Journal of Cleaner Production 448 (2024) 141453

Contents lists available at ScienceDirect

Journal of Cleaner Production

journal homepage: www.elsevier.com/locate/jclepro

Achieving social sustainability through lean manufacturing practices: Insights from structural equation model and system dynamics

José Roberto Díaz-Reza [a], S. Hooman Mousavi [b], Cuauhtémoc Sánchez-Ramírez [c], Jorge Luis García-Alcaraz [d,*]

[a] Department of Electrical Engineering and Computer Science, Universidad Autónoma de Ciudad Juárez, Ave Del Charro 450 North. Col. Partido Romero, Ciudad Juárez, Chihuahua, CP 32310, Mexico

[b] Department of Civil Engineering, K. N. Toosi University of Technology, Tehran, 19967-15433, Iran

[c] Graduate Studies and Research Division, Tecnológico Nacional de México/I.T, Orizaba. Ave. Oriente 9 No. 852, Col. Emiliano Zapata, Orizaba, Veracruz, Mexico

[d] Department of Industrial Engineering and Manufacturing, Universidad Autónoma de Ciudad Juárez, Ave. Del Charro 450 North. Col. Partido Romero, Ciudad Juárez, Chihuahua, CP 32310, Mexico

A R T I C L E I N F O

Handling editor: Jian Zuo

Keywords:
Social sustainability
Lean manufacturing
Maquiladora industry
SEM
System dynamics

A B S T R A C T

The relationship between Lean Manufacturing (LM) practices and their impact on Social Sustainability (SOS) remains an area that warrants further investigation, especially in developing countries and industrial sectors with a high level of manual work in which there are many occupational diseases, where well-being is required by labor laws, such as Mexican maquiladora (MM) companies. Recognizing this research gap, this study explores and assesses the influence of LM practices on MM's SOS. The study proposed and evaluated a structural equation model (SEM) with eight hypotheses tested statistically using information obtained from 411 responses to a questionnaire distributed across the MM. WarpPLS software (version 8.0) was employed to validate the SEM and STELLA ARCHITECT V3.0.1, to evaluate a system dynamics model to simulate the longitudinal behavior of LM practices on SOS. The findings underscore the critical role of the 5 S methodology in facilitating the adoption of practices, such as Total Productive Maintenance, Quick changeover, and One-piece Flow, exhibiting positive repercussions on SOS. Notably, the study's estimates suggest a timeline of approximately 6.5 years to attain 100% implementation of these tools, while achieving complete SOS may extend to approximately 11.75 years. It is imperative to approach these projections cautiously, because of the dynamic nature of business environments, wherein unforeseen alterations may significantly influence these timelines. These estimates offer valuable insights into the potential temporal dynamics of LM practices and SOS implementations in industrial contexts.

1. Introduction

Lean Manufacturing (LM) prioritizes waste reduction along with heightened productivity and efficiency. It streamlines processes, curtails expenses, elevates quality, and bolsters overall competitiveness (Alexander and Iskandar, 2023). LM refines operations by eliminating wasteful practices and enhancing efficiency, cutting costs, time, and workforce. It targets waste elimination, such as motion, fostering resource efficiency by curbing unnecessary consumption, while improving quality and reducing human labor, development time, and production space (Arshad Ali et al., 2020). Moreover, LM facilitates agile manufacturing, ensures operational processes, and supports cost-effective standardization, enabling high-volume and high-quality operations (Khalfallah and Lakhal, 2021).

LM finds extensive applications across diverse industrial sectors, including the Mexican maquiladora industry (MMI). Its impact extends beyond environmental benefits, encompassing supply oversight, transparency, fair workforce treatment, and community engagement (Piercy and Rich, 2015). Previous studies have explored LM's effect of LM on sustainable company performance, identifying impactful practices (Iranmanesh et al., 2019); however, LM's alignment with environmental and social sustainability (SOS) indicates positive effects on supply chain sustainability through just-in-time (JIT) delivery, quality and environmental management, and employee engagement (Rupasinghe and

* Corresponding author.
E-mail addresses: inv.pos07@uacj.mx (J.R. Díaz-Reza), h.mousavi@mail.kntu.ac.ir (S.H. Mousavi), cuauhtemoc.sr@orizaba.tecnm.mx (C. Sánchez-Ramírez), jorge.garcia@uacj.mx (J.L. García-Alcaraz).

https://doi.org/10.1016/j.jclepro.2024.141453
Received 16 October 2023; Received in revised form 10 February 2024; Accepted 24 February 2024
Available online 6 March 2024

Wijethilake, 2021).

The Mexican Maquiladora Industry (MMI) has driven the US–Mexico border economy for decades, favoring job creation and economic growth. Academics and the government are interested in it (Cañas et al., 2011), and it is considered one of Mexico's essential economic activities as it contributes to employment, trade, and overall economic development. LM in the Maquiladora industry can enhance performance and sustainability by implementing tools that positively impact social, economic, and environmental aspects (García-Alcaraz et al., 2022). From a social point of view, LM can lead to improvements in occupational health, safety, and living conditions of society (Ghaithan et al., 2021).

Studies have shown that *5S* is the most influential LM tool for employee SOS, and *TPM* contributes to success in this area of MMI (Samadhiya et al., 2023). This MMI has attracted foreign investment, and 2.96 million Mexicans work in 5156 maquiladoras nationwide (Index, 2023). Ciudad Juarez, located in northern Mexico, has 322 companies, which is equivalent to 6.24% nationwide, of which 32% are in the automotive sector, 29% in the electronics sector, 12% in the medical sector, 8% in the call center, 8% in packaging, 7% in plastics/mechanics and 4% in other sectors (Index, 2022), generating 339, 065 jobs locally. These companies apply LM to generate efficiency, reduce waste, improve quality, and improve employee well-being.

Some studies examined the relationship between LM practices and sustainability outcomes in MMI. For example, García-Alcaraz et al. (2022) analyzed visual LM tools, such as andon and visual management, to measure their impact on economic and environmental sustainability by avoiding errors, while García Alcaraz et al. (2022) analyzed the relationship of MMI tools associated with machinery and equipment that favor social, environmental, and economic sustainability by avoiding accidents and defects due to poorly calibrated or malfunctioning equipment. Concerns about the environmental implications linked to MMI, including their proximity to residential areas, insufficient risk assessment, and inadequate attention to energy efficiency, have been raised (Grineski et al., 2015). Effective strategies, such as cleaner production and pollution prevention programs, have been recognized as successful tools for establishing sustainable production systems in the MMI, ensuring the safety of workers, communities, and the environment (Velazquez et al., 2014). Although these studies analyzed community well-being, they did not investigate the well-being of workers within the MMI.

Traditional approaches to analyzing the relationship between LM and SOS are based on the structural modeling of variables (Burawat, 2019) and the cross-functional involvement of executives and workers to understand strategic alignment mechanisms (Longoni and Cagliano, 2015). Moreover, this relationship has been explored from a cultural perspective (Iranmanesh et al., 2019), and the mediating role of green technology adoption and product innovation has been analyzed (Afum et al., 2021). However, such causal relationships or qualitative analyses have been criticized for the time invariance they assume is inconsistent with dynamic complexity theory (Zhang, 2022), such as applying LM practices in open systems such as MMI.

However, despite the long-standing history of MMI, few studies have analyzed the relationship between LM and SOS within the company, such as workers' well-being, safety, and sense of belonging in the production lines. This research seeks to address this gap by analyzing the impact of LM tools such as 5 S, TPM, Quick Changeover (QCO), and One-Piece Flow on SOS using a structural equation model (SEM) that quantitatively analyzes the impact of these LM tools on SOS. Additionally, through the system dynamics (SD) model, the behavior of these practices within companies is simulated, thus allowing an understanding of their dynamics over time and improving the SEM disadvantages. This methodological combination seeks to determine the optimal point to reach the desired levels of LM tools and implementation of SOS in the MMI. It was validated using information from industries established in Ciudad Juarez. This strategy offers a more complete and detailed perspective on how these tools influence long-term operational sustainability in this context, providing valuable insights for the academic community and companies involved.

This study will allow managers and those responsible for implementing lean manufacturing tools to focus on those vital to ensure SOS in their workers and increase their sense of belonging, job security, and well-being in production lines. The structure of the paper is as follows: Section 2 encompasses a literature review, defining LM tools and SOS elements, and justifying the proposed hypotheses. Section 3 details the methodology, which is divided into SEM and SD descriptions. Section 4 presents the results of each methodological step. Finally, Section 5 presents the conclusions of the study.

2. Theoretical background and hypotheses

In IMM, some tools have been shown to relate to economic and environmental sustainability because there is a focus on eliminating waste, which means lower costs and less material being sent to sanitary depots. However, specific LM tools are directly related to workers' safety and well-being on production lines, such as 5 S, TPM, quick changeovers, and one-piece flow, which impact efficiency and well-being indexes, as discussed below.

2.1. 5 S (5S)

The 5S is an LM tool to standardize routines and cleanliness in the workplace, and it refers to a business concept that minimizes the time and resources used in manufacturing. It emphasizes eliminating waste, such as transportation, inventory, movements, waiting, overproduction, and overprocessing, and has been useful for sorting, organizing, cleaning, and other basic requirements (Senthil Kumar et al., 2022). *5S* facilitates saving by reducing operating space, time, energy, and health risks, and improving working conditions, staff morale, product quality, and safety (Shahriar et al., 2022). *5S* are the pillars for working with more systematic techniques such as Single Minute Exchange of Dies (SMED) and Poka Yoke.

The 5S has been implemented in different sectors. In the health sector (Nahmens et al., 2011), a hematology laboratory (Marín et al., 2013), university engineering laboratories (Jiménez et al., 2015), a small-scale manufacturing company (Gupta and Jain, 2015), and the automotive cable production industry (Veres et al., 2018), among others.

2.2. Total productive maintenance (TPM)

TPM significantly reduces machine downtime, manufacturing losses, and material waste and improves personnel and equipment productivity. *TPM* supports predictive and autonomous maintenance by detecting equipment irregularities and degradation (Agustiady and Cudney, 2018). Controlled maintenance, lower maintenance costs, production stoppages, and downtime boost labor productivity using *TPM*. By promoting employee knowledge and abilities, *TPM* enhances internal communication, team building, cooperation, equipment specifications, audits, diagnostics, OEE and crisis management. It increases employee trust, workers feel ownership of the machine, and all workers collaborate to achieve organizational goals (Agustiady and Cudney, 2018). In this sense, maintenance is vital to manufacturing organizations.

