Proceedings of the 8th IEOM Bangladesh International Conference on Industrial Engineering and Operations Management, Dhaka, Bangladesh, December 20-21, 2025

Proceedings of the International Conference on Industrial Engineering and Operations Management

Publisher: IEOM Society International, USA DOI: 10.46254/BA08.20250394
Published: December 20, 2025

Efficiency Improvement Based on Lean Service and Machine Learning in a SME of Services Sector

Gianella Guadalupe Turín-Cabrera
Facultad de Ingeniería, Universidad de Lima, Peru
201833354@aloe.ulima.edu.pe

Wendy Carolayn Pérez-Ruiz
Facultad de Ingeniería, Universidad de Lima, Peru
20171174@aloe.ulima.edu.pe

Nicolás Salazar-Medina
Research Professor
Facultad de Ingeniería, Universidad de Lima, Peru
nsalazar@ulima.edu.pe

Abstract

This research work analyzes a company that operates a contact center, which provides closer communication with its customers through chats, calls and emails. The objective of this research is to demonstrate how the integration of Machine Learning together with the Lean service methodology can improve the company's efficiency in order to reduce processing time and unnecessary costs, in addition to providing better quality in the services provided by the company.

Keywords
Lean service, Machine learning, 5S, Big data, Standardization, Poka-Yoke and Efficiency.

1. Introduction
The problem we're trying to solve is how to improve contact center service by offering better customer care and using digital tech to streamline service processes. Right now, Peru's service sector is growing, especially in retail (7.48%), restaurants (92.06%), and business services (3.06%). (INEI), 2022.

It began with the idea of services in the economy, since in the past a chain production system was implemented, then there were many organizational changes to improve efficiency, such as knowledge management, the use of information, the incorporation of technology, and innovations, in order to offer improvements in the service sector. In addition, the service sector contributes 40% of the country's GDP. Therefore, it is necessary to seek improvements in the customer service process.

In this scenario, research was conducted to help optimize service efficiency in a contact center. To achieve this, a Lean Service model is proposed in conjunction with Machine Learning, which integrates four tools: Standardization, 5S, Poka-Yoke, and Machine Learning. This model will be implemented to improve the service offered to contact center customers. It is worth mentioning that one of the main limitations was that workers often make mistakes in customer service, especially in call registration and classification, in addition to generating downtime that affects the efficiency of the process.

1.1 Objectives

The research seeks to demonstrate that the model based on 5S, Standardization, Poka-Yoke and Machine Learning will improve the efficiency in the service of a contact center. First, the 5S will be used to organize digital information, eliminate unnecessary elements and facilitate quick and orderly access to information. Secondly, Standardization will be used to define, document and disseminate the best way to carry out service processes. Thirdly, Poka-Yoke will be used to implement error-proof mechanisms, such as automatic validations, thus reducing failures and rework. Finally, Machine Learning will be used to analyze data, predict demands and provide customer service support.

2. Literature Review

2.1 5S in the service sector

Based on the available literature, the most influential work for contact centers is that of Piercy and Rich (2009), because it demonstrates—in a "pure service environment"—that a call center can simultaneously improve quality and costs through a "lean" transformation, where space/flow organization and standardization (practices consistent with 5S) are pillars of change. Along the same lines, Laureani, Antony, and Douglas (2010) confirm, in a real call center case study, that a Lean Six Sigma program increases first contact resolution and streamlines processes. Although the article does not focus on 5S, the improvements are based on eliminating waste and stabilizing work, which is typically operationalized with 5S in services. To explicitly support the applicability of 5S to the service sector, Kanamori et al. (2016) review evidence in public health and show that 5S (sort, set in order, shine, standardize, sustain) improves safety, times, and user focus—findings that are transferable to remote care environments where information, screens, and digital "gemba" must be organized. At the administrative office level (information-intensive services, close to the back office of a contact center), Yusof et al. (2015) document that the sustainability of the QE/5S scheme depends on discipline, audits, and staff participation, which converges with Piercy and Rich (2009) on the need for change management and standardization for improvements to last. Finally, Sreerag and Pillai (2018) synthesize "lean thinking" in services and include 5S as a basic technique for reducing time and errors in public services, providing a general framework but also introducing a nuance: the impact of 5S is enhanced when integrated with process mapping and problem solving (not as an isolated intervention), suggesting a slight divergence from simplistic readings of 5S as a panacea. Overall, the five studies converge in that 5S—as a form of visual organization and standardization—is an enabling condition for efficiency in services and, by extension, in contact centers; they diverge in the degree of centrality they give to 5S (from implicit in broad lean transformations to explicit in sectoral reviews) and in emphasizing that its effectiveness depends on integrating it with other lean practices and with governance that ensures its sustainability.

2.2 Standardization in the service sector

The most relevant piece of research for understanding standardization in contact centers is that of Piercy and Rich (2009), as it documents a lean transformation in service centers where the standardization of processes, roles, and flows is presented as the core for simultaneously improving quality and reducing costs in a call center (Piercy & Rich, 2009). From this framework, Laureani, Antony, and Douglas (2010) show in a case study in a call center that implementing standardized controls (procedures, metrics, and analysis templates) increases first-contact resolution and reduces operational variability, thus converging with Piercy and Rich on the idea that standardization enables performance. The report/review by Doellgast and O'Brady (2019) complements this perspective with extensive empirical evidence on call center management practices: it documents how standardization (scripts, SOPs, QA metrics) can improve service consistency and measurement, but also warns that excessive standardization—without autonomy or support—increases stress and turnover, which qualifies Piercy and Rich's optimistic proposal. In the field of language and communication standardization, Woydack and Lockwood (2017) analyze the use of scripts and point out that, while they promote consistency in interaction and facilitate training processes (in line with Piercy and Laureani's findings), their effectiveness depends largely on both the quality of the design and the degree of flexibility granted to staff. In this sense, they partially diverge by highlighting the possible negative effects on the authenticity of communication and the customer experience when scripts are applied too rigidly. On the other hand, the recent application of standardized operating procedures in the virtualization of a specialty-pharmacy call center (Pierce et al., 2022) offers practical proof: after developing SOPs and organizing remote workflows, the center managed to maintain service indicators and reduce errors, which coincides with the conclusions of Piercy et al. regarding operational benefits. in terms of operational benefits, but adds a decisive technological/organizational nuance—standardization must consider remote capabilities, security, and digital collaboration—which was not central to classic lean studies. In summary, these studies agree that standardization (procedures, scripts, metrics, and templates) is a necessary condition for consistency, measurement, and continuous improvement in contact centers. They differ in degree and form (standardization as a purely positive lever vs. standardization conditioned by human design and flexibility) and agree that its effectiveness requires accompanying training, feedback mechanisms, and governance that preserve minimum operational autonomy for handling complex cases (Piercy & Rich, 2009; Laureani et al., 2010; Doellgast & O'Brady, 2019; Woydack & Lockwood, 2017; Pierce et al., 2022).

