

KaizenAI: Methodology for the Integration of Machine Learning in Manufacturing Processes Based on Kaizen Principles.

Case Study: Bottling Industry

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Abstract:

Purpose: Digital transformation in manufacturing has placed artificial intelligence (AI) at the center of the debate on efficiency and sustainability. However, its adoption in established plants faces barriers related to cultural resistance, data quality, and the absence of methodologies that guide its progressive implementation. In this context, the article proposes KaizenAI, a hybrid methodology that integrates the principles of continuous improvement with the predictive capabilities of AI.

Methodology: This article presents KaizenAI, a hybrid methodology that integrates the principles of the PDCA cycle with user-centered design (UCD) tools, quality function deployment (QFD), Kata routines, and digital 5S principles, combining them with machine learning models to anticipate failures and optimize processes. The proposal was validated through a case study in a bottling plant, applying a predictive model based on 18 months of operational data from the overall equipment effectiveness (OEE) system.

Findings: Preliminary results show that a plant with intermediate digital maturity (2.6/6) can develop effective predictive capabilities by integrating the Kaizen approach with interpretable statistical models. The SARIMA model outperformed Random Forest and XGBoost with a 98.2% reduction in MAE, demonstrating that methodological simplicity can surpass algorithmic complexity in industrial environments with high variability. Moreover, the Kaizen–AI convergence acts as a methodological bridge for introducing digital capabilities without breaking the incremental logic of continuous improvement.

Originality/value: The main contribution of the study lies in integrating the Kaizen philosophy with AI within a hybrid framework that connects the human with the digital and the incremental with the predictive. This approach facilitates the gradual adoption of AI without disrupting continuous improvement and offers a practical pathway toward Industry 4.0 while minimizing organizational resistance.

Keywords: machine learning, kaizen, continuous improvement, manufacturing, industry 4.0

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1. Introduction

The digitalization of manufacturing, driven by the so-called Industry 4.0, has transformed the way organizations conceive their production processes. Technologies such as artificial intelligence (AI), the industrial internet of things (IIoT), and cyber-physical systems have demonstrated high potential to optimize operations, anticipate failures, and improve the OEE. However, the effective implementation of these tools in established manufacturing environments continues to be a challenge. Barriers persist related to data quality and availability, organizational resistance to change, and the absence of structured methodologies that guide their gradual and sustainable adoption.

In parallel, the Kaizen philosophy has consolidated its value as a continuous improvement framework in the industry, promoting worker participation, waste elimination, and process standardization. Unlike disruptive approaches, Kaizen is characterized by fostering incremental changes that, accumulated over time, generate significant improvements in productivity, quality, and organizational commitment. Nevertheless, the specialized literature reveals a gap in the systematic integration between Kaizen and AI, which limits the possibility of articulating the participatory logic of continuous improvement with the predictive capabilities of advanced digitalization.

This methodological gap represents a critical opportunity. Although there are partial proposals for technological adoption in manufacturing, few offer a hybrid framework that coherently and progressively connects Kaizen principles with the development of AI-based solutions. In this context, there arises the need for a methodology that not only addresses the technical aspects of digitalization but also respects and strengthens the existing organizational culture.

This article proposes KaizenAI, a structured methodology that combines the PDCA cycle with participatory design tools (UCD), quality function deployment (QFD), Kata routines, and digital 5S principles, while integrating machine learning models for process prediction and optimization. Unlike purely technological approaches, KaizenAI is conceived as a bridge between the human and the digital, enabling the transformation of operational data into strategic decisions while minimizing resistance to change.

The research questions guiding this work are as follows:

- How can Kaizen principles be effectively integrated with AI solutions in a real manufacturing environment?
- What methodological adaptations are necessary to apply the PDCA cycle in advanced digitalization projects?
- To what extent can a hybrid methodology facilitate the progressive adoption of AI without breaking the incremental logic of continuous improvement?

To answer these questions, this article develops a case study in a bottling plant where KaizenAI was implemented up to the construction and validation phase of a predictive model. The data were processed and managed using the Mentor Monitor platform, an industrial monitoring system that collects, visualizes and analyzes production data in real time (Mentor Monitor, 2025). The preliminary results show relevant technical improvements and, above all, provide a replicable framework that connects the Kaizen tradition with the opportunities of AI in contemporary manufacturing.

The remainder of this paper is organized as follows: Section 2 presents the background. Section 3 details the proposed methodology. Section 4 presents the results. Section 5 provides a detailed discussion of the findings, and Section 6 addresses potential threats to validity. Section 7 concludes the study, and Section 8 highlights directions for future research.

2. Background

The selected studies were grouped based on the following aspects:

2.1. Traditional Lean and Smart Kaizen

Wolniak and Grebski (2023) and Tashkinov (2024) positioned Kaizen as an indispensable element for Industry 4.0, demonstrating that the philosophy of continuous improvement facilitates the adoption of smart

technologies by preparing the organizational mindset. However, their limitation is the theoretical nature of the study, which lacks a framework of operational steps for a manufacturing plant with processes that no longer meet quality standards. Tashkinov (2024) proposed a framework that combined Lean principles with technological tools, demonstrating that this integration allows department heads to make decisions based on up-to-date data, improving overall efficiency. Nevertheless, this integration requires a thorough review of organizational practices, which can be slow in manufacturing plants with rigid hierarchies. Additionally, Sangwa and Sangwan (2020), Kareska (2024a, 2024b), and Medina et al. (2024) provided quantitative evidence of success in reducing cycle times and defects using traditional Kaizen, achieving drastic reductions in cycle times and defects. However, reliance on manual data collection and the lack of an industry 4.0 technological vision make the improvements difficult to scale.