TPM has improved autonomous maintenance, education and training, safety, and quality maintenance in several industries (Ireland and Dale, 2001), and has been implemented in different industrial sectors. For example, Tsarouhas (2007) reported an increased production rate, product quality, and cost reduction, while Gupta and Garg (2012) reported increased efficiency and machine productivity with regard to OEE.

However, other LM tools support *the TPM*. For example, *5S* helps make the workplace efficient, improves safety (Ishijima et al., 2016), and maintains a clean and organized work environment, facilitating the *implementation of TPM*. In addition, *TPM* improves the efficiency of production processes, and *5S* provides a solid implementation, *5S* helps to keep organization, identification, and cleanliness, as it reduces the search time for parts and replacements (Ribeiro et al., 2019). The 5 S simplifies the identification of fluid leaks, material spills, metal shavings from unanticipated wear, and minor fractures in mechanisms for speedy maintenance (Agustiady and Cudney, 2018). Thus, we propose the following hypothesis.

H1. *5S* has a direct and positive effect on *TPM*

2.3. Quick changeover (QCO)

Product setup is crucial to manufacturing lead-time, and QCO is an LM approach that improves production efficiency and reduces changeover time (COT) (Vo et al., 2019). *QCO* simplifies and streamlines the remaining processes to streamline production and decreases the model COT by performing as many operations as feasible while the equipment is running. *QCO* reduces non-product-value tasks and has four steps (Singh et al., 2018): the preliminary stage, separating internal and external activities, converting internal to external activities, and simplifying all preparation operations.

The *QCO* cuts lead time and boosts competitiveness. Cost and waste reduction, production capacity, equipment adaptability, machine efficiency, customer happiness, and the OEE index are *QCO* advantages (Ribeiro et al., 2022). Numerous studies on *QCO* implementation have been reported in sectors such as the foundry industry (Jit Singh and Khanduja, 2010), manufacturing companies (Singh et al., 2018), aerospace industry (Amrani and Ducq, 2020), and ready-made garment industry (Toki et al., 2023), among others.

The preparation of tools and devices for assembly and disassembly is one of the most significant tasks spent in a model changeover. With the application of *5S,* these times are reduced to almost zero because everything that is needed is prepared in advance, is at hand, and is in proper operating conditions (Posada, 2007). *The 5S* may be used to categorize tools faster and prevent looking for them (Vieira et al., 2019), saving time while searching for model change tools, and supporting the *QCO*. Thus, we propose the following hypothesis.

H2. *5S* has a direct and positive effect on *QCO*

QCO and *TPM* minimize lead-time and boost competitiveness, and their success relies on machinery diagnosis and operator competence (Espinoza-Huamash et al., 2022). *TPM* is directly related to *QCO* because it helps eliminate all forms of time loss in maintenance and tries to have the machines in optimal conditions. In addition, planned maintenance attempts to avoid stops in machines to maximize their availability. Therefore, *QCO* supports *TPM* in reducing idle time in machinery, preventing low quality, and improving availability and delivery rates (Correia Pinto et al., 2020). Thus, the following theory is proposed.

H3. *TPM* has a direct and positive effect on *QCO*

2.4. One-piece flow (OPF)

OPF wants employees and goods to move together. *OPF* pieces go between machines or processes without waiting for the remainder of the batch (Wang and Li, 2013); therefore, the goal is to manufacture the product parts one at a time in more organized and sequenced processes to avoid long queues and inventory processes. *OPF* reduces non-product-value activities by minimizing mobility (Tang et al., 2016); improves quality, productivity, and value-added; and decreases production cycle time, work-in-process, and transportation (Ortega del Castillo, 2019).

OPF has been applied in different sectors to improve production operations, such as in the automotive industry (Ioana et al., 2020), healthcare systems (Chadha et al., 2012), and manufacturing (Tang et al., 2016). However, *5S* is closely related to *OPF* as it helps create an environment conducive to a smooth and uninterrupted product workflow (Heaton and Abdelazim, 2021). One of the critical elements of *5S* is Seiton, which consists of arranging tools, equipment, and materials logically and efficiently (Randhawa and Ahuja, 2017); since organizing the workplace, unnecessary movement and transportation can be minimized for a more streamlined and continuous workflow.

In addition, by eliminating waste and improving workspace utilization, *5S* can lead to more efficient and streamlined processes, resulting in higher productivity and cost optimization (Randhawa and Ahuja, 2017). In addition, *5S* aims to minimize movement and transportation, resulting in a more efficient and organized work environment (Putri et al., 2022). Thus, we propose the following hypothesis.

H4. *5S* has a direct and positive effect on *OPF*

Implementing a continuous flow system in production processes aims to reduce waiting time, equipment stoppages, and process defects by eliminating waste and standardizing sequences. By improving the equipment, procedures, and workers, *TPM* eliminates machine failures, minor machine stoppages, and production errors (Heravi et al., 2021). By implementing *the TPM*, the six significant losses related to failures, setups and adjustments, speed losses and minor stoppages, process defects, and yield losses can be eliminated; consequently, the continuous flow of parts is hindered (Chand and Shirvani, 2000).

TPM pillars, such as autonomous maintenance, can reveal latent problems that cause failures and dust and grime that impede continuous flow (Alarcón Bernal et al., 2014). In conclusion, *the TPM* is necessary for optimal production flow, and the following hypothesis is proposed.

H5. *TPM* has a direct and positive effect on *OPF*

Waiting times are wasteful during a model change and generate waste when setting the correct parameters to produce the first good part. These waiting times hinder and slow down the continuous flow of processes, and reducing the model COT facilitates the flow of a single part (De Vries and Van der Poll, 2018). By reducing times, smaller batches can be produced more frequently, giving flexibility and agility; *OPF* moves a single product through each phase of the process in the quickest feasible time rather than dividing work items into batches to send products to the market and offer value to consumers more regularly (Peron et al., 2021). In that sense, reducing the model COT allows for continuous product flow without lengthy lead times and, more importantly, without loss of throughput (Antosz and Pacana, 2018). Therefore, we propose the following hypothesis.

H6. *QCO* has a direct and positive effect on *OPF*

2.5. Social sustainability (SOS)

Langhelle (1999) called *SOS* the “ethical code of behavior for human survival and progress to be realized in a mutually inclusive and sensible manner." *SOS* prioritizes population welfare, equity, public awareness and cohesiveness, and local labor and enterprise use (Olawumi and Chan, 2018). *SOS* outcomes “are the products and processes that determine human health and safety well-being under proactive supply chain initiatives" (Husgafvel et al., 2015).

By reducing COT and increasing OEE, organizations can achieve higher levels of productivity, which can positively impact employees by reducing stress and increasing job satisfaction (Bevilacqua et al., 2015). *QCO* contributes to improving companies’ competitiveness and long-term viability, which can result in job security and economic stability of employees (Emamisaleh and Taimouri, 2021). *The QCO* fosters *SOS* by promoting innovation, addressing societal challenges, streamlining processes, and reducing waste, allowing organizations to focus on sustainable practices (Emamisaleh and Taimouri, 2021).

Adapting to client expectations can help *SOS* fulfill evolving customer and societal needs (Eldardiry et al., 2021). In this sense, *QCO* contributes to *SOS* by improving working conditions, promoting job security, fostering innovation, and addressing social challenges, and the following hypothesis is proposed.

H7. *QCO* has a direct and positive effect on *SOS*

OPF reduces the risk of fatigue and injury to workers by eliminating the need for excessive manual handling and heavy lifting (Ghaithan et al., 2023). In addition, reducing waste and optimizing workflow leads to a cleaner and safer work environment, minimizing exposure to hazardous materials, and reducing the risk of accidents (Papetti et al., 2020). *OPF* improves worker well-being and satisfaction, performance and productivity, and supply chain management practices (Papetti et al., 2020), contributing to *SOS* by creating a more equitable and inclusive manufacturing industry. Thus, the following hypothesis is proposed.

H8. *OPF* has a direct and positive effect on *SOS*

Fig. 1 shows the hypotheses described above and the proposed model.

3. Methodology

This section describes every step of this study, and Fig. 2 summarizes the steps developed in two stages.

3.1. Stage 1. structural equation modeling (SEM)

The SEM technique was used to validate the relationships between the variables in Fig. 1 because it allows the analysis of complex relationships, enabling direct and indirect relationships to be quantified. This is particularly useful when traditional regression methods based solely on observed data are ineffective (Takele et al., 2023). In addition, SEM is useful for discovering heterogeneous groups and analyzing complex interactions in a system (Kiefer et al., 2022). In addition, SEM has been used to relate LM tools and their interdependence (J.R. Díaz-Reza et al., 2022a, b) and to quantify the effect of Six Sigma on operational capability (Muraliraj et al., 2020). However, SEM requires information to validate the hypotheses, and the following activities were developed.

3.1.1. Step 1. development and application of the questionnaire

A questionnaire was developed through literature review to collect information about the reported LM practices and sustainability benefits. In this study, the items that integrated the LVs were *5S* (Attri et al., 2017), *TPM* (García Alcaraz et al., 2022), *QCO* (Díaz-Reza et al., 2016), *OPF* (Wang and Li, 2013), and *SOS* (García Alcaraz et al., 2022; ul Haq and Boz, 2020). This literature review generated the first draft of the questionnaire and represents a rational validation (García-Alcaraz et al., 2022).

Some items integrated into the LVs came from studies conducted in other regions and different industrial environments, so the questionnaire underwent a judge validation process to adapt it to the MMI environment. Five academics and five managers specialized in LM and *SOS* issues from MMI and regional universities were asked to evaluate whether they met the quality criteria according to Hernández-Nieto (2002), focusing on relevance, conceptual clarity, wording and terminology, appropriate distracters difficulty, and cognitive levels.

The questionnaire consists of 207 activities divided into 35 LMTs and 27 benefits divided into SOS, ENS, and ECS; however, this study reports only four LMTs (*5S, TPM, OPF,* and *QCO*) and SOS were used. The questionnaire had three sections: the first section referred to demographic information; the second section listed the LMT and divided them into quality, production, planning, control, and material flow tools. The third section addresses the ECS, ENS, and *SOS* benefits. The questionnaire was uploaded to Google Forms and a link was generated to access it. It was answered using a five-point Likert scale, where five means strongly agree that the activity is performed, and one means strongly disagree that the activity is performed. The complete questionnaire appears as supplementary material.

The Manufacturing, Maquiladora, and Export Services Industry Program were used to identify regional companies implementing LM. The sample consisted of managers, engineers, technicians, supervisors, and operators, all with previous LM implementation experience. Initial contact was made via email, in which each potential participant was invited to participate, and a link to the questionnaire was provided. A second email was sent if no response was received within the 12 days. The application and data collection period was from January 15 to April 15, 2023. The final questionnaire was attached as supplementary material to ensure transparency and repeatability.