2.3 Poka-Yoke in the service sector

The Poka-Yoke method applied in contact centers prevents errors and improves efficiency and service quality (Prabowo, 2020). Designing workflows using this approach reduces losses and errors in call management, which leads to greater customer satisfaction (Prabowo, 2020). It also reduces response times, improving operational efficiency. Furthermore, recent studies confirm that these practices create more stable environments that are less prone to human error, a fundamental factor in the fast-paced dynamics of contact centers (James et al., 2024).

2.4 Machine Learning in the service sector

Among the studies reviewed, the most influential is that of Shah et al. (2023), which presents a comprehensive review of the use of machine learning and natural language processing in contact center automation, identifying how these technologies improve efficiency in intent classification and customer satisfaction. In line with this, Li, Wang, and Koole (2019) empirically demonstrate that predictive machine learning models optimize call management and staffing levels, providing practical evidence that converges with the findings of Shah et al. (2023). Complementarily, Ibrahim et al. (2016) focus on call arrival forecasting and show that the incorporation of advanced statistical techniques together with machine learning significantly improves accuracy, although they warn of the need for more robust hybrid models, which qualifies the more optimistic view of Shah et al. (2023). Likewise, Chacón et al. (2023) validate with temporal memory networks and gradient boosting models that predictions in call centers can be more reliable and adaptive, reinforcing the central thesis of Shah et al. (2023) on the relevance of artificial intelligence for operational efficiency. Overall, the articles converge on the idea that machine learning is a key driver of efficiency and innovation in contact centers, despite the current limitations of its practical implementation and the need to integrate these tools with hybrid and human approaches to ensure sustainable results.

3. Methods

A three-phase approach is proposed for the development of the model, as shown in Fig. 1. Each phase is designed to combine Lean Service tools with Machine Learning techniques, generating a comprehensive system of continuous improvement.

Phase 1: Planning

The first phase focuses on preparing the ground, ensuring that tasks can be carried out with greater efficiency. To do this, we apply tools like 5S, which help separate what is really needed from what only creates clutter, and keep the workspace ready for daily operations. Along with this, process standardization is introduced so that activities follow the same sequence and rules, avoiding unnecessary differences and ensuring that the information generated is reliable. It serves as the framework that supports and enables future enhancements.

Phase 2: Development

Once the processes are organized and the work environment is stable, attention shifts to preventing mistakes. Here the Poka-Yoke philosophy plays a central role, since it focuses on detecting the points where failures usually appear and placing simple but effective controls in those places. This is especially important when there is direct contact with customers, as even small errors can have an impact. This phase also supports the idea of ongoing improvement, turning each error into both a correction and a source of learning for process refinement.

Phase 3: Implementation

The final phase consists of incorporating Machine Learning as a strategic resource to enhance service processes. By using algorithms, it becomes possible to discover patterns in the data, anticipate customer behavior, and even suggest specific actions. When applied to a contact center, the integration allows services to be adjusted to each client’s needs, reduces waiting times, and supports a more balanced use of personnel and technology. This combination improves how the service operates while also enhancing customer satisfaction. Finally, the third phase proposes the integration of Machine Learning to support the Lean Service approach. Machine learning can be applied in services to spot patterns and make predictions that support everyday decisions. In practice, contact centers have used these models to anticipate when a client might leave, to manage staff and resources more efficiently, and even to capture the mood expressed in online conversations. By linking Lean methods with artificial intelligence in this way, organizations are able to reduce errors, work with greater efficiency, and deliver a service that feels both more personal and more consistent (Figure 1).

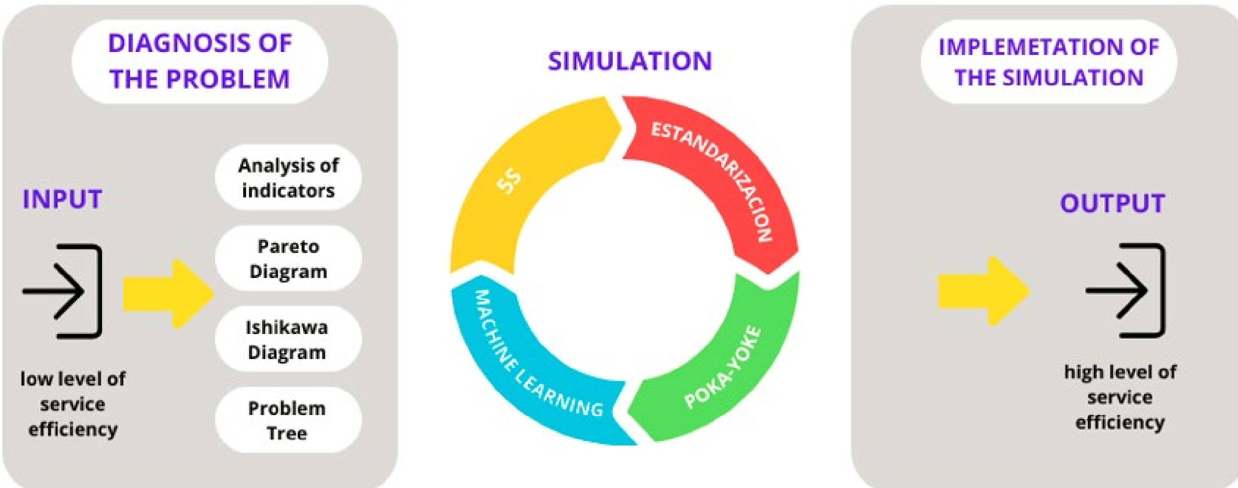


Figure 1. Proposed model

4. Data Collection

This research relied on several sources, such as scientific articles and books on Lean Service. To complement this information, interviews were carried out with managers from departments like quality and operations. Their contributions provided a broader view of the company and made it possible to assess different performance indicators.