From an organizational perspective, Sangwa and Sangwan (2020) describe Kaizen as a socio-technical system supported by standardization, PDCA cycles, visual management, and active staff participation, elements that promote organizational learning and continuous incremental improvement. Additionally, these authors validated tools such as Gemba Walk and ECRS to improve line balancing and efficiency. However, their results are based on a single manual case study, making it difficult to generalize the success to highly automated environments. The most significant contribution toward a hybrid approach comes from Mendoza-Sotomayor et al. (2024), who achieved a 42.4% reduction in quality control times using hybrid Lean-ML models. The authors managed to reduce the waste and analyzed line changeover times using predictive models. Additionally, García-Alcaraz et al. (2022) demonstrated that tools such as Single-Minute Exchange of Die (SMED) and preventive maintenance are fundamental to economic and environmental sustainability in Mexican maquiladoras, although they do not incorporate predictive AI to automate these improvements.

The Smart Manufacturing Kaizen Level (SMKL) model, proposed by Otoki et al. (2023), is a tool for evaluating the maturity of digital transformation. As it is an evaluation model rather than an implementation model, it leaves a gap regarding how to progress operationally from one level to another.

2.2. Advanced Technology and OEE

Xu et al. (2022) and Selvarani et al. (2023) identified deep learning architectures that allow for managing data uncertainty in predictive maintenance. In a review focused on deep learning approaches, Xu et al. (2022) highlight the sensitivity of these models to process drift, operational variability, and dependence on large volumes of labeled data, factors that affect their scalability in real production environments. According to Simkute et al. (2024), these models are often “black boxes,” and this lack of transparency acts as a critical barrier to usability, as humans are forced to monitor a technology whose behavior they cannot fully anticipate or explain. In operational control, Lucantoni et al. (2025) and Ramadhani et al. (2023) identified hidden events that affect OEE using data mining and Six Sigma. This requires a mature data infrastructure; without prior sensors and connectivity (IoT), these models cannot run. Santillan et al. (2024) attempted to address this gap through advanced HMI systems and IoT. A rule-based framework to support Total Productive Maintenance (TPM) was developed by Lucantoni et al. (2025), identifying hidden events that negatively impact OEE. This requires a high level of digital maturity, which excludes many traditional manufacturing plants still in the early stages of digitalization.

Mitkovska-Trendova et al. (2024) and Mortada and Soulhi (2023) used Markov Decision Processes and Fuzzy Logic to prioritize defects more accurately and rigorously than the traditional Pareto method. However, the main drawback was the “curse of dimensionality,” since as the manufacturing process becomes more complex, these models require technological capabilities that most traditional plants lack, as well as technical expertise rarely found among plant personnel.

The main contribution of the work carried out by Aissani et al. (2008) lied in the proposal of the SPART system, which used reinforcement learning for heterarchical production control. The authors demonstrated that agents can learn optimal behaviors in response to real-time risks, improving task success rates. However, the lengthy convergence time required by reinforcement learning hinders agile adaptation to unforeseen changes in the manufacturing plant environment. Furthermore, the high technical complexity of designing precise reward functions when scaling the system, can compromise its real-time processing and response capabilities.

2.3. Governance and Barriers to Adoption

Taxonomy proposals to rank AI adoption barriers in the manufacturing industry have been put forward by Cannas et al. (2024) and Windmann et al. (2024). They ranked the barriers across the following critical dimensions: infrastructure, data, economic, human, and technical. Cannas et al. (2024) provided a roadmap for overcoming structural barriers in emerging economies, while Windmann noted that even after overcoming these barriers, the technical challenge of systemic integration and data reliability remains the biggest obstacle. Sharma et al. (2025) identified constraints related to data availability and quality, system interoperability, and implementation costs. These studies are diagnostic, identifying barriers but not offering a hybrid implementation methodology that simultaneously addresses data and process issues.

On the other hand, Gao et al. (2024) developed a state-of-the-art overview that positions LLMs and generative design as the future of modern manufacturing. The limitations to AI implementation in manufacturing center on complex technical and operational challenges, such as data, models and infrastructure, transfer and security, and technological knowledge. They highlight the gap between the success of AI in controlled environments and the volatility of the real world in the manufacturing industry.