To calculate the minimum sample size when conducting this research, the inverse square root method is shown in equation (1) proposed by Kock and Hadaya (2018).

$$\widehat{N} = \left(\frac{Z_{.95} + Z_{.80}}{|\beta|_{min}}\right)^2 \tag{1}$$

where.

$Z_{.95}$ is the Z-score for a confidence level of 95% from a standard normal distribution with a mean of 0 and a standard deviation of 1. $|\beta|_{min}$ is the absolute minimum path coefficient in the model and is obtained after the PLS-SEM evaluation.

3.1.2. Step 2. Latent variables debugging and statistical validation

An XLS file was downloaded from Google Form and opened in SPSS

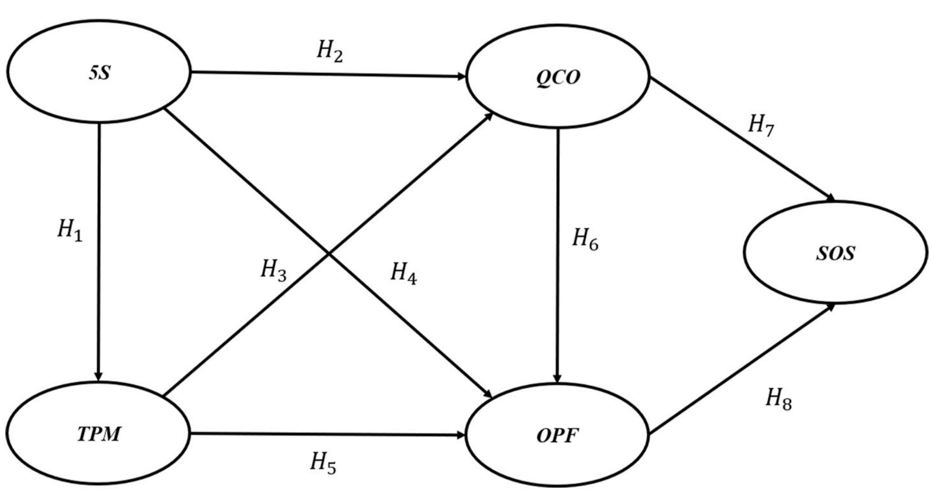


Fig. 1. Proposed model.

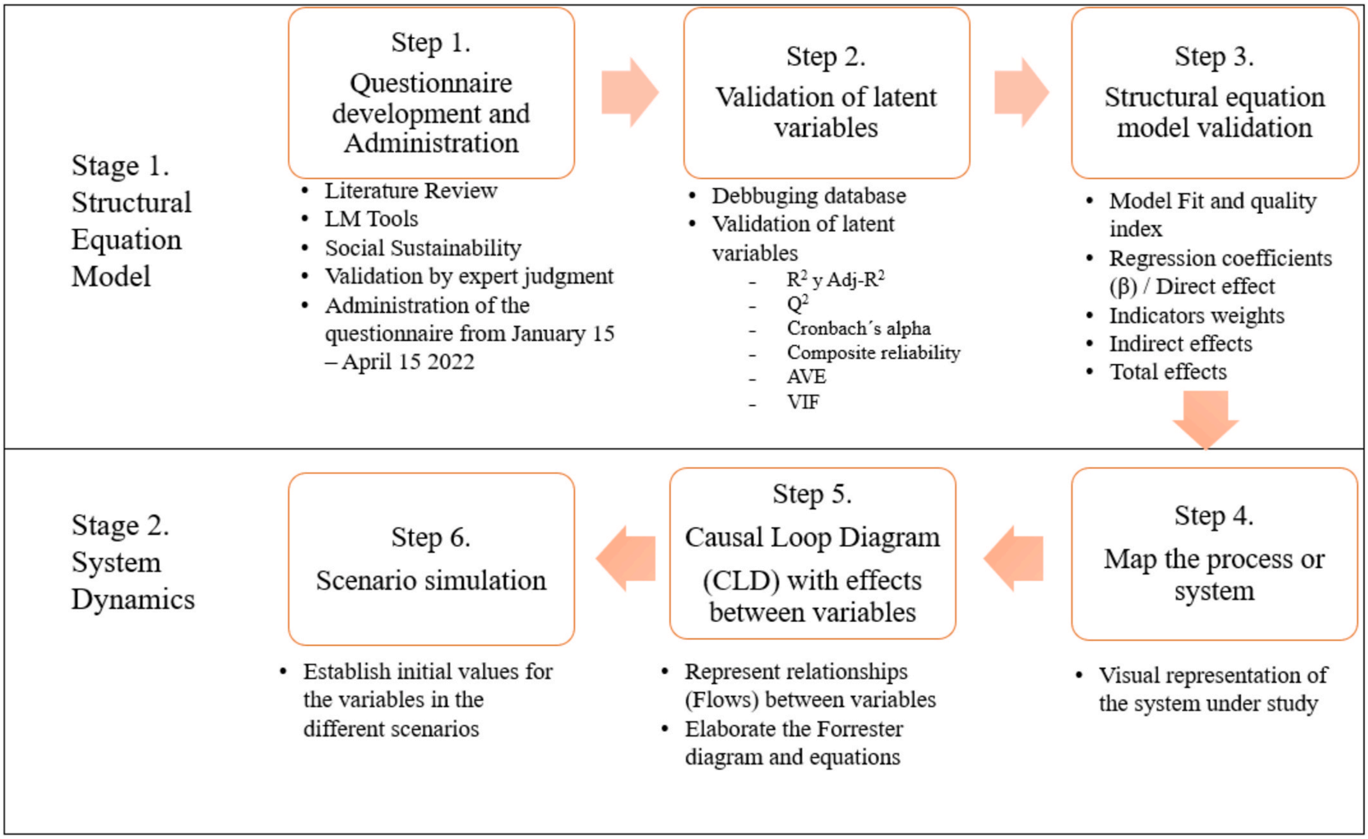


Fig. 2. Methodology applied to conduct the study.

25® for debugging, according to

- The standard deviation was calculated to identify non-committed participants. If the deviation was less than 0.5, the questionnaire was deleted.
- Items were standardized to identify outliers, where values greater than four and less than −4 were considered extreme values and were replaced by the median.

With a debugged database, the next step was statistical validation using indexes that appear in Table 1 and were proposed by Kock (2021a).

3.1.3. Step 3. SEM validation

The partial least squares (PLS) approach was used to validate the SEM, and it was integrated into WarpPLS 8.0® software, given that it is recommended for small sample sizes and non-normal data distributions (Kock, 2021a). The PLS-SEM approach was used to find interdependencies among the LM tools (J.R. Díaz-Reza et al., 2022a, b) and the effects of LM and economic sustainability (José Roberto Díaz-Reza et al., 2022). In this study, the PLS-SEM approach was used to generate dependence equations for the variables.

Before interpreting the results from PLS-SEM, the following model quality and fit indices recommended by Kock (2021b) were analyzed: average path coefficient (APC), average R^2 and Average Adjusted R-squared (AARS) to measure predictive validity; average block VIF (AVIF) and full collinearity VIF (AFVIF) to measure collinearity; and the Tenenhaus GoF index (GoF) to measure data fit. PLS-SEM reports the direct effects, the sum of indirect and total effects, using a standardized β value. Every effect was tested using a hypothesis test, where H_0: $\beta = 0$ and H_1: $\beta \neq 0$ with a confidence level of 95%. For every dependent LV, R^2 was reported and the effect size (ES) was obtained for every effect.

Table 1
Validation Index to be Evaluated.

Indexes	Measurement	Suggested value
R^2 Adjusted R^2	Predictive parametric validation	≥0.20
Composite Reliability Cronbach's Alpha	Internal consistency	≥0.70
Average Variance Extracted (AVE)	Discriminant validity	≥0.50
Full Collinearity variance inflation factor (VIF)	Collinearity	≤3.30
Q^2	Predictive non-parametric validity	>0.00 and similar to R^2

3.2. Stage 2. system dynamics (SD)

Because SEM reports static values over time, SD is used to similarly determine when a manager can obtain the benefits of LM tools and an acceptable SOS. The coefficients generated from SEM were used to generate the dependency equations, and different scenarios were used for the simulation. SD has been used to simulate innovation problems efficiently (Delgado-Maciel et al., 2020), but the combination of SEM - SD has also been reported because of its ability to incorporate dynamism into the models; for example, Mohandes et al. (2022) evaluated the critical factors of sewer system overflow and Kara (2018) evaluated the quality systems in universities in developing countries. This stage comprises of three steps.

3.2.1. Step 4. Map the process or system

As a first step in Stage 2, the LVs involved in the models in Figs. 2 and 3 were graphically represented, that is, the system components were identified, how they interact with each other, and how they influence the overall system behavior to have a visual and structured

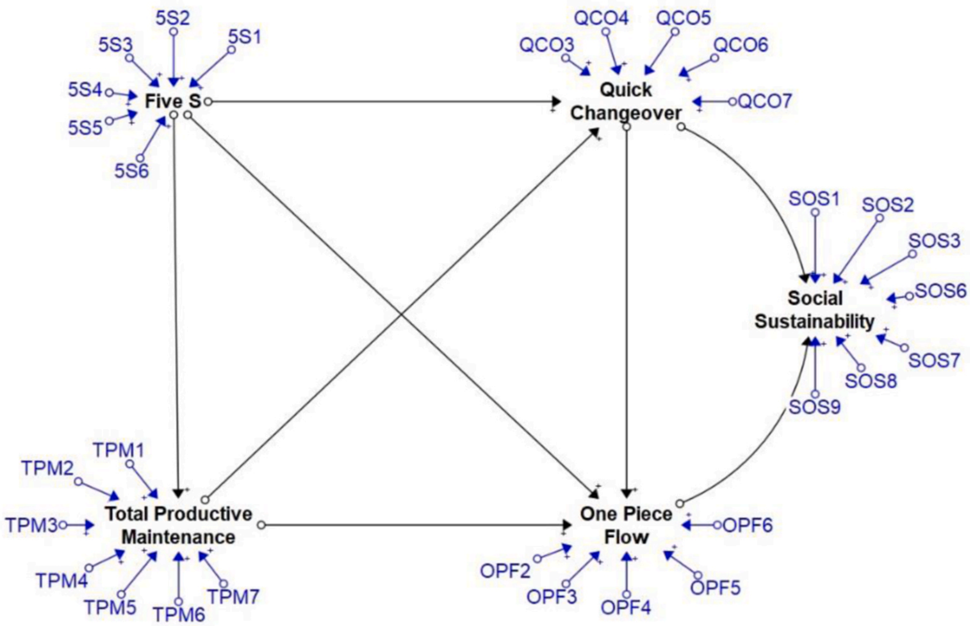


Fig. 3. Causal loop diagram.

understanding of how the system works. This process is one of the most important since improvement in industry begin when all variables are identified (Gholami et al., 2019).