Using this input, a model was designed that began by observing how processes flowed within the contact center. The analysis focused on detecting waste, delays, and recurring errors. From there, key indicators such as Average Handling Time (AHT), First Call Resolution (FCR), and abandonment rates were examined.

During the simulation stage, the 5S method was applied to bring order to both the physical and digital environments. At the same time, scripts, procedures, and escalation routes were standardized to achieve consistency. Poka-Yoke practices were introduced to minimize human mistakes through automatic validations. Machine Learning was also incorporated, which made it possible to predict call demand and suggest actions. With these tools, simulations were developed in Orange and other specialized programs.

In the final stage, the models were tested with the proposed improvements, and the results of the efficiency indicators were reviewed. This evaluation led to the creation of a monitoring and control system, which ensured ongoing process improvement and higher efficiency in the contact center. Figure 2 shows the results step by step

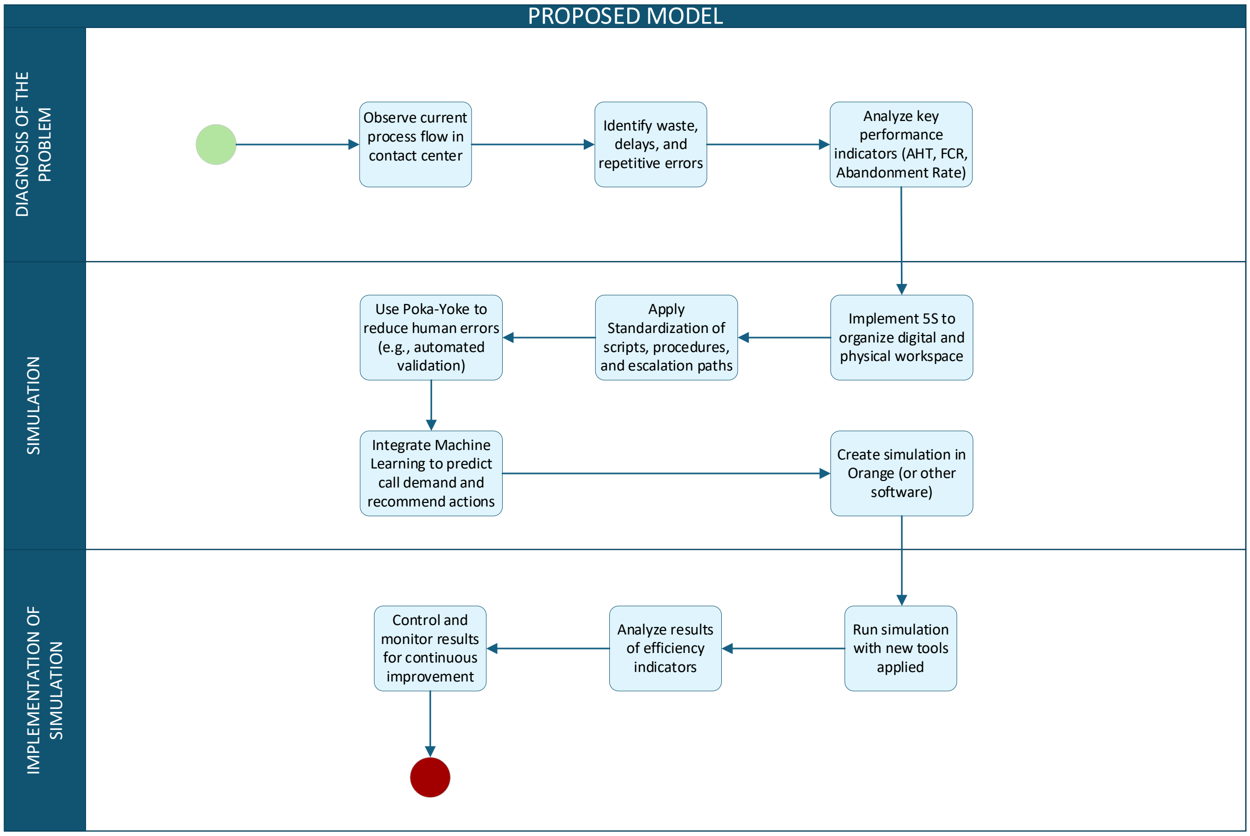


Figure 2. Diagram to achieve results

4.1 Implementation of 5S, Standardization, Poka-Yoke and Machine Learning

During this phase, various Lean Service tools and machine learning techniques were applied through pilot tests within the organization. Implementation began with the 5S methodology, used to organize both the physical space and the digital environment. Next, a process was developed to standardize scripts, procedures, and escalation routes in order to ensure consistency in operations. Subsequently, the Poka-Yoke approach was incorporated, aimed at reducing the incidence of human error through automated validation mechanisms. Finally, machine learning models were introduced to anticipate call demand and generate recommendations for decision-making.

In relation to the 5S methodology, an internal audit was carried out to diagnose the initial situation of the work environment. The Sort phase involved identifying and eliminating documents, files, and digital tools that did not contribute to the process. In Set in Order, both electronic folders and the layout of workstations were reorganized, ensuring accessibility and operational fluidity. The Clean stage incorporated a preventive maintenance plan aimed at preventing the accumulation of physical and digital clutter. Subsequently, in Standardize, organizational protocols were defined to maintain the improvements achieved; and in Sustain, training and awareness activities were carried out, in addition to a follow-up audit that confirmed the progress made.