2.4. User-Centered Automation

Regarding this aspect, Toxtli (2024) proposed Human-Centered Automation (HCA), arguing for intuitive interfaces (such as LLMs or agents) to democratize AI and thus reduce the technical gap. This gap stems from the absence of a design framework that prioritizes human needs, values, and capabilities over algorithmic efficiency. The paper proposed that as long as automation continues to be designed from a purely technical and system-centric perspective, the loss of productivity resulting from a tool that should help becoming a burden or a risk to productivity cannot be mitigated. Additionally, Simkute et al. (2024) made a critical finding on the “irony of automation,” explaining why poorly implemented AI reduces productivity by disrupting workflows. Alshurideh et al. (2023) highlighted that team creativity is the driving force behind continuous improvement; however, the authors do not offer technological tools to channel that creativity into decision support systems. Overall

Overall, research on hybrid industrial optimization approaches suggests that combining classical engineering methods with data-driven models can improve the robustness and adaptability of production systems. However, these works remain at a conceptual level and do not develop operational mechanisms for their incorporation into daily improvement practices. Similarly, studies on the integration between Lean and digital management show improvements in process visibility and feedback speed, without incorporating predictive analytics into structured continuous improvement cycles. Lean and Kaizen provide operational discipline, methodological structure, and cultural alignment, although they depend on retrospective information and manual analysis. Existing studies address both approaches in parallel, without proposing a methodological framework that systematically articulates predictive analytics with continuous improvement routines in manufacturing

Studies oriented toward Kaizen rely mainly on historical indicators and descriptive analysis. Although data play a central role in performance monitoring, predictive models and advanced analytics techniques are not integrated into continuous improvement routines (Kareska, 2024a; Sangwa & Sangwan, 2020). AI is the key to modern efficiency, but the level of technological maturity in industrial plants is uneven. Furthermore, while engineering studies (Xu et al., 2022) focus on algorithm accuracy, management studies (Kareska, 2024a) direct on employee engagement, revealing a clear methodological difference. Current literature is fragmented, leaving a gap for a proposal that operationally unites both perspectives.

Furthermore, existing studies do not adequately address how to sustain data quality over long-term in harsh industrial environments. AI requires clean data, something Kaizen ensures through standardization. KaizenAI sits at the intersection of Toxtli's Human Capital Analysis (HCA) (Toxtli, 2024) and Wolniak's Smart Kaizen (Wolniak & Grebski, 2023), offering the necessary structured framework, which is not defined in the literature. Studies highlight that most AI implementation failures are not technical, but rather cultural and related to data governance.

Our proposal seeks to bridge the methodological integration gap, as it responds to the need for a methodology that guides traditional industrial plants through the barriers identified by Cannas et al. (2024), using AI as the predictive

engine of the continuous improvement cycles validated by Kareska (2024a) and Mendoza-Sotomayor (2024). KaizenAI, being a hybrid approach, utilizes the contributions of AI for big data analysis and the achievements of Kaizen to ensure progressive implementation, overcoming the limitations of technological isolation and cultural resistance identified earlier.

3. KaizenAI Methodology

Before presenting the KaizenAI methodology (see Figure 1), three recent references that support its formulation are analyzed. Kareska (2024a) documents how the implementation of Kaizen principles in manufacturing improves quality and efficiency through incremental adjustments articulated with staff participation. In another context, Dong and Li (2025) analyze the usefulness of the PDCA cycle in small and medium-sized enterprises, highlighting its effectiveness in reducing defects through standardized procedures. Finally, Akhtar (2024) proposes a hierarchical approach that organizes AI applications at different levels of the production system, addressing issues such as data integration, operational traceability, and the practical applicability of models.



Figure 1. KaizenAI methodology based on the PDCA cycle and UCD integration (Kareska, 2024a; Dong & Li, 2025; Akhtar, 2024)

3.1. Plan Phase

3.1.1. Mission Statement (Hoshin Kanri for AI)

The planning phase requires a structured alignment between organizational objectives and AI project goals. The Hoshin Kanri approach enables the translation of strategic guidelines into operational actions through tools such as the X-matrix, which can incorporate indicators adapted to digital environments, including the level of automation and the technical readiness of personnel (Abubakr et al., 2020).

To establish the initial scope, digital and organizational maturity diagnostics have been used. The organizational maturity model by Schumacher et al. (2016) evaluates nine dimensions including culture, strategy, leadership, and processes providing a starting point for deployment.

Managerial control acts as a feedback system in digital transformation scenarios, facilitating monitoring and decision-making through iterative cycles (Kraus & Schlegel, 2021). This principle is reinforced in cyber-physical architectures, where each functional layer contributes processed real-time data to guide planning (Lee et al., 2014).

3.1.2. Digital Gemba Walk (Identification of Needs)

The identification phase begins with a digital version of the Gemba Walk, aimed at detecting conditions that affect the actual performance of the plant. Through structured observation tools, interviews, and data analysis, evidence is sought to justify AI-based interventions. Assisted reality technology is used to conduct on-site tours guided by a remote sensei. This practice, known as Virtual Sensei, maintains the logic of situational learning and has been successfully applied in real industrial environments (Powell, 2022). In addition, perceptions are gathered from different organizational levels, allowing the recording of events not formally documented, such as improvised adjustments, frequent micro-stoppages, or other conditions that affect process stability (Romero et al., 2020).

In parallel, historical operating data are analyzed to characterize factors that directly influence OEE, such as operating time, actual versus theoretical speed, and the frequency of micro-stoppages. These data allow the estimation of a reliability level of system behavior, represented by the IVM index. This approach helps prioritize preventive actions beyond traditional maintenance (Ucar et al., 2024).