3.2.2. Step 5. Causal loop diagram (CLD)

CLD illustrates the cause-and-effect relationships between variables and helps understand the dynamic behavior of a system over time. CLDs consist of nodes that represent variables, and arrows indicate the causal relationships between variables. Positive feedback loops indicate reinforcing relationships, whereas negative feedback loops indicate equilibrium relationships (Rockow et al., 2019). In these models, SEM allows the relationships between variables, and SD captures the dynamic behavior of a system over time, considering the accumulation of stocks and the flow of variables (Bai et al., 2016).

Fig. 3 shows the CLD obtained from the SEM model shown in Fig. 1. The blue arrows represent the item loadings for each variable with a positive flow. The black arrows represent the hypotheses or effects between variables with a positive flow. For example, *5S* positively affects *QCO*, indicating that if *5S* increases, QCO also increases. Moreover, because the effect is positive, if *5S* decreases, so does *QCO*. The same applies to *TPM* and *OPF* because *5S* directly and positively affects these two. Observe also that *TPM* has a direct and positive effect on *QCO* and *OPF, and QCO* has a direct and positive effect on *OPF*, *QCO,* and *OPF* directly and positively affects *SOS.*

3.2.3. Step 6. Scenarios simulation

Several scenarios were created to understand how the system responded to different conditions and influences by manipulating its variables. These scenarios allowed the testing of various configurations and strategies to anticipate their future impact. It also facilitated the identification of key variables and prioritization of areas for improvement or risk management. In addition, the simulation of these scenarios provided projections of the future evolution of the system. The scenarios addressed are as follows.

- The first scenario was the simulation extension over time, that is, the simulation period was 13 years to observe the time at which 100% implementation of each variable would be achieved and at what point 100% social sustainability would be achieved.
- Scenarios 2–6 were established with different initial values for each variable over five years.
  - o Scenario 2. The initial values of 5 S, TPM, QCO, OPF, and SOS were set to 0.25.
  - o Scenario 3. The initial values for 5 S, QCO, and SOS were set at 0.25, and those for TPM and OPF were set at 0.5.
  - o Scenario 4. The initial values of 5 S, TPM, QCO, OPF, and SOS were set to 0.50.
  - o Scenario 5. The initial values for 5 S, QCO, and SOS were set at 0.75 and for TPM and OPF at 0.50.
  - o Scenario 6. The initial values of 5 S, TPM, QCO, OPF, and SOS were set to 0.75.

4. Results

4.1. SEM results

4.1.1. Descriptive analysis of the sample

The questionnaire application resulted in 428 responses, leaving 411 valid questionnaires after the data debugging process. 79.80% of respondents had over two years of experience, 46% had more than five years, and 21% had more than ten years. Engineers had the highest participation rate (38%) (Table 2).

Table 3 illustrates the companies' sizes and industrial sectors. The most participative sector was the automotive sector with 36%, followed by the medical sector with 17.5%. Approximately 16% of the information came from large companies with more than 1000 workers.

Table 2
Job Position vs. Years of Experience.

Years	Job position					
	Manager	Engineer	Supervisor	Technician	Other	Total
0 to <1	1	6	0	3	13	23
1 to <2	3	22	4	15	16	60
2 to <5	4	61	25	26	23	139
5 to <10	17	44	21	6	15	103
≥10	25	23	10	8	20	86
Total	50	156	60	58	87	411

Table 3
Company size vs. Industrial sector.

Company Size	[a]Industrial Sector										Total
	1	2	3	4	5	6	7	8	9	10	
<50	1	0	0	1	2	3	1	0	1	18	27
50 to <300	8	1	4	4	3	3	8	1	0	14	46
300 to <1000	29	1	3	13	6	3	10	4	1	19	89
1000 to <5000	70	2	7	23	3	3	21	3	1	14	147
5000 to <10,000	18	0	2	9	0	0	20	0	0	5	54
>10,000	22	1	0	6	1	1	12	0	0	5	48
Total	148	5	16	56	15	13	72	8	3	75	411

[a] 1-Automotive; 2-Aeronautics; 3-Electric; 4-Electronics; 5-Logistics; 6-Machining; 7-Medical; 8-Rubber and Plastics; 9-Textile and Clothing; 10–Other.

4.1.2. *Validation of latent variables*

The LVs validation indices are listed in Table 4. There was no collinearity, and the variables had appropriate predictive, convergent, and internal validity. The normal-JB normality test and non-parametric predictive validity demonstrate that none of the variables are normal, which justifies the PLS-SEM approach.

4.1.3. *Model validation*

Table 5 indicates sufficient predictive validity because the APC, ARS, and AARS indices are statistically significant, there is no collinearity, and the data fits the proposed model well. Therefore, this model can be interpreted.

4.1.4. *Structural equation model*

The model evaluation using PLS-SEM in WarpPLS v.8 is shown in Fig. 4. The effects (β), p-value, effect size, and total R^2 for the dependent LVs are shown. All the direct effects were statistically significant at $p < 0.001$.

Table 6 shows the direct, indirect, and total effects of the initial model.

SEM also analyzes reciprocal relationships, so a regression model was proposed, reversing the directions of the arrows (see Fig. 5), where the independent LV is *SOS* and the independent variables are *OPF, QCO, TPM,* and *5S*. This regression model also shows the effect values (β), p-values, and R^2 for each dependent LV. All hypotheses were statistically significant according to the p-values.

Using the SEM analysis, the regression coefficients and weights of each variable's indicators were obtained, as shown in Table 6. The regression coefficients represent the direct effect sizes and the weights represent the contribution of each item or indicator to its respective variables.

4.2. *SD results*

4.2.1. *Development of the SD model*

Fig. 6 illustrates the feedback CLD, which integrates the SEM of Figs. 4 and 5. Five feedback loops existed (B1, B2, B3, B4, and B5). Each of these tools aims to achieve 100% implementation through the development of its activities. Therefore, a variable (*Desired Level*) was added to measure the percentage of implementation over time. Likewise, two variables were added: one that measures the *Gap* to reach 100% implementation, and the *adjustments* that must be made to reach the *desired level*.

Table 4
LV validation.

	5 S	TPM	QCO	OPF	SOS
R^2		0.397	0.571	0.521	0.344
Adj. R^2		0.396	0.569	0.517	0.341
Composite Reliability	0.964	0.957	0.952	0.930	0.956
Cronbach's Alpha	0.955	0.948	0.936	0.906	0.947
Avg. var. Extrac. (AVE)	0.816	0.762	0.798	0.727	0.758
Full. Collin. VIF	2.404	2.190	2.518	2.081	1.628
Q^2		0.399	0.572	0.522	0.346
Normal - JB	No				

Table 5
Model fit and quality indexes.

Index and criteria	Value	p-value	Best if
Average Path Coefficient (APC)	0.397	p < 0.001	p < 0.05
Average R-Squared (ARS)	0.458	p < 0.001	
Average Adjusted R-Squared (AARS)	0.456	p < 0.001	
Average block VIF	1.865		≤3.3
Average full Collinearity VIF	2.164		
Tenenhaus GoF	0.595		≥0.36

The same process was followed for each tool, differentiated only by the influence of certain variables. Meanwhile, for *the SOS*, the influence comes from *QCO* and *OPF*. For *QCO*, the influence comes from 5 S, TPM, SOC, *and OPF. OPF, TPM, and QCO influence the 5S. The TPM* is affected by *5S, QCO*, and *OPF*. Finally, *the OPF is* influenced by *5S*, *TPM,* and *SOS*. This means that there is feedback from each variable on the other variables. In this sense, if the level of development of each tool's activities is 0, the *Gap* will be 100, and the adjustments that must be made to reduce this Gap will be significant. However, if there is already a level of implementation in these companies, for example, 30%, the Gap will be 70% and the adjustments to be made will be minor.

4.2.2. *Equations*

Once the causal loop model was defined, a mathematical representation of the model was created, including the equations that describe the relationships between the variables. The proposed equations are as follows:

5S is the LV that analyzes the activities performed to implement this methodology and is defined by:

$$\boldsymbol{FS_t = FS_{t=0} + \int_0^t (AFS)\, dt} \tag{1}$$

where.

- *A:* represents the adjustment in activities.
- *G:* represents the difference between the desired and implemented levels.
- *w:* represents the weights of the indicators for each LV.

A5S represents the adjustment made to the activities in *5S* implementation. This is the result of the sum of the product of each regression coefficient (RC) of *OPF, QCO, and TPM multiplied by the weights of the 5S indicators (w), that is, 5S*1, *5S*2, *5S*3, *5S*4, *5S*5, *and 5S*6.

G5S represents the difference (*Gap*) between the desired level of *5S* implementation and the level implemented at a particular instant in time.

The equations for the four LVs were set up similarly.

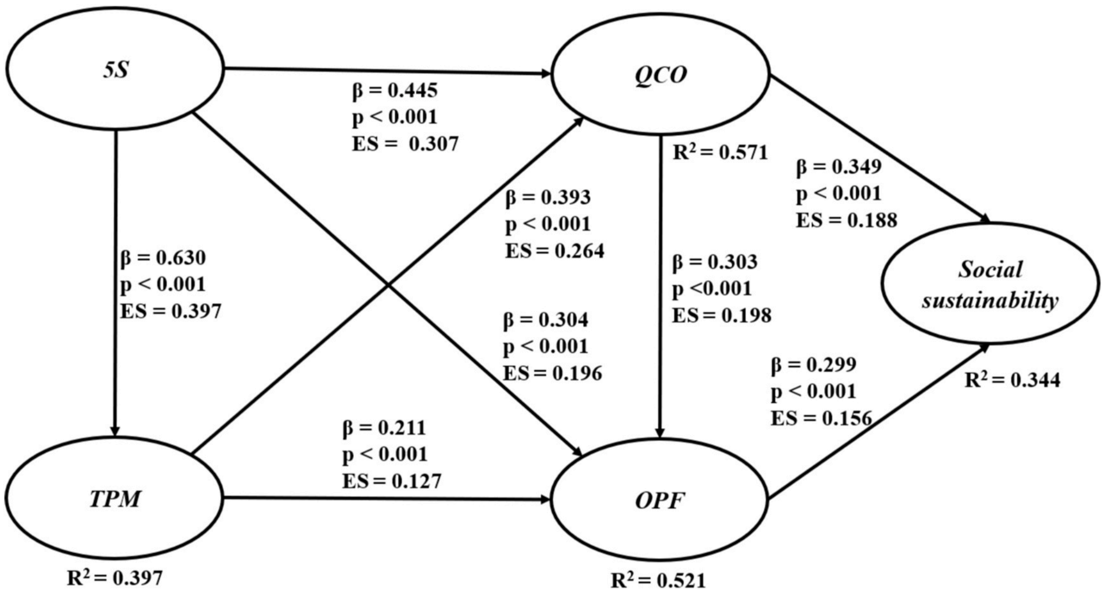


Fig. 4. Initial model evaluated.