Process standardization focused on reviewing and documenting communication scripts, incident resolution procedures, and escalation routes. The analysis identified redundancies and inconsistencies, which were corrected by developing unified formats and precise guidelines. To support the agents, flowcharts and decision trees were prepared. Their use made it easier to respond quickly and kept service more consistent. This change also showed positive results in key measures, including AHT and FCR.

For the application of Poka-Yoke, Failure Mode and Effects Analysis (FMEA) was used, which allowed for the identification of the most common sources of error during customer interactions. The most frequent errors identified were incomplete records, inaccurate data entry, and calls routed to inappropriate destinations. Each error was evaluated based on its severity, frequency, and probability of non-detection. Based on this review, automatic controls were designed, such as mandatory fields, real-time alerts, and escalation triggers. These mechanisms acted as preventive barriers that reduced the probability of human error and increased the reliability of the process.

The use of machine learning was based on the collection and analysis of historical call data to identify behavior patterns in different periods. Supervised models were trained to estimate the expected volume, which facilitated more efficient resource and schedule planning. Likewise, classification algorithms were implemented that were capable of recommending operational actions, such as dynamic adjustments in staffing or automatic redirection based on the projected load. In this way, the predictive component was integrated with real-time decision-making, strengthening the cycle of continuous improvement.

The sequential implementation of these four tools made it possible to consolidate a structured, data-driven management model focused on reducing waste, optimizing efficiency, and achieving sustainable improvements in service processes.

The results obtained from the analyzed scenario in the contact center are presented below. To determine the level of efficiency, management records from several months were considered, using a monthly average of the main performance indicators.

- Effectiveness level (%): $\frac{Calls\ resolved\ on\ first\ contact}{Total\ calls\ answered} * 100\% = \frac{800}{1200} * 100\% = 66.67\%$
- Efficiency level (%): Effectiveness×(1−Defective) =66.67%× (1−0.015) = 65.67%
- First Contact Resolution level (FCR) (%): $\frac{\Sigma\ Orders\ resolved\ at\ first\ contact}{\Sigma\ Total\ orders} * 100\% = \frac{750}{1200} * 100\% = 62.5\%$
- Right-First-Time level (RFT) (%) : $\frac{\Sigma\ Orders\ without\ rework\ and\ without\ valid\ complaint}{\Sigma\ Total\ orders} * 100\% = \frac{822}{1200} * 100\% = 68.5\%$

5. Results and Discussion

Following the diagnostic stage of the Contact Center process, the analysis of operational performance revealed significant inefficiencies in the service area. During the months, the Effectiveness level reached an average of 66.7 %, while the Efficiency level was 65.7 %, confirming that the organization operates below the 70 % standard required for the service sector. Only two-thirds of the total customer cases were resolved within the expected response time and without errors, reflecting delays, bottlenecks, and the absence of standardized procedures.

In addition, the First Contact Resolution (FCR) indicator reached 62.5 %, indicating that more than one-third of the cases required a second interaction or escalation before completion. Similarly, the Right-First-Time (RFT) level achieved 68.5 %, showing that a considerable percentage of requests still required rework due to data entry errors or lack of proper classification. These results demonstrate that inefficiency was mainly associated with repetitive manual work, lack of information flow between operators, and limited use of predictive tools for prioritizing cases.

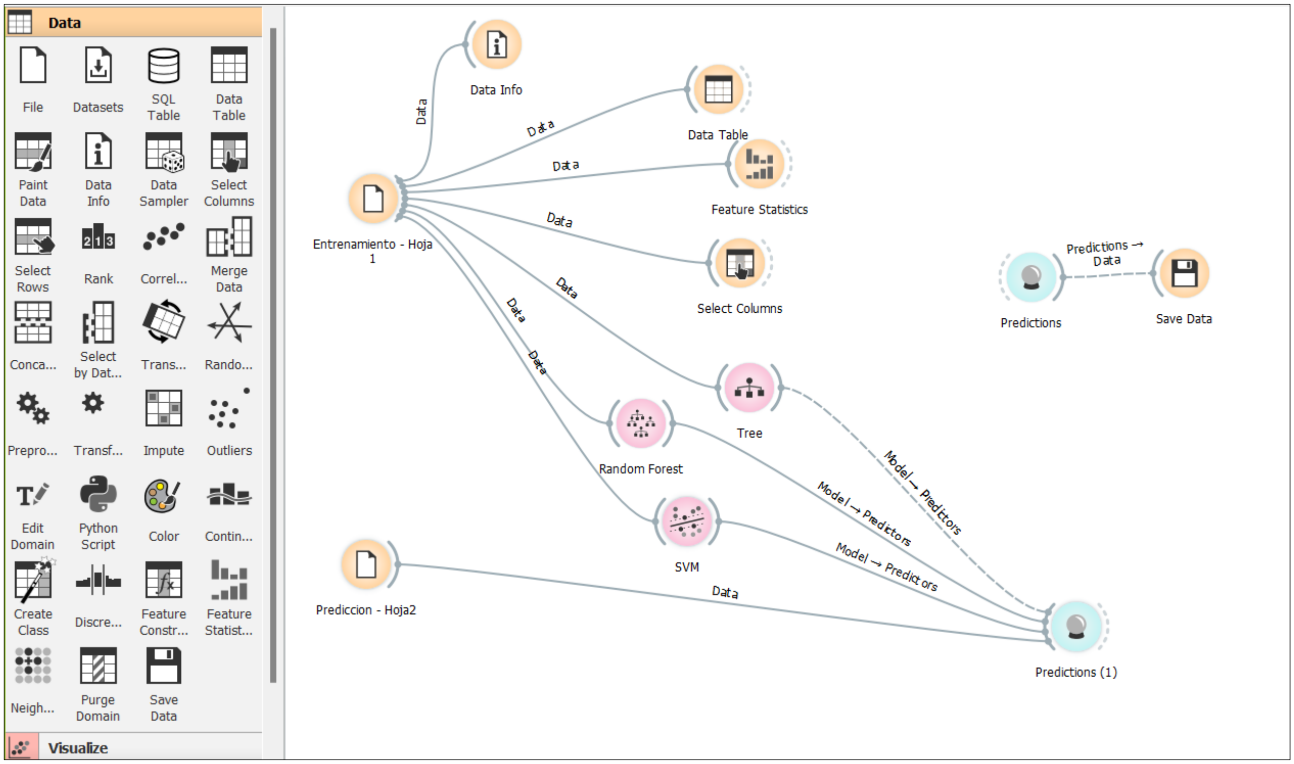
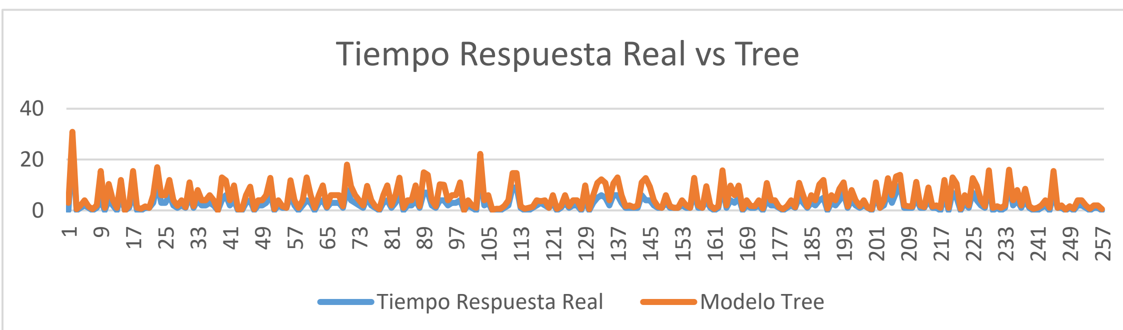