To represent the production system, the Digital Value Stream Twin model is applied, which simulates the real flow of the process and identifies zones of energy loss, overload, or accumulation (Frick & Metternich, 2022). The final product is an AI Opportunity Map, which classifies processes according to their level of loss and ease of technical intervention.

3.1.3. User-Centered Design (UCD) for AI Solutions

User-centered design is based on understanding the context of use, the tasks, and the characteristics of the people who interact with a system. According to ISO 9241-210 (International Organization for Standardization, 2019), this approach incorporates active user participation, iterative evaluation, and consideration of the complete experience throughout the products life cycle. The standard defines six principles that guide the creation of effective, safe, and satisfactory interactive systems, promoting cooperation between design and engineering disciplines.

Maguire (2001) describes methods that operationalize these principles through the elicitation of requirements, the generation of alternatives, and continuous evaluation. Among the identified techniques are contextual interviews, people development, usage scenarios, and usability testing. These procedures integrate user feedback at each stage of development, ensuring that the system responds to real needs and improves its acceptance.

Both authors agree that the effectiveness of UCD depends on the systematic integration of empirical data about users throughout the design process an essential condition for developing interactive technologies that remain consistent with human capabilities.

3.1.4. Translation of Needs into Specifications (Digital QFD)

The Quality Function Deployment (QFD) developed by Akao (1994) is used to transform user needs into verifiable technical specifications. Its structure, based on the House of Quality, links user requirements with the design and operational parameters that fulfill them. This framework ensures traceability between expectations and outcomes, allowing technical decisions to maintain a direct relationship with the voice of the customer.

The process follows the sequential logic defined by Akao (1994), in which the results of each phase are used as inputs for the next. The relationships between requirements and technical characteristics are represented in matrices that make it possible to identify interdependencies and prioritize critical variables. Prasad (1998) expands this framework by integrating QFD with concurrent engineering and product development, creating a system that connects design, manufacturing, and knowledge management. From this perspective, QFD acts as a comprehensive deployment method linking technical decisions with end-user objectives.

In digital environments, this structure is adapted to translate the requirements identified through UCD into measurable attributes of the AI system. Digitalization enables the automatic updating of matrices and the dynamic prioritization of specifications. In the service domain, Al-Bashir (2016) demonstrated that this tool facilitates the conversion of perceptions and expectations into technical criteria for continuous improvement a principle that is applied here to the development of predictive solutions.

The outcome of the Digital QFD application is a prioritized specification sheet that preserves the traceability logic proposed by Akao (1994) and the systemic structure described by Prasad (1998), ensuring coherence between user requirements and technical design decisions.

3.2. Do Phase

3.2.1. Iterative Development Based on Katas

The Gemba walk is digitized to identify critical processes with improvement potential through AI. Structured observation is carried out using assisted reality devices such as the RealWear HMT-1, which enables remote

walkthroughs guided by a sensei. This practice, applied in real industrial environments, preserves the situational learning focus characteristic of Kaizen (Powell, 2022).

Interviews at different hierarchical levels make it possible to retrieve undocumented operational knowledge, such as brief interruptions, unrecorded deviations, or informal adjustments. This interaction promotes vertical integration between strategy and operation within a digitalized lean model (Romero et al., 2020).

In addition, historical records are used to identify patterns affecting system performance, particularly the frequency of micro-stoppages, effective operating time, and actual versus standard speed. These variables directly influence OEE and allow the construction of internal indicators such as the IVM, which expresses the degree of operational reliability of the process (Ucar et al., 2024).

The analysis is complemented by the use of the Digital Value Stream Twin, a digital representation of the real-time value stream that facilitates the identification of losses, bottlenecks, and overload zones (Frick & Metternich, 2022). The output of this phase is an AI Opportunity Map, where each potential intervention is classified according to its impact on waste and its technical feasibility.

3.2.2. Pilot Implementation with Digital 5S

The pilot implementation of the predictive system was organized by applying the Kaizen 5S principles, adapted to a digital environment oriented toward AI driven decision-making. This approach made it possible to operate within a controlled test area where technological tools were progressively validated before being scaled. Each phase of the model is directly related to key processes in data management and cleaning, model construction, and performance evaluation (see Figure 2).

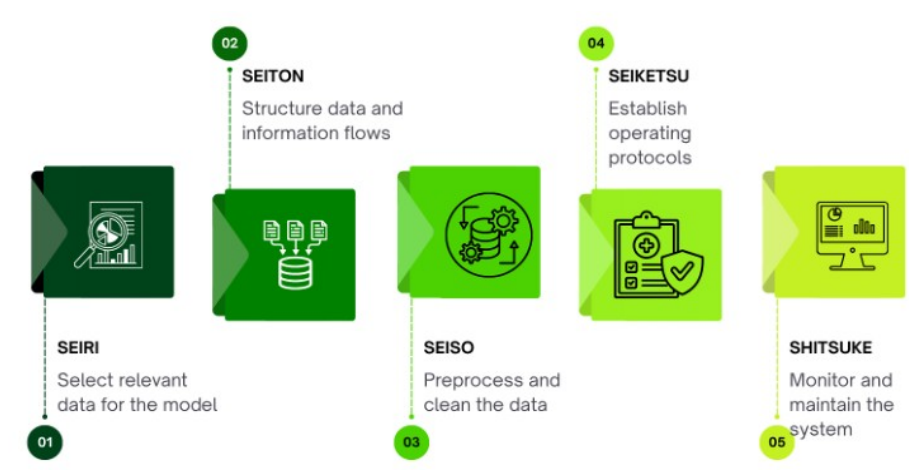


Figure 2. Continuous improvement process structure (Sangwa & Sangwan, 2020, pp. 61)