Table 6
Regression coefficients and indicator weights.

Relation	Regression Coefficient	Indicators	Weights (w)	Indicators	Weights (w)
[a]*5S → TPM*	0.630	*5S1 → 5S*	0.184	*OPF2 → OPF*	0.229
[a]*5S → QCO*	0.445	*5S2 → 5S*	0.180	*OPF3 → OPF*	0.240
[a]*5S → OPF*	0.304	*5S3 → 5S*	0.186	*OPF4 → OPF*	0.239
[a]*TPM → QCO*	0.393	*5S4 → 5S*	0.182	*OPF5 → OPF*	0.244
[a]*TPM → OPF*	0.211	*5S5 → 5S*	0.187	*OPF6 → OPF*	0.220
[a]*QCO → OPF*	0.303	*5S6 → 5S*	0.187	*SOS1 → SOS*	0.166
[a]*QCO → SOS*	0.349	*TPM1 → TPM*	0.164	*SOS2 → SOS*	0.162
[a]*OPF → SOS*	0.299	*TPM2 → TPM*	0.165	*SOS3 → SOS*	0.168
[b]*SOS → QCO*	0.266	*TPM3 → TPM*	0.158	*SOS6 → SOS*	0.160
[b]*SOS → OPF*	0.500	*TPM4 → TPM*	0.163	*SOS7 → SOS*	0.169
[b]*OPF → QCO*	0.523	*TPM5 → TPM*	0.162	*SOS8 → SOS*	0.159
[b]*OPF → TPM*	0.282	*TPM6 → TPM*	0.165	*SOS9 → SOS*	0.163
[b]*OPF → 5S*	0.274	*TPM7 → TPM*	0.168		
[b]*QCO → TPM*	0.485	*QCO3 → QCO*	0.217		
[b]*QCO → 5S*	0.366	*QCO4 → QCO*	0.222		
[b]*TPM → 5S*	0.299	*QCO5 →QCO*	0.227		
		QCO6 → QCO	0.225		
		QCO7 → QCO	0.228		

[a] Direct effects of Initial model Evaluated.
[b] Direct effects of Evaluated Feedback Model.

$$A5S = G5S\left[(RC_{OPF\rightarrow 5S} * OPF) * \sum_{i=1}^{6} w5S_i + (RC_{QCO\rightarrow 5S} * QCO) * \sum_{i=1}^{6} w5S_i + (RC_{TPM\rightarrow 5S} * TPM) * \sum_{i=1}^{6} w5S_i\right] \tag{2}$$

Equations (3) and (4) correspond to the *TPM* variables and are as follows:

$$TPM_t = TPM_{t=0} + \int_0^t (ATPM)\, dt \tag{3}$$

$$ATPM = GTPM\left[(RC_{5S\rightarrow TPM} * 5S) * \sum_{J=1}^{7} wTPM_j + (RC_{OPF\rightarrow TPM} * OPF) * \sum_{J=1}^{7} wTPM_j + (RC_{QCO\rightarrow TPM} * QCO) * \sum_{J=1}^{7} wTPM_j\right] \tag{4}$$

Equations (5) and (6) describe the behavior of the *QCO* variable:

$$QCO_t = QCO_{t=0} + \int_0^t (AQCO)\, dt \tag{5}$$

$$AQCO = GQCO\left[(RC_{5S\rightarrow QCO} * 5S) * \sum_{k=1}^{5} wQCO_k + (RC_{SOS\rightarrow QCO} * SOS) * \sum_{k=1}^{5} wQCO_k + (RC_{OPF\rightarrow QCO} * OPF) * \sum_{k=1}^{5} wQCO_k\right] + (RC_{TPM\rightarrow QCO} * TPM) * \sum_{k=1}^{5} wQCO_k \tag{6}$$

Equations (7) and (8) describe the behavior of the *OPF* variable.

$$OPF_t = OPF_{t=0} + \int_0^t (AOPF)\, dt \tag{7}$$

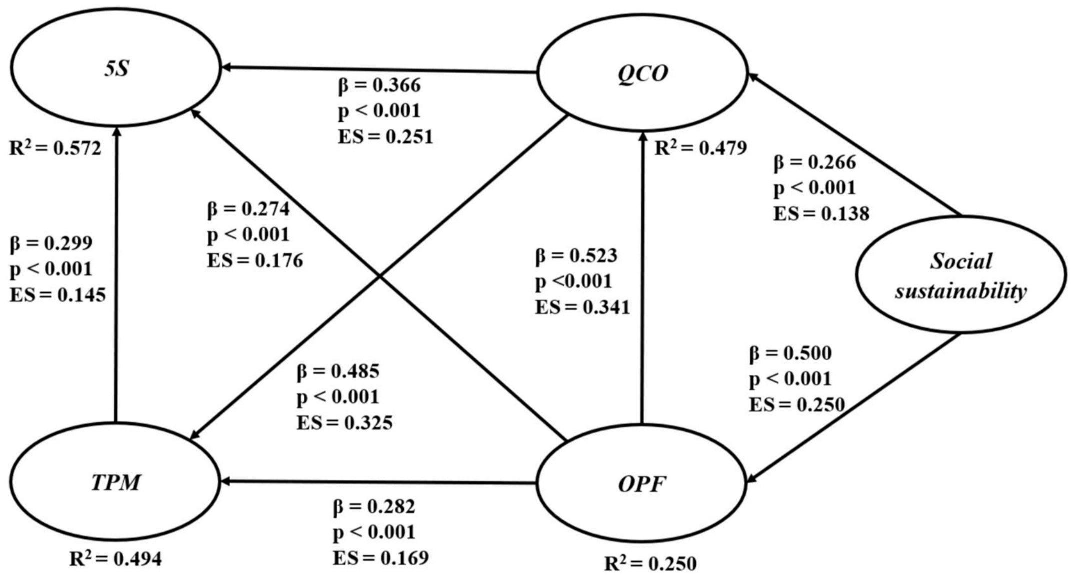


Fig. 5. Evaluated feedback model.

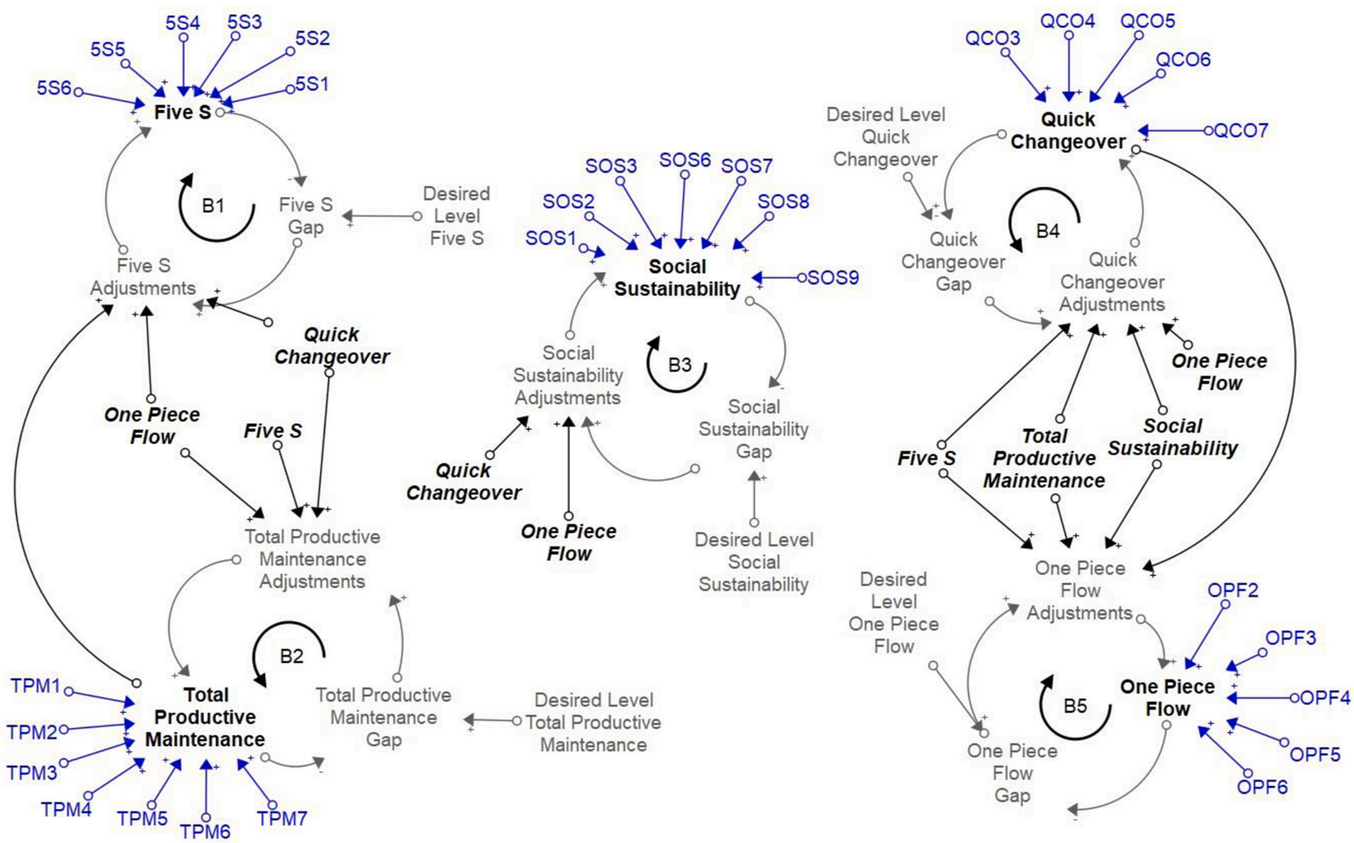


Fig. 6. Causal feedback loop diagram.

$$AOPF = GOPF\left[(RC_{5S\rightarrow OPF} * 5S) * \sum_{l=1}^{5} + (RC_{TPM\rightarrow OPF} * TPM) * \sum_{l=1}^{5} wOPF_l + (RC_{SOS\rightarrow OPF} * SOS) * \sum_{l=1}^{5} wOPF_l + (RC_{QCO\rightarrow OPF} * QCO) * \sum_{l=1}^{5} wOPF_l\right] \tag{8}$$

Equations (9) and (10) describe the behavior of the *SOS* variables.

$$SOS = SUP_{t=0} + \int_0^t (ASOS)\, dt \tag{9}$$

$$ASOS = GSOS\left[(RC_{QCO\rightarrow SOS} * QCO) * \sum_{m=1}^{7} wSOS_m + (RC_{OPF\rightarrow SOS} * SOS) * \sum_{m=1}^{7} wSOS_m\right] \tag{10}$$

4.2.3. Initial parameters

The next step was to perform the simulation model using STELLA ARCHITECT® V3.3 software. In Fig. 7, the water tanks represent the adjustments to be made in the activities of each tool fed by the weights of the indicators, gaps, and *desired level* for each LV. All of these are auxiliary variables because the water tank is fed by other LVs that directly affect them.

