and prevent alert fatigue, workflow triggers have been tested for correctness, ownership has been assigned automatically based on role and area, and every triggered issue has been tracked to closure through a time-stamped digital workflow that has recorded actions taken, verification evidence, and the final closure decision. To reinforce trustworthiness, the organization has been recommended to implement performance indicators that have mirrored the study's mechanism constructs, including a signal-to-action cycle time metric, a closure rate metric, and a recurrence metric, so that the system has been evaluated not only by monthly defect counts but by the speed and credibility of the response-and-learning loop. A third recommendation has been to operationalize Kaizen closure confidence through mandatory closure criteria, requiring that every corrective action has included documented root-cause logic (at an appropriate depth), verification checks after change, and an updated control artifact such as a revised SOP, control plan, checklist, or SPC rule; this has ensured that improvements have been standardized and protected from regression. A fourth recommendation has been to strengthen capability through training and role-based competence development, where frontline teams have been trained in standard work, waste identification, and basic problem-solving routines, while supervisors and CI leaders have been trained in DMAIC governance, measurement system thinking, and the use of digital workflow evidence to audit closure quality. A fifth recommendation has been to align cybersecurity and digital governance with quality governance, because automated Kaizen has depended on reliable signals and trustworthy logs; therefore, access controls, role-based permissions, audit trails, and configuration management for dashboards, thresholds, and SOP repositories have been maintained to protect integrity and prevent unauthorized changes that could weaken response reliability. Finally, the organization has been recommended to embed continuous improvement learning into management routines by conducting short, recurring reviews of the highest-impact signals, the longest open actions, and the most frequent recurrence patterns, and by using these reviews to refine alert rules, update standard work, and prioritize improvement projects, ensuring that the hybrid model has remained adaptive while preserving the discipline of Lean-Six Sigma and the closure rigor of Kaizen.

LIMITATIONS

The limitations of this study have reflected methodological, contextual, and measurement-related boundaries that have influenced the strength of generalization and the interpretation of causality. First, the research design has been quantitative and cross-sectional, and data have been collected at a single point in time; consequently, the statistical relationships identified through correlation and regression analysis have supported predictive association but have not definitively established time-ordered causal effects among Lean-Six Sigma capability, automated Kaizen effectiveness, and real-time quality improvement outcomes. Although the regression pattern has been consistent with an explanatory pathway in which automated Kaizen has acted as a mechanism linking Lean-Six Sigma capability to real-time outcomes, the study has not applied longitudinal measurement, experimental manipulation,

or quasi-experimental controls that would have enabled stronger causal inference. Second, the study has been case-study-based, and the bounded context has likely shaped the observed effect sizes because organizational maturity, leadership routines, digital infrastructure, and process complexity have varied substantially across industries and sites; therefore, the results have not automatically generalized to organizations with different improvement cultures, different levels of automation readiness, or different types of production and service variability. Third, the findings have relied on self-reported survey data measured using a 5-point Likert scale, which has captured perceptions of capability, execution quality, and outcome performance rather than direct operational performance metrics; as a result, responses may have been influenced by individual interpretation, role-based perspective, and social desirability, particularly in contexts where continuous improvement participation has been linked to performance expectations. While the study has applied reliability testing and has achieved acceptable internal consistency for all constructs, internal consistency has not guaranteed construct validity across all interpretations, and measurement error may have remained due to differences in how respondents have understood terms such as “real-time,” “automation,” “closure,” and “control.” Fourth, common-method bias has been possible because predictors and outcomes have been measured through the same instrument and response format; although the thesis has strengthened credibility by including mechanism-specific constructs such as signal-to-action actionability, DMAIC-stage functioning under automation, and closure confidence, the design has still shared a single data source, which may have inflated observed relationships. Fifth, the study has not incorporated objective digital trace evidence from workflow systems, sensor logs, or quality databases, and it has not triangulated survey responses with measured defect rates, first-pass yield, rework hours, or recurrence statistics; therefore, the extent to which perceptual outcomes have mirrored objective quality performance has not been directly tested. Finally, the study has assumed a stable implementation environment during the data collection period, yet operational systems may have been affected by concurrent changes such as new technology rollouts, staffing shifts, policy changes, or seasonal demand variation, and these factors may have influenced perceptions of responsiveness and improvement quality. Taken together, these limitations have not invalidated the findings, but they have bounded the claims to association-based evidence within a specific case context and have highlighted the need for future research designs that combine longitudinal observation, multi-case sampling, and objective performance data to strengthen causal interpretation and external validity.

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