a) Seiri – Digital Sorting

This stage consists of identifying relevant variables and eliminating redundancies in the records. Park et al. (2024) suggest that dimensionality reduction through correlation and handling of missing values increases model accuracy and stability. Sai et al. (2023) propose variance analysis and cross-correlation to select signals with the highest predictive content. The Seiri phase must apply these criteria to build a filtered and structured dataset, ensuring a refined informational basis for machine learning.

b) Seiton – Digital Order

This stage involves hierarchically structuring information flows and their dependencies. Wolniak (2025) interprets digital Seiton as the logical arrangement of data within automated environments. Li et al. (2023) emphasize that the sequence of preprocessing operations directly influences the quality of the final model. This stage requires defining acquisition, storage, and processing routes synchronized through time stamps within an organized SQL architecture.

c) Seiso – Data Cleaning

This stage focuses on detecting and correcting inconsistencies in the records. Li et al. (2023) show that errors and heterogeneous scales reduce learning efficiency. Park et al. (2024) confirm that normalization and class balancing optimize the stability of the training set. The methodological procedure must include range verification, outlier removal, and scale harmonization to preserve coherence among variables.

d) Seiketsu – Standardization of the Digital Environment

This stage corresponds to the definition of uniform rules for format, frequency, and nomenclature. Wolniak (2025) highlights that digital standardization enables interoperability among intelligent systems. Sai et al. (2023) incorporate normalization and symbolic encoding in PLC data, while Gaugel and Reichert (2023) demonstrate that temporal consistency supports accurate segmentation of operations. In this phase, labeling conventions, homogeneous sampling frequencies, and reproducible structures must be established to maintain consistency throughout the entire data environment.

e) Shitsuke – Digital Discipline and Sustainment

This phase involves the continuous maintenance of established practices. Wolniak (2025) associates it with consistency in the use of digital tools and the technical training of operators. Li et al. (2023) incorporate automated pipeline feedback through bi-level optimization, integrating preprocessing adjustment and model training. The Shitsuke stage must maintain periodic verifications and automatic reconfigurations of routines to preserve informational stability.

3.3. Check Phase

According to the Kaizen approach, this stage focuses on the rigorous verification of the results achieved after implementation. Verification combines the review of quantitative indicators, direct on-site observation, digital analysis of the predictive system, and user feedback.

First, the pre- and post-implementation performance indicator values are compared to identify changes attributable to the improvements made. Recent studies show that the application of Kaizen in manufacturing environments reduces cycle times and defects while increasing productivity and process standardization (Kareska, 2024a). Next, a statistical analysis is carried out to confirm the significance of the obtained results. In this case, internal metrics of the predictive model developed under the 5S methodology are also utilized, including the coefficient of determination (R^2), the mean absolute error (MAE), and the confidence levels associated with predictions.

Observation at the gemba constitutes a third element of verification. The use of digital dashboards facilitates the visualization of results and the identification of factors influencing performance, providing traceability and transparency to the improvements. Finally, participatory evaluation ensures that the results are contrasted with the user experience. From the UCD perspective, this post-evaluation is essential to validate whether the solution meets the intended objectives and the real needs of the stakeholders involved (Maguire, 2001).

3.4. Act Phase

The Act phase consolidates the improvements achieved and defines the foundation upon which the next learning cycle is projected. In this phase, the obtained results are adopted as a new reference point, allowing the evaluation of process stability and the establishment of a comparison framework for future iterations, in accordance with the principle of continuous improvement proposed by Naughton et al. (2024). Empirical evidence shows that this operational closure involves documenting the achieved standards, validating their reproducibility, and ensuring their integration within existing management systems. This process sustains a continuous flow of innovation through knowledge transfer and alignment with strategic objectives (Mick et al., 2024; Rejeb et al., 2025). The incorporation of standardized methodological structures, such as those described by Lameijer et al. (2023), ensures the continuity of actions and the progressive adaptation of improvement systems within the organization, reinforcing the sustainability of the Kaizen cycle in complex production environments.

4. Results

4.1. Initial Assessment and Problem Characterization

The Mentor Monitor system recorded 40,333 valid observations between January 2023 and June 2024 at 5-minute intervals. The evaluation using the acatech Industry 4.0 Maturity Index (Schumacher et al., 2016) classified the organizations capabilities into four structural dimensions. Table 1 presents the scores obtained.