Figure 3. Predicted vs. Actual Response Time using Decision Tree model.



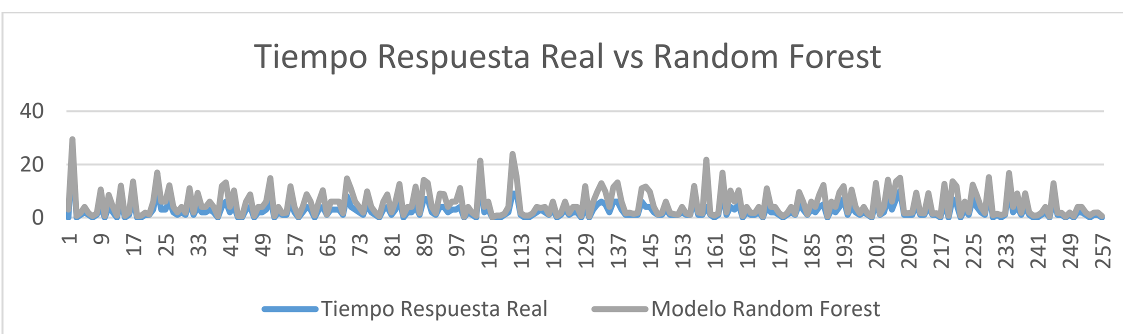


Figure 4. Predicted vs. Actual Response Time using Random Forest model.

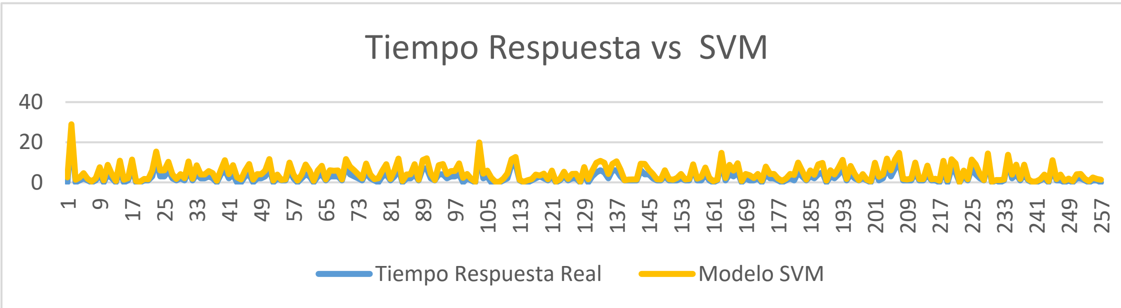


Figure 5. Predicted vs. Actual Response Time using SVM model**.**

Based on the initial diagnosis, three Lean Service tools—5S, Standardization, and Poka-Yoke—were implemented together with Machine Learning techniques to address the operational inefficiencies detected (Figure 3- Figure 5).

Through 5S, the work environment and digital database were organized to eliminate duplicated files and ensure faster retrieval of client information, which reduced the average order processing time from 52.08 hours to 40.00 hours. Standardization was applied to unify procedures and response formats among operators. As a result, the Effectiveness level increased from 66.7 % to 88 %, demonstrating greater consistency and quality in service delivery.

Justification of the improved indicators (To-Be).
To estimate the improved Effectiveness level of 88%, the same volume of cases used in the current scenario (1,200 cases) was considered. Under the Lean Service + Machine Learning improvements, it is projected that **1,056** cases would be resolved within the expected time:

$$Effectiveness_{To-Be} = \frac{1056}{1200} \times 100 = 88\%$$

Likewise, the improved Efficiency level was calculated using the formula defined in the study:

$$Efficiency = Effectiveness \times (1 - Defective)$$

Assuming a reduced defective rate of 2% due to Standardization and Poka-Yoke, the improved Efficiency is:

$$Efficiency_{To-Be} = 88\% \times 0.98 = 86\%$$

This confirms the consistency of the projected performance improvements.