To run the simulation, initial parameters were established to establish a starting scenario, simulate the time at which the *desired level* of implementation would be reached, and analyze the system's behavior under different conditions. The simulation was carried out for five years because most of the participating companies are large, and the implementation time of tools such as *TPM* is not a short-term project and requires continuous improvement and maintenance until it becomes an integral part of the culture of the company's operations.

An initial value of 0.1 was established for each LV, meaning that the companies already have 10% implementation of each tool. The aim was to investigate the time at which this level of implementation is 1 or 100%. Therefore, different initial values (between 0 and 1) can be established to determine the behavior in these scenarios. Thus, 0 represents zero implementation in the development of the activities and 1 indicates that 100% has been achieved.

4.2.4. Evaluation of the simulation model

Fig. 8 shows the simulation with initial values of 0.1 (10% implementation) for each LV. The feedback loops generated between the LV are shown. The positive (red arrow) and negative (blue arrow) flows are shown. Regarding positive influences, the *Gap* for each variable directly influences the water tanks, that is, the LV. If this *Gap* increases, the adjustments should increase. In the case of negative influence, if the level of implementation increases, the *Gap* decreases, that is, the higher the level of implementation, the lower the desired level. Click here to observe the simulation's behavior for each scenario: https://exchange.iseesystems.com/public/jose-roberto-diaz-reza/diaz-reza-et-al/index.html#page1.

Fig. 9 shows the companies' *SOS* progress over five years. This illustrates that in five years, only 89.4% of *SOS* will have been achieved when it was initially simulated and counted as 10% of the scope.

Fig. 10 illustrates that *5S* has reached 100% over the five years, *TPM* at 99.7, *QCO* at 99.8, and *OPF at* 99.2%, which makes them practically one step away from the desired level of 100% implementation.

Fig. 11 illustrates the period in which the *desired level* is reached for each tool. Fig. 11 a shows that the first variable to reach the desired level of 100% will be *5S* in 4.5 years, followed by *QCO* in 5.75 years (Fig. 11b), *TPM* at 6 years (Fig. 11c), *OPF* at 6.5 years (Fig. 11d) and, finally, *SOS* in a time of 11.75 years (Fig. 11e).

4.3. Scenarios evaluation

Fig. 12 shows the simulation results for each proposed scenario. The initial values of the variables range from 0.25 to 0.75. It was observed that the different initial values of the LM and SOS variables significantly affected the time required to reach the desired levels of implementation. In general, a higher initial value for LM tools leads to a faster implementation of these tools and, consequently, to faster achievement of SOS objectives. The scenario with lower initial values for all the LM and SOS tools (Fig. 12a) demonstrates that even if starting with lower

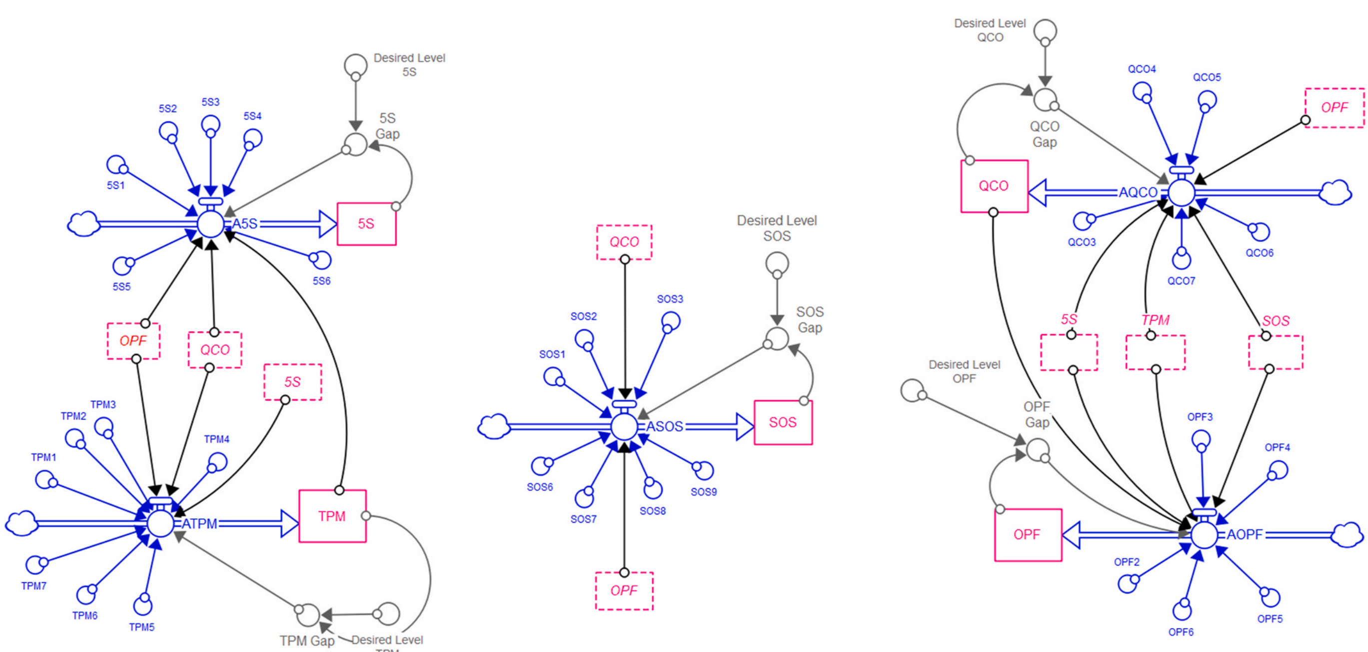


Fig. 7. Simulation model made in STELLA ARCHITECT® Software.

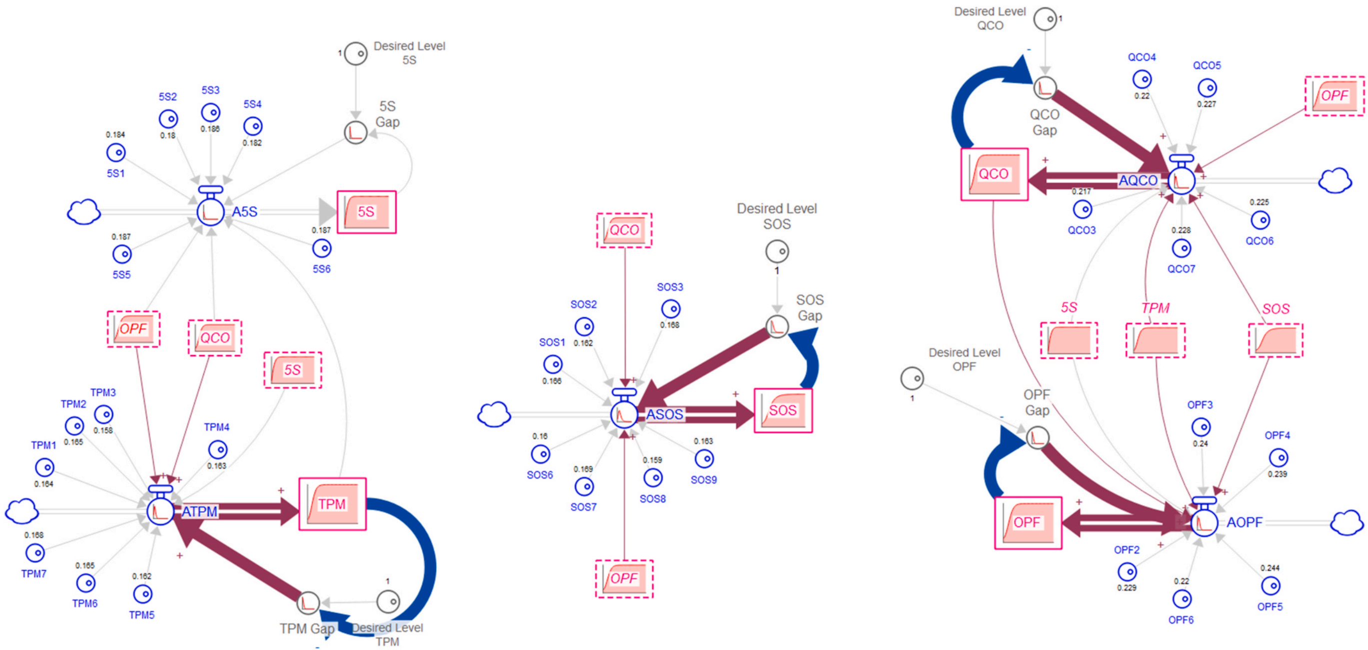
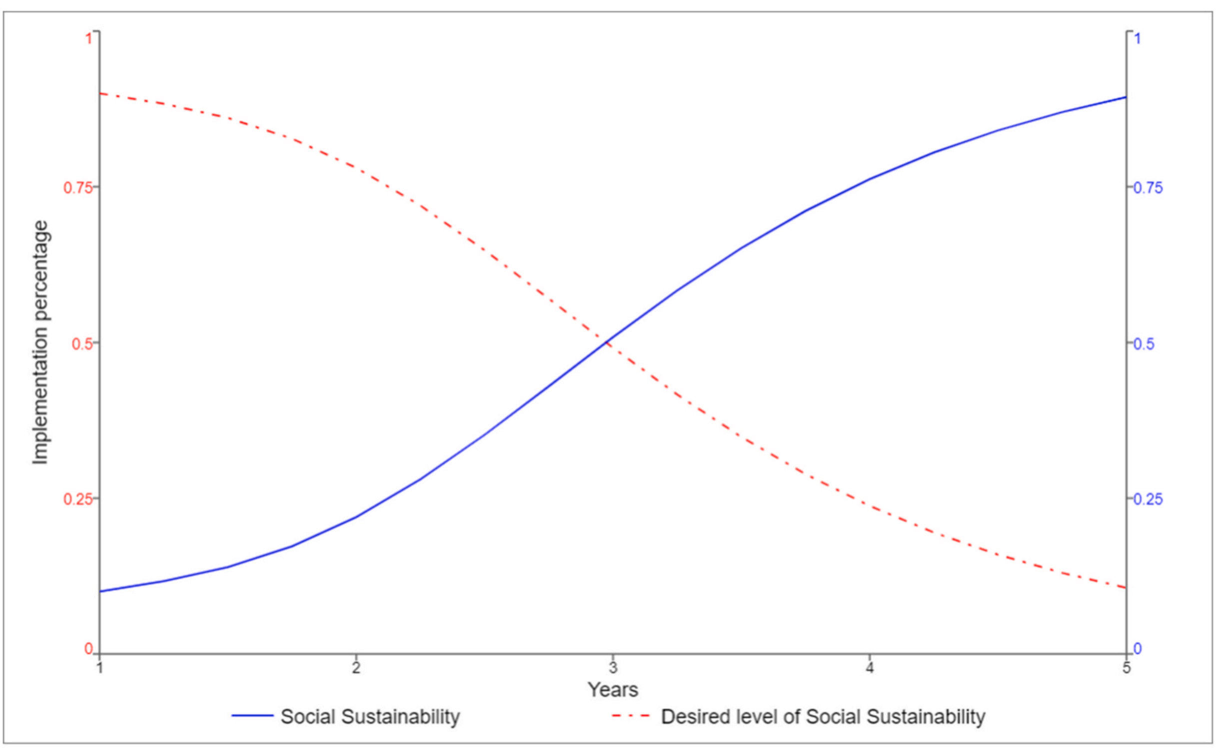