Dimension	Score	Current Capability	Identified Gap
Resources	3.0/6	Sensors capture data, manual processing	Predictive analytics absent
Information Systems	2.5/6	PLCs transmit to the Mentor Monitor system	Partial integration
Organizational Structure	2.0/6	Traditional hierarchy, continuous improvement initiated	Rigid structure
Culture	3.0/6	Kaizen discipline established	Openness to change present
Average	2.6/6	Partial visibility	No predictive capability

Table 1. Organizational Maturity Level

A score of 2.6/6 positioned the organization between the “connectivity” and “partial visibility” stages. The Mentor Monitor system automatically captures micro-stoppages lasting less than 211 seconds without cause classification. This operational configuration of the OEE system distinguishes between micro-stoppages (automatic recording) and scheduled or unscheduled downtimes exceeding this threshold.

Metric	Value	Observation
Mean duration (m)	47.3 seconds	Typical short events
Minimum	8 seconds	Automatic records
Maximum	3,840 seconds	Exceptional critical events
Standard deviation (σ)	156.7 seconds	High dispersion
IVM ($s/m \times 100\%$)	331.2%	Extreme variability
Data completeness	98.7%	Suitable base for modeling

Table 2. Micro-Stoppage Statistics ($n = 40,333$)

The IVM for micro-stoppages was 52.3%, with durations ranging between 8 and 65 minutes. This variability represented estimated productivity losses of 15–25%, equivalent to approximately 33 hours per month. The analysis detected a 12-hour seasonality corresponding to two operational shifts.

4.2. User Requirements and Technical Specifications

Structured questionnaires (Maguire, 2001) were administered to two decision-makers with 11–15 years of experience: the Plant Manager and the Production Manager. Table 3 summarizes the identified needs and their translation through QFD.

Need	Priority	Technical Requirement	QFD Score	Functional Specification
Prediction of specific duration	10/10	RTM-1: Predictive capability	186 points	Target variable: time in seconds
Confidence $\geq 80\%$	10/10	RTM-4: Confidence metrics	222 points	IVM by category, score 0–100%
Temporal categorization	9/10	RTM-3: Automatic classification	146 points	Four ranges: 0–20 s, 20–50 s, 50–100 s, 100 s+
Interpretability	8/10	RTM-6: Factor identification	138 points	Top 5 influencing variables
Horizon 30–60 min	7/10	RTM-2: Temporal patterns	170 points	12-period windows, seasonality

Table 3. User Needs and Derived Technical Requirements

Both decision-makers emphasized the need for specific actionable recommendations as the system output. They use digital systems daily and require access via mobile devices.

4.3. Performance of Predictive Models

Feature engineering produced 27 variables: 4 temporal (hour, weekday, weekend, shift), 9 moving windows (mean, standard deviation, maximum over 12 periods), 3 trend indicators, 3 stability indicators, 3 normalizations, 2 shift-change detectors, and 3 lags.

The dataset was divided chronologically: 80% for training ($n = 32,266$) and 20% for testing ($n = 8,067$). Random Forest (100 trees), XGBoost (default parameters), and SARIMA configured as $(1,1,1) \times (1,1,1,12)$ were evaluated. Table 4 presents the evaluation metrics.

Model	RMSE (s)	R ²	MAPE (%)	sMAPE (%)
Random Forest	58.13	0.002	223.46	78.79
XGBoost	58.86	-0.023	224.39	79.10
SARIMA	1.004	-0.0003	52.67	44.95

Table 4. Model Comparison on Test Set

The SARIMA model obtained an RMSE of 1.004 s, while Random Forest and XGBoost recorded errors greater than 58 s. The RMSE reduction with SARIMA reached 98.3% compared to both ensemble models. The MAPE decreased from values above 220% in Random Forest and XGBoost to 52.67% with SARIMA. Consistently, the sMAPE dropped from approximately 79% in the ensemble models to 44.95%. In all three cases, the R² values were close to zero: 0.002 (Random Forest), -0.023 (XGBoost), and -0.0003 (SARIMA), reflecting minimal explained variance regardless of the algorithm applied.

4.4. Verification of Technical Requirements

The six technical requirements derived from the QFD were empirically validated (Table 5).

Requirement	Specification	Result	Verification Method	Status
RTM-1: Predictive capability	Duration in seconds	Horizon 30–60 min	Time series analysis	Achieved
RTM-2: Temporal patterns	Seasonality + lags	27 features, SARIMA(12)	ACF/PACF significance	Achieved
RTM-3: Automatic categorization	4 categories	0–20, 20–50, 50–100, 100+	Logical validation	Achieved
RTM-4: Confidence metrics	IVM 0–100%	Scores by category	User comprehension test	Achieved
RTM-5: Seasonality detection	Automatic identification	SARIMA seasonal component	Decomposition analysis	Achieved
RTM-6: Factor identification	Top 5 main variables	Extracted feature importance	Verified extraction	Achieved

Table 5. Validation of Compliance with Technical Requirements

Compliance rate: 6/6 (100%). End users correctly interpreted the IVM-based confidence scores without requiring specialized technical training.