Meanwhile, Poka-Yoke mechanisms were designed as digital validation controls within the registration platform to prevent missing data, double cases, or incorrect classifications. These error-proofing actions improved the Right-First-Time (RFT) indicator from 68.5 % to 87 %, confirming a 70 % reduction in registration errors. Finally, the integration of Machine Learning algorithms, particularly the Decision Tree model with an average prediction error of 3.45 %, enabled predictive prioritization of cases and further increased Efficiency to 86 % and FCR to 83 % (Table 1).

Table 1. Simulation Indicators – As-Is and To-Be Comparison

Simulation Indicators	As-Is (Current State)	To-Be (Improved State)	Improvement (%)
Effectiveness level (%)	66.7	88.0	+32 %
Efficiency level (%)	65.7	86.0	+31 %
First Contact Resolution (FCR) (%)	62.5	83.0	+33 %
Right-First-Time (RFT) (%)	68.5	87.0	+27 %
Average order processing time (h)	52.08	40.00	−23 %

The Lean Service + Machine Learning model was simulated in two stages: the As-Is scenario (current state) and the To-Be scenario (improved state). After implementing the proposed model, the indicators showed a notable improvement in all dimensions: Effectiveness rose to 88 %, Efficiency to 86 %, FCR to 83 %, and RFT to 87 % (Figure 6), Likewise, the average processing time decreased to 40.00 hours, representing a 23 % reduction in service lead time.

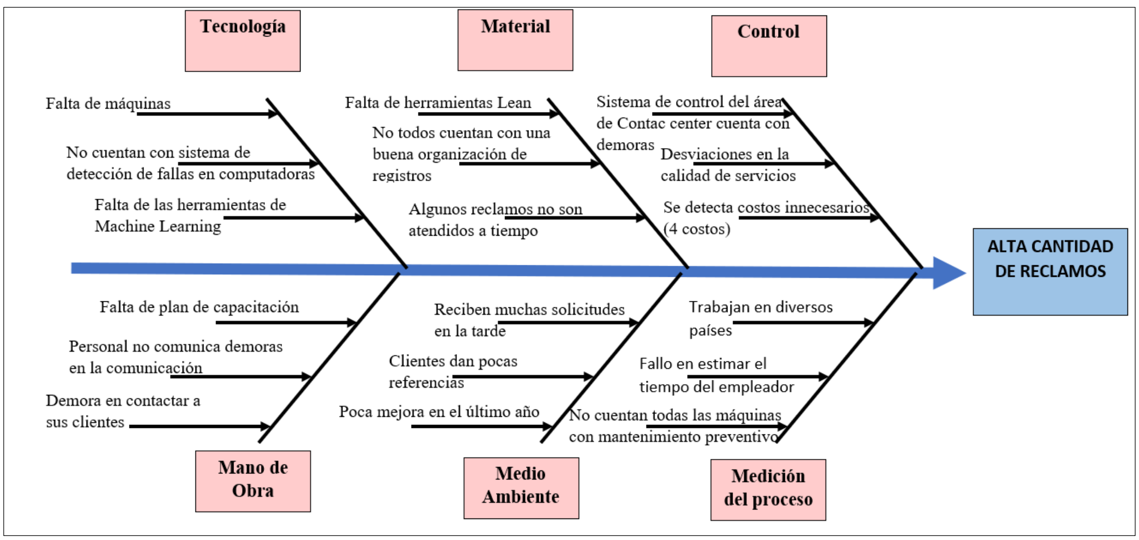


Figure 6. Cause-and-Effect (Ishikawa) Diagram of the High Number of Customer Complaints

Paso/ Entrada del proceso	Modalidad de falla potencial	Efectos de fallas potenciales	GRAVEDAD	Causas Potenciales	FRECUENCIA	Controles vigentes de Prevención	Controles vigentes de Detección	DETECTIBILIDAD	RPN	Acciones Recomendadas	Responsable y fecha	Acciones Tomadas	GRAVEDAD	FRECUENCIA	DETECTIBILIDAD	RPN
¿Cuál es el paso y entrada del proceso que se está investigando?	¿En que formas está equivocada la entrada clave?	¿Cuál es el impacto en las variables de salida clave (requisitos del cliente)?		¿Qué hace que la entrada clave esté equivocada?		¿Cuáles son los procedimientos o controles vigentes que previenen o detectan las causas o fallas potenciales?	¿Qué controles y procedimientos existen? (inspección y pruebas que detectan cualquier causa del Modo de Falla)			¿Qué acciones se podrían recomendar para reducir la frecuencia de las causas potenciales, o mejorar la detectiblidad de la falla?		¿Qué acciones se han ejecutado? ¿Qué medidas se han tomado? ¿Cómo se justifica el				
Recepción de datos del cliente	Demorada debido a la toma de datos	Retraso en servicio	8	No hay una verificación especifica	7	Sin control	Inspeccion de los servicios	6	336	Realizar controles diarios en los mensajes y las llamadas	FY	-	8	3	2	48
Trabajo de máquinas	Pocas máquinas	Paro de operaciones	9	La máquina a veces presenta fallas mecánicas	4	Falta de un buen mantenimiento preventivo	No existe	8	288	Elaborar un correcto programa de mantenimiento	FY	-	9	1	2	18
Resultado final	Demorada debido a personal no apto	Molestia del cliente	6	Entrega fuera del plazo	4	Reclamaciones	Tiempos referenciales en el servicio	5	120	Capacitaciones constantes y mayor rapidez del equipo	FY	-	6	2	5	60

Figure 7. AMEF Matrix of Operational Failures and Risk Priority Numbers.

Moreover, the Root Cause Analysis (Ishikawa Diagram) and the AMEF Matrix confirmed that the main causes of inefficiency were related to lack of training (Figure 7), absence of supervision, and weak technological integration. After applying Lean Service principles and data-driven decision-making, these deficiencies were systematically corrected through continuous feedback loops and digital tracking of operator performance.