Fig. 8. Simulated model.



SOS	0.894

Fig. 9. Level of implementation of *SOS*.

implementations, an equitable strategy for improving all tools can lead to steady and significant progress toward SOS objectives in a relatively short period. In contrast, when specific LM tools had higher initial values than others (Fig. 12b, 12c, and 12d), it is observed that these tools reach the desired levels earlier, but progress toward SOS objectives is slower. This suggests that an unbalanced approach to implementing LM tools may affect the overall improvement in organizational and social sustainability.

5. Discussion of results

5.1. *From the structural equation model*

Regarding SEM, eight statistically validated hypotheses were

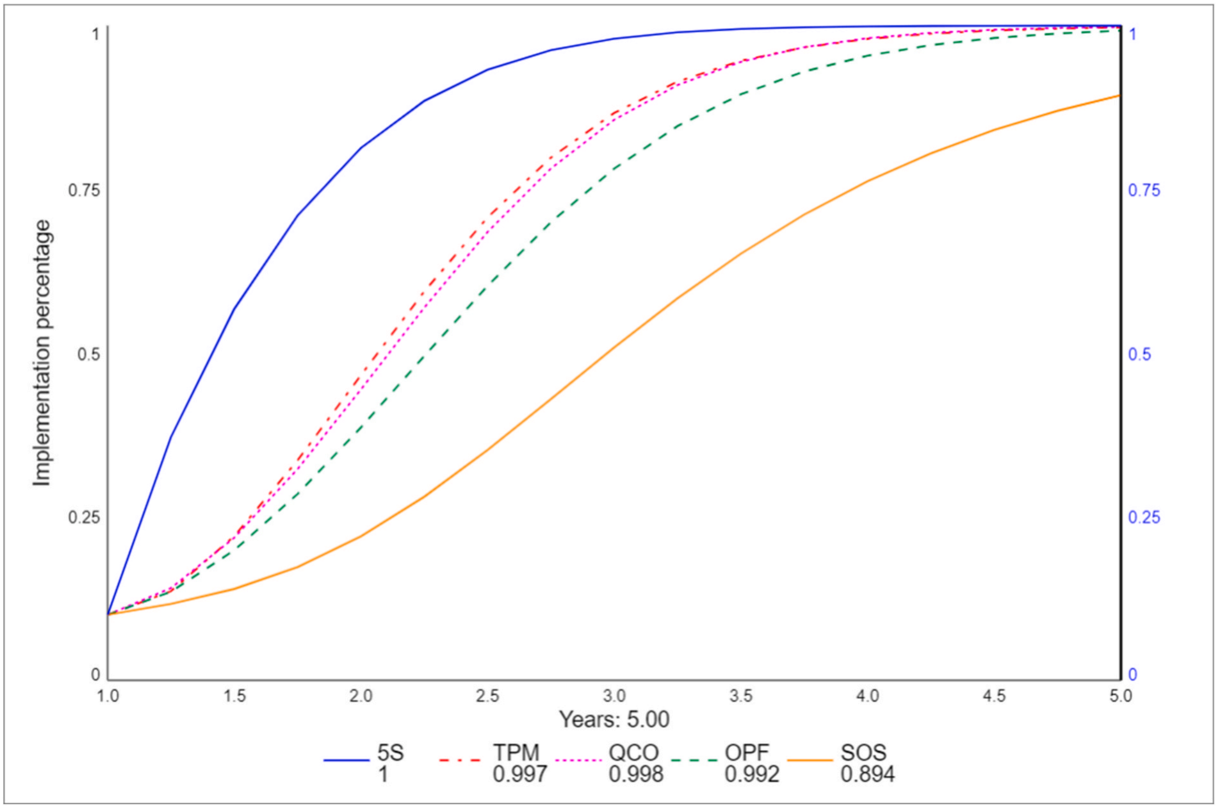


Fig. 10. Percentage achieved by variable over five years.

evaluated, where *5S* was the independent variable, *TPM, QCO*, and *OPF* were mediating variables, and *SOS* was the dependent variable. All relationships were statistically significant between *5S* and *TPM* with $\beta = 0.630$ for H_1 and explained 39.7% of it. This finding demonstrates that *5S* is the first step in *TPM* implementation (Randhawa and Ahuja, 2017) and that is why managers should focus on having clean, safe, and standardized workplaces before implementing it to reduce accidents, inefficiencies, idle time in machines, and increase quality with calibrated machines (Kumar et al., 2018).

5S directly affects *QCO* (H_2) and *OPF* (H_4), with $\beta = 0.445$ and $\beta = 0.304$, explaining 30.7% and 19.6% of its variability, respectively. This indicates the importance of organization, cleanliness, and hygiene within the workplace before implementing a product change and improving production flow. This indicates that *5S* helps reduce tool search time during changeover, improving efficiency and productivity, and increasing the OEE index, reducing accident risk and stress on workers when performing fast-paced (José Roberto Díaz-Reza et al., 2022).

In addition, *TPM* directly affects *QCO* (H_3) with $\beta = 0.393$, explaining 26.4% of the variability, and *OPF* with $\beta = 0.211$ (H_5), explaining 12.7% of the variability. These results indicate that *TPM* reduces the number of setups, equipment downtime, breakdowns, accidents, and maintenance costs, while increasing equipment productivity and operating efficiency (Ondra, 2022). However, *TPM* also supports machinery availability, increasing OPF mainly because of high OEE and machinery reliability, which facilitates on-time deliveries and customer satisfaction (Vital and Lima, 2020).

The findings indicate that *QCO* positively influenced *OPF* with $\beta = 0.303$ (H_6) and *SOS* with $\beta = 0.349$ (H_7), explaining 19.8% and 18.8% of its variability, respectively. This indicates that *QCO* increases flexibility, improves efficiency, yields a higher throughput, enables shorter production runs, responds faster to demand, and increases productivity (Haddad et al., 2021). However, it also generates job satisfaction, improved safety, enhanced skill development, and reduced physical strain, allowing employees to spend less time on non-value-added activities and leading to higher job satisfaction (Garcia-Garcia et al., 2022).

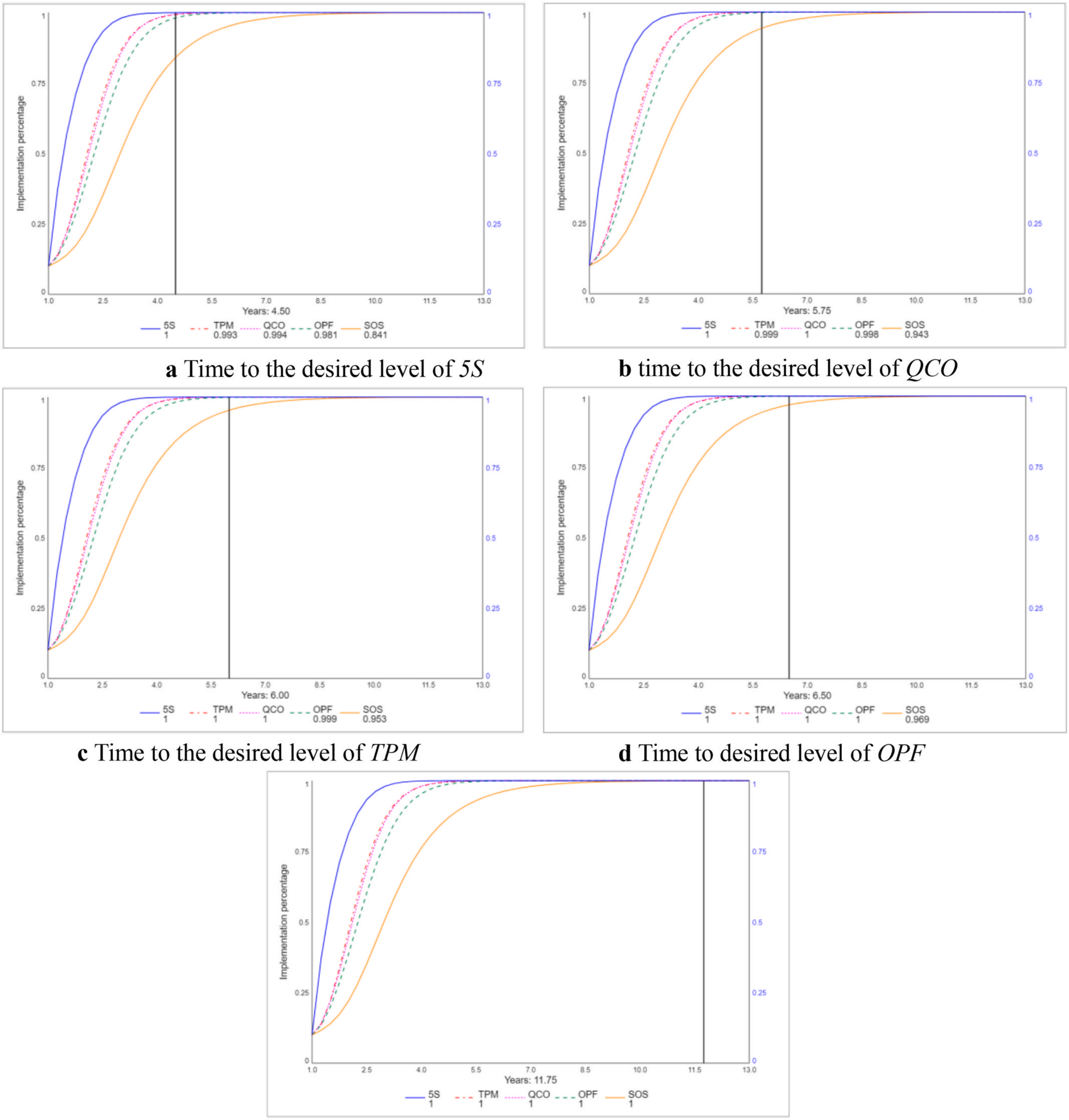
Finally, *OPF* positively influenced *SOS* with $\beta = 0.299$ (H_8), explaining 15.6% of its variability. Maintaining a continuous flow within the production processes will improve working conditions, work safety, and employee health, and reduce work pressure. This agrees with Vaddula et al. (2015), who concluded that continuous flow can improve worker safety by reducing manual handling and exposure to hazards, and promoting work balance, which increases job satisfaction.