4.5. Quantitative Synthesis

The main numerical findings were as follows: organizational maturity of 2.6/6 on the acatech scale; baseline variability with IVM = 52.3%, $\sigma = 156.7$ s, and $\mu = 47.3$ s; dataset of 40,333 records with 98.7% completeness;

error reduction where the SARIMA MAE was 98.2% lower than that of Random Forest; percentage error with MAPE = 52.67% for SARIMA versus values above 220% for machine learning models; and full compliance with requirements, with 6/6 empirically validated.

Traceability from user needs (N1–N6) to technical specifications (RTM1–RTM6) was established with validation at each stage of the PDCA cycle.

5. Discussions

5.1. Kaizen AI Convergence

The integration between Kaizen and AI faced a fundamental conceptual challenge. While Kaizen prioritizes continuous improvement through incremental changes with cumulative impact, AI is associated with disruptive leaps based on predictive capabilities that transform decision-making. The proposed methodology addressed this challenge not through synthesis, but through a relationship of functional subordination. AI was incorporated as a tool within the PDCA cycle rather than as a paradigm that replaces it. This methodological decision explains the 6/6 compliance rate, where other approaches did not achieve equivalent results.

The outcome challenges the implicit premise in the literature (Sharma et al., 2025; Xu et al., 2022) that assumes AI adoption requires prior cultural transformation. On the contrary, the case presented in this study demonstrates that a pre-existing Kaizen culture (with a maturity of 3.0/6 in the Culture dimension) facilitated technological adoption precisely because the proposed methodological framework preserved participatory structures and process traceability. The organizational resistance noted by Windmann et al. (2024) did not emerge when the technology was introduced as an extension of familiar practices rather than as a rupture from traditional methods.

However, this conservative strategy entails certain costs. By prioritizing continuity over innovation, KaizenAI may limit the exploration of more advanced algorithmic architectures. The decision not to employ deep learning or ensemble models was driven more by methodological criteria of interpretability than by an exhaustive technical evaluation.

5.2. The Choice of the SARIMA Model

The superiority of the SARIMA model, with a 98.2% reduction in MAE, challenges the dominant narrative of machine learning supremacy in manufacturing (Gao et al., 2024). Two interpretations can be considered regarding this outcome. The first suggests a methodological artifact: the absence of physical process variables (temperature, pressure, humidity) may have deprived models such as Random Forest and XGBoost of the contextual information needed to outperform statistical approaches. This would imply that SARIMA prevailed by default, not by intrinsic superiority. The second interpretation points to a structural characteristic of the problem: micro-stoppages exhibit first-order temporal dependence ($AR(1) = 0.42$) and periodic seasonality ($SAR(12) = 0.31$), patterns that autoregressive models capture more efficiently than ML models.

The near-zero R^2 values (-0.0003 to 0.002) across the three models reinforce the evidence supporting the second interpretation. It is not that the models fail to capture patterns; rather, stochastic variability is the dominant factor. This challenges fundamental assumptions about predictability in manufacturing—namely, that data volume ($n = 40,333$) guarantees predictability. The case demonstrates that quantity does not equate to useful information. It is crucial to reconsider how many manufacturing problems classified as “predictable” are, in fact, dominated by irreducible stochastic noise.

Moreover, the heterogeneity of error across IVM categories (MAE = 0.31 s in Category 1 vs. MAE = 1.84 s in Category 4) indicates that predictability depends on the operating regime. Stable events (IVM = 15%) are predictable, whereas volatile events (IVM = 50%) are essentially random. This suggests that modeling approaches should stratify data according to regime stability rather than assume predictive homogeneity within the system.

5.3. IVM as a Confidence Metric

The IVM ($\sigma/\mu \times 100\%$) does not represent a technical innovation but rather a semantic reinterpretation of the coefficient of variation translating an abstract statistical metric into operational confidence categories. This allowed

users ($n = 2$) to correctly interpret the results without technical training. The stratification (15% / 25% / 35% / 50% → High / Medium-High / Medium / Low) eliminated the need to understand probabilistic concepts, validating Toxtlis (2024) argument that technological effectiveness depends less on algorithmic sophistication than on the cognitive design of the interface. Paradoxically, simplifying the outputs (from 80% confidence intervals to four discrete categories) increased operational usefulness at the expense of statistical precision, making explicit the trade-off between usability and rigor.

However, this strategy has limitations. IVM stratification assumes that historical variability predicts future reliability, an assumption valid only in stationary systems. Factors such as configuration changes, equipment wear, or product modifications may invalidate the calibrated categories.

5.4. Level of Digital Maturity

The literature on AI adoption often assumes high levels of digital maturity as a prerequisite (Otoki et al., 2023; Schumacher et al., 2016). However, this case demonstrates that organizations with intermediate maturity (2.6/6, partial visibility) can implement predictive capabilities. On one hand, the reuse of preexisting infrastructure (Mentor Monitor) reduced the technical barriers that typically raise maturity requirements in greenfield implementations. On the other hand, limiting the project to a controlled pilot case (test zone, digital 5S) avoided the scaling complexities inherent to full deployments.