Finally, the implementation of this hybrid model positions the company as a reference for process innovation in SMEs within the service sector. By combining human factors (Lean culture, Standardization, and Poka-Yoke) with data analytics (Machine Learning), it is possible to create an agile, standardized, and predictive management system that ensures sustained efficiency improvements and supports future scalability.

5.1 Validation

The proposed improvement model was validated using Machine Learning techniques implemented in the Orange software. For this purpose, a database of 351 clients from the Contact Center was used, including both categorical and numerical variables related to the service, such as type of service, non-conformity/complaint, communication channel, schedule and invoice information.

The categorical variables were transformed into numerical codes through a data dictionary so that the software could correctly interpret the information and generate precise predictions of the call handling time. Three supervised learning models were evaluated: Decision Tree, Random Forest and Support Vector Machine (SVM). Each model was trained and tested using the historical data to predict the response time and then compared against the real times obtained by the Contact Center.

The last three graphs generated in Orange show the real response time vs. the predicted time for each algorithm. The Decision Tree and Random Forest models presented curves that were very close to the real values, while the SVM model showed greater dispersion. According to Orange's results, the Decision Tree model was selected as the most suitable, since it achieved the lowest error rate (3.45%) and predicted an average resolution time close to 3 days, which is the desired target established by the company for solving customer claims.

The following Table 2 summarizes the validation results for each algorithm:

Table 2. Validation of Machine Learning models in Orange

Model	**Error rate (%)**	**Fit with real response time**	**Decision**
Decision Tree	3.45	Very high similarity to real times	Selected as final model
Random Forest	Higher than 3.45	High similarity, but less stable	Alternative model
Support Vector Machine (SVM)	Highest among the three	Greater dispersion and variability	Not recommended

With these results, the Decision Tree model was adopted to support the Lean Service improvement proposal, since it allows predicting the handling time of new cases and prioritizing them according to their expected resolution time. This validation confirms that the integration of Machine Learning into the process is reliable and consistent with real data, strengthening the objective of the research: to improve efficiency in a SME of the services sector by combining Lean Service and Machine Learning.

6. Conclusion

This research demonstrated that the combination of Lean Service and Machine Learning constitutes a comprehensive, effective, and sustainable strategy for improving operational efficiency in an SME in the service sector. Based on the initial diagnosis, structural problems were identified in the Contact Center process, such as delays in service, reprocessing, inconsistencies in case classification, and a lack of standardization. The Effectiveness (66.7%), Efficiency (65.7%), First Contact Resolution (62.5%), and Right-First-Time (68.5%) indicators confirmed the existence of a significant gap between current performance and acceptable levels of efficiency for the sector.

The application of Lean Service tools allowed these problems to be addressed from a systemic perspective. The 5S methodology helped to organize and streamline the digital environment, optimizing access to critical information and reducing unproductive time associated with searches and duplication. Standardization made it possible to homogenize operating procedures, ensuring a uniform workflow among operators, which reduced variability in service and facilitated decision-making. For their part, digital Poka-Yoke mechanisms proved essential in reducing recurring human errors by incorporating automatic controls that prevented incomplete, duplicate, or inconsistent records. This prevention structure increased the reliability of the process and reinforced the integrity of the processed data.

Complementarily, the integration of Machine Learning—particularly the Decision Tree model, which obtained a predictive error of 3.45%—made it possible to transform operational management into a data-driven process, oriented toward the prediction and intelligent prioritization of cases. This model facilitated reliable estimates of resolution time and provided a technical basis for optimizing workload allocation, reducing bottlenecks, and improving the area's responsiveness. The synergy between Lean Service and ML not only eliminated waste and failures but also anticipated system behavior, promoting a cycle of continuous improvement based on evidence.

At the end of the proposal, the indicators for the improved scenario (To-Be) showed significant progress: the level of effectiveness increased to 88%, efficiency to 86%, FCR to 83%, and RFT to 87%, while the average response time was reduced from 52.08 hours to 40 hours, representing an improvement of 23%. These variations demonstrated that the combined application of the selected tools managed to close the operational gap identified in the initial diagnosis, validating the effectiveness of the model developed.

In conclusion, the results obtained confirm that the integration of Lean Service and Machine Learning is a viable, scalable, and highly effective solution for improving efficiency, service quality, and productivity in companies in the service sector. The research provides empirical evidence that hybrid models based on technology and continuous improvement methodologies can transform traditional processes into agile, standardized, and predictive systems. It also highlights that the adoption of these practices not only optimizes internal operations but also contributes to improving the customer experience and the operational sustainability of the organization. This study therefore makes a valuable contribution to both the literature and professional practice, serving as a reference for future research and applications in similar organizations.

References

Al-Anqoudi, Y., Al-Hamdani, A., Al-Badawi, M., and Hedjam, R., Using machine learning in business process re-engineering, *Big Data and Cognitive Computing*, vol. 5, no. 4, pp. 1–14, 2021. doi: 10.3390/bdcc5040061

Chacón, H., Koppisetti, V., Hardage, D., Choo, K. K. R., and Rad, P., Forecasting call center arrivals using temporal memory networks and gradient boosting algorithm, *Expert Systems with Applications*, vol. 224, pp. 119983, 2023. doi: 10.1016/j.eswa.2023.119983

Cichosz, M., Wallenburg, C. M., and Knemeyer, A. M., Digital transformation at logistics service providers: Barriers, success factors and leading practices, *International Journal of Logistics Management*, vol. 31, no. 2, pp. 209–238, 2020. doi: 10.1108/IJLM-08-2019-0229

Clancy, R., O'Sullivan, D., and Bruton, K., Data-driven quality improvement approach to reducing waste in manufacturing, *TQM Journal*, 2021. doi: 10.1108/TQM-02-2021-0061

Dučić, G., Savić, D., and Popović, V., Efficiency measurement of customer service call center, *Proceedings of the International Scientific Conference "Economic and Business Trends Shaping the Future" (EBTSF 2020)*, 2020. doi: 10.47063/EBTSF.2020.0026

Ibrahim, R., Ye, H., L'Ecuyer, P., and Shen, H., Modeling and forecasting call center arrivals: A literature survey and a case study, *International Journal of Forecasting*, vol. 32, no. 3, pp. 865–874, 2016. doi: 10.1016/j.ijforecast.2015.11.012

James, A. T., Kumar, G., Goyal, M., and Prakash, P., Development of a framework for Poka-Yoke system performance assessment during the service design for attaining leanness, International Journal of Lean Six Sigma, pp. 1–30, 2024. doi: 10.1108/IJLSS-04-2024-0081

Kanamori, S., Shibanuma, A., and Jimba, M., Applicability of the 5S management method for quality improvement in healthcare facilities: A review, *BMC Health Services Research*, vol. 16, pp. 11, 2016. doi: 10.1186/s41182-016-0022-9

Li, S., Wang, Q., and Koole, G., Predicting call center performance with machine learning, in *Advances in Service Science*, H. Yang and R. Qiu, Eds., pp. 193–199, Springer, 2019. doi: 10.1007/978-3-030-04726-9_19

Mendoza, R. and Sabogal, J. A., Optimización de la fabricación de bebidas: integración de la fabricación eficiente y el aprendizaje automático para mejorar la eficiencia y reducir el desperdicio, *International Journal of Engineering Trends and Technology (IJETT)*, vol. 72, no. 11, 2024. doi: 10.14445/22315381/IJETT-V72I11P118

Mendelová, D. and Strnádová, M., Performance evaluation of call centres using data envelopment analysis, *E+M Ekonomie a Management*, vol. 23, no. 1, pp. 108–121, 2020. doi: 10.15240/tul/001/2020-1-007

Mikl, J., Herold, D. M., Ćwiklicki, M., and Kummer, S., The impact of digital logistics start-ups on incumbent firms: A business model perspective, *International Journal of Logistics Management*, vol. 32, no. 4, pp. 1461–1480, 2020. doi: 10.1108/IJLM-04-2020-0155

Noto, G. and Cosenz, F., Introducing a strategic perspective in lean thinking applications through system dynamics modelling: The dynamic Value Stream Map, *Business Process Management Journal*, vol. 27, no. 1, pp. 306–327, 2021. doi: 10.1108/BPMJ-03-2020-0104

Prabowo, R. F., Poka-Yoke method implementation in industries: A systematic literature review, Indonesian Journal of Industrial Engineering and Management (IJIEM), vol. 1, no. 1, pp. 1–12, 2020. doi: 10.22441/ijiem.v1i1.8803

Rawindaran, N., Jayal, A., and Prakash, E., Machine learning cybersecurity adoption in small and medium enterprises in developed countries, *Computers*, vol. 10, no. 11, pp. 1–19, 2021. doi: 10.3390/computers10110150

Sala, R., Bertoni, M., Pirola, F., and Pezzotta, G., Data-based decision-making in maintenance service delivery: the D3M framework, *Journal of Manufacturing Technology Management*, vol. 32, no. 9, pp. 122–141, 2021. doi: 10.1108/JMTM-08-2020-0301

Shah, S., Ghomeshi, H., Vakaj, E., Cooper, E., and Fouad, S., A review of natural language processing in contact centre automation, *Pattern Analysis and Applications*, vol. 26, no. 3, pp. 823–846, 2023. doi: 10.1007/s10044-023-01182-8

Sihol Marito Purba, J. and Hidayati, J., Performance improvement strategies to increase call center service level: A literature review, *IOP Conference Series: Materials Science and Engineering*, vol. 801, no. 1, pp. 1–8, 2020. doi: 10.1088/1757-899X/801/1/012147

Tamang, M. D., Kumar Shukla, V., Anwar, S., and Punhani, R., Improving Business Intelligence through Machine Learning Algorithms, *Proceedings of the 2nd International Conference on Intelligent Engineering and Management (ICIEM)*, pp. 63–68, 2021. doi: 10.1109/ICIEM51511.2021.9445344

Tan, H., Luo, B., Liu, M., Guo, G., and Xie, X., Study on Line Loss Status Classification Based on Decision Tree, *IOP Conference Series: Earth and Environmental Science*, vol. 585, no. 1, pp. 1–9, 2020. doi: 10.1088/1755-1315/585/1/012121

Wang, L. C., Chao, Y. S., Cheng, S. H., and Han, Z., An Integrated Affinity Propagation and Machine Learning Approach for Interference Management in Drone Base Stations, *IEEE Transactions on Cognitive Communications and Networking*, vol. 6, no. 1, pp. 83–94, 2020. doi: 10.1109/TCCN.2019.2946864

Biographies

Gianella Guadalupe Turín-Cabrera is a Bachelor of Industrial Engineering from the University of Lima with academic and professional experience in process optimization, service operations, and data-driven decision-making. She has participated in projects related to operational improvement, KPI management, and continuous improvement in the mining, industrial services, and human resources sectors. Her current research interests include Lean Service, predictive analytics, operational efficiency, and the application of Machine Learning to service systems.

Wendy Carolayn Pérez-Ruiz is a Bachelor of Industrial Engineering from the University of Lima and has three years of experience in sales and project management within the retail sector. She specializes in overseeing leading brands in the supermarket industry, ensuring operational efficiency and optimizing project execution. She currently works as a sales assistant for a company that is part of the supermarket's administrative team.

Nicolás Salazar-Medina is a professor and researcher at the Faculty of Engineering and Architecture of the University of Lima, Peru. He holds a PhD degree in Industrial Engineering from West Virginia University, United States, and two master's degrees: one in Management Systems from the University of Puerto Rico and the other in Industrial Hygiene from West Virginia University. He is an industrial engineer from the University of Lima and has accumulated extensive professional experience in industries of diverse sectors, including textile, fiber cement and paper, working in the areas of management, process optimization and industrial safety. He has also worked as a consultant in industrial engineering and has been a professor at the University of Lima, where he has contributed to the training of new professionals. His research work is reflected in the publication of academic articles in specialized journals, addressing issues related to operational efficiency, industrial risk management and innovation in production processes.