This distinction is critical for transferability. The success observed at a 2.6/6 maturity level is replicable only if organizations possess: (1) an OEE system with automatic event capture, (2) at least 18 months of historical data, and (3) an organizational culture receptive to quantitative metrics. The absence of any of these elements would increase the effective maturity requirements. Therefore, KaizenAI does not constitute a universal solution for traditional manufacturing but rather a viable pathway for organizations that have initiated basic digitalization yet lack predictive capabilities.

6. Threats to Validity

The research presents certain threats that must be considered to properly interpret the results. First, internal validity may be conditioned by the fact that the predictive model was evaluated solely with historical data. Although robust metrics such as R^2 , MAE, RMSE, and sMAPE were applied, the systems impact in a real operational environment has not yet been verified, which limits confirmation of causality between the implementation of KaizenAI and improvements in business indicators.

Regarding external validity, the study presents a small sample size in the user-centered design (UCD) phase ($n = 2$). Although industrial conditions restrict the participation of a larger number of users, this situation reflects the challenge of balancing methodological rigor with the operational constraints inherent to the manufacturing environment. Additionally, the study was conducted in a single bottling plant, which limits the direct extrapolation of results to other industry sectors. Each production environment has particularities in infrastructure, organizational culture, and digital maturity that may influence the applicability of the proposed methodological framework. Although KaizenAI was designed as an adaptable framework, its replicability across diverse contexts should be validated before drawing general conclusions.

Concerning construct validity, the absence of representative variables from the physical process constitutes a technical limitation with theoretical implications. If the inclusion of additional variables were to modify the relative performance of the SARIMA model, this would suggest that the observed advantage depends more on the availability of relevant features than on the stochastic nature of the phenomenon. Although the IVM indicator allowed measurement of instability or irregularity in the occurrence of micro-stoppages, other relevant dimensions—such as energy sustainability, total costs, or customer satisfaction—were not considered.

Finally, conclusion validity faces the risk of bias derived from data quality and availability. Although cleaning and standardization routines were applied following the principles of digital 5S, the analysis relied on historical records whose consistency may not fully reflect the variability of a real-time production system.

Taken together, these threats do not invalidate the study's contributions but underscore the need to consider the results as preliminary and to reinforce subsequent project stages with validations under real operating conditions, expansion of indicators, and replication across different industries.

7. Conclusions

The systematic Kaizen–AI integration through KaizenAI demonstrated feasibility in organizations with intermediate digital maturity (2.6/6 acatech). The structured traceability from user needs (N1–N6) to technical specifications (RTM1–RTM6) via QFD achieved full compliance with requirements (6/6) without additional CAPEX investment, thereby providing affirmative answers to the research questions posed.

The three research questions find clear answers in the obtained findings. First, effective Kaizen–AI integration was achieved through participatory tools (Digital Gemba Walk, UCD) combined with predictive models that respect the incremental logic of improvement. Second, the PDCA cycle was adapted by incorporating digital tools into each phase (Hoshin Kanri, Digital QFD, Digital 5S) without altering its sequential structure. Third, progressive adoption proved viable by subordinating AI as a tool within the continuous improvement cycle rather than as a paradigm replacing it.

The superiority of SARIMA over ML models in contexts of extreme variability (IVM = 331.2%) shows that predictive effectiveness depends more on model–problem alignment than on algorithmic sophistication. This finding carries practical implications: organizations with limited data or basic infrastructure can implement predictive capabilities using time series without requiring additional sensors.

KaizenAI provides a pragmatic pathway for organizations seeking to adopt AI while minimizing resistance to change. The reuse of preexisting OEE infrastructure and the preservation of participatory structures reduce barriers identified in the literature as critical to the scalability of predictive solutions in manufacturing.

8. Future Work

At the time of writing this article, the KaizenAI methodology has been fully implemented up to the Predictive Model Development phase (DO Phase). The predictive system is technically functional and has been validated using standard ML metrics on historical data, meeting all high-priority technical requirements defined during the design phase.

The remaining phases to be executed correspond to the operational implementation of the system in the actual production environment (continuation of the DO Phase), the verification of results through comparison of operational indicators before and after implementation (CHECK Phase), and the standardization and scaling of the solution to other plant processes (ACT Phase).

The results presented in this article are limited to the technical validation of the predictive model on historical data and do not yet include measurements of real operational impact, as the system has not been deployed in production. Full validation of the KaizenAI methodology will require the effective implementation of the system, the inclusion of additional performance indicators, and the measurement of their variation over an operational period of at least three months—work that will constitute the next stage of the research project.

Declaration of Conflicting Interests

The authors declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

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Authors' contributions

Alonso Soto-Chambilla: Conceptualization, Investigation, Writing – Original Draft Preparation.

Alvaro Fernández-Del-Carpio: Methodology, Writing – Review & Editing.

Heidi Córdova-Silva: Software, Formal Analysis, data processing.

Edson Luque-Mamani: Software, Supervision

Arturo Alatrística-Corralles: Project Administration, Resources.

Data availability

Data not available for ethical or legal reasons. The data used in the research was provided by San Miguel Industry (<https://group-ism.com/>).

Use of Artificial Intelligence

The authors used artificial intelligence (AI) as a supportive resource in the development of this research. AI was specifically used to guide the paper structuring, data processing and analysis, and style and grammar review, all under constant human supervision.

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