Although they were not added as hypotheses, it is important to discuss some indirect effects, where the most important are the relationships that *5S* has on *SOS*, *QCO*, and *OPF*, which have values of $\beta = 0.435$, $\beta = 0.248$, and $\beta = 0.342$, respectively, all of which are statistically significant. These findings indicate the importance of having selected and ordered tools to be used with proper cleanliness and discipline in the workplace, as this facilitates the achievement of other objectives associated with the continuous flow of production lines, rapid changes, and the well-being of workers.

Other significant indirect effects are those of TPM on SOS and OPF, with $\beta = 0.236$ and $\beta = 0.119$, respectively, and both are statistically significant. This indicates the importance of mediating variables such as QCO in facilitating OPF in production lines and QCO and OPF in facilitating SOS. That is, TPM facilitates flow in the production system through rapid changes, and at the same time, this impacts the welfare of workers, their safety, and job satisfaction.

5.2. From the system dynamics model

Fig. 11 a shows that the first variable to reach the desired level of 100% will be *5S* in 4.5 years, followed by *QCO* in 5.75 years (Fig. 11b), *TPM* in 6 years (Fig. 11c), *OPF* in 6.5 years (Fig. 11d) and, finally, *SOS*in a time of 11.75 years (Fig. 11e). With the initial values for all LVs at 0.25 in Scenario 2 (Fig. 12 a), that is, a 25% implementation for each LM tool



a Time to the desired level of *5S*

b time to the desired level of *QCO*

c Time to the desired level of *TPM*

d Time to desired level of *OPF*

e Time to the desired level of *SOS*

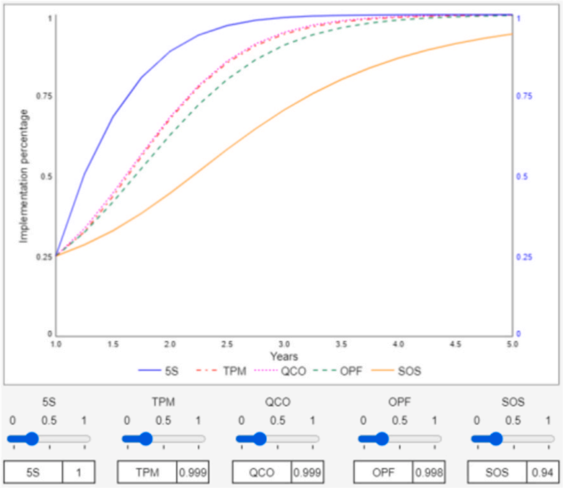
Fig. 11. Time to reach the desired level of implementation.

and a 25% achievement in *SOS*. It is observed that, after five years, *5S* will reach the desired level of 100%, and practically, *TPM* and *QCO* will reach it simultaneously since both have 99.9% and *OPF* will have reached 99.8%, while *SOS* will achieve only 94% in 5 years.

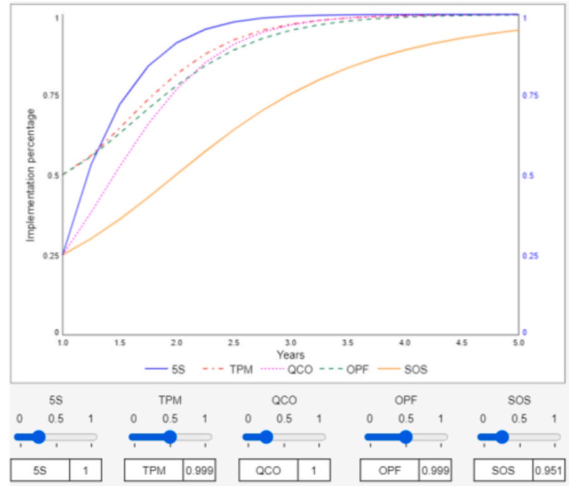
From Fig. 12 b for Scenario 3, the initial values for *5S*, *QCO*, and *SOS* were set to 0.25 and *TPM* and *OPF* were set to 0.5. The simulation showed that *5S* and *QCO* reached the desired level, while *TPM* and *OPF* reached 99.9%, and *SOS* reached 95.1%. Scenario 4 (Fig. 12c) sets the initial values of all the variables at 0.5.*5S*, *TPM*, and *QCO* reached the desired levels, while *OPF* was 99.9% and *SOS* was 97.3%. Fig. 12 d for Scenario 5 sets the initial *5S*, *QCO*, and *SOS* values at 0.75 and *the TPM* and *OPF* at 0.5. The simulation yielded the desired levels of 100% for *5S*, *TPM*, *QCO*, and OPF and 98.8% for SOS. Finally, for Scenario 6, initial values of 0.75 (Fig. 12e) were established for each variable, yielding values of 100% for *5S*, *TPM*, *QCO*, and *OPF* and 98.9% for *SOS*.

6. Conclusions

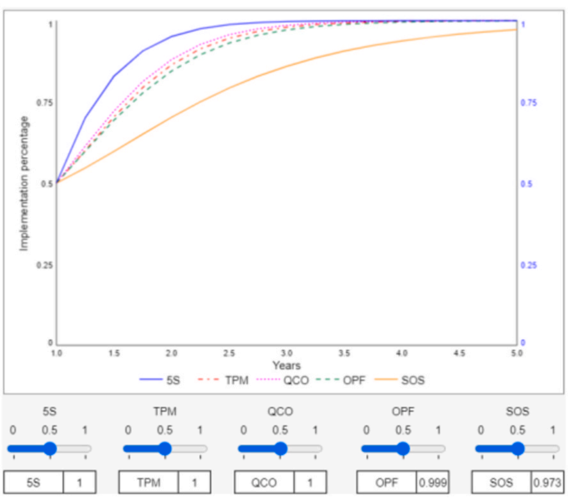
The analysis of 411 responses to a questionnaire using a structural equation model, in which the effects of 5 S, TPM, OPF, QCO, and SOS



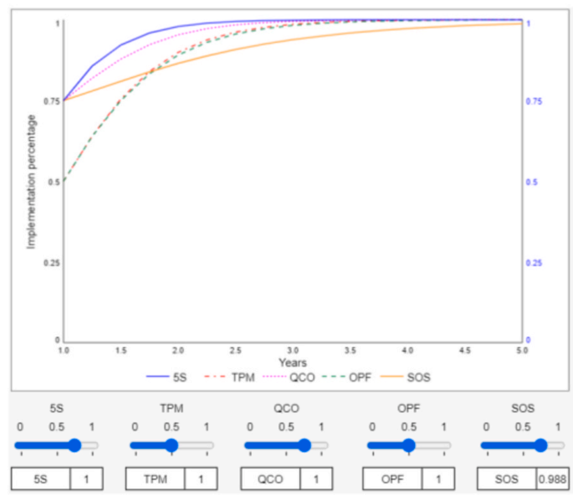
a initial values at 0.25



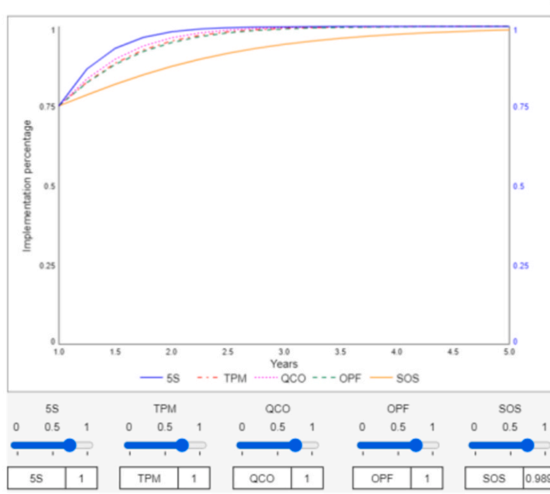
b Initial values *5S*, *QCO* and *SOS* 0.25; *TPM* and *OPF* 0.5



c Initial values of 0.25



d Initial values *5S*, *QCO*, *SOS* 0.75; *TPM* and *OPF* 0.5



e Initial values at 0.75

Fig. 12. Initial values for every scenario.

were analyzed, concluded that all of them were interrelated. Based on the magnitude of the direct effects, the results indicate that the 5 S tool is vital for TPM and QCO, because it is the highest in the model, indicating the relevance of having clean, orderly, standardized, and disciplined workplaces. This, in turn, allows for quick machine changeovers, minimizing downtime and facilitating the continuous flow of raw materials and products through production lines.

This indicates that implementing 5 S, TPM, OPF, and QCO can increase productivity and companies' social sustainability. Therefore, managers should focus on improving workplace conditions to facilitate the implementation of TPM and quick changeovers that provide safety for workers, increase hygienic conditions, and improve the social sustainability of the company. However, it is essential to mention that it is important to invest in training and development to improve employees' skills to create a culture that values efficiency, continuous improvement, and social responsibility within the company.

Regarding the SD presented, it is crucial to interpret with caution the initial projections of 100% implementation of *SOS* in 11.75 years, as these timelines are subject to change due to the changing dynamics of business environments, such as new worker satisfaction and technological advances. In addition, achieving the optimal value of 100% may be challenging for companies, which may be satisfied with a lower value depending on the needs of their environment. In other words, these estimates should be indicative targets and may be adjusted because of the possible unforeseen changes in the business environment. Therefore, the successful implementation *of 5S*, *OPF*, *TPM*, *and QCO* and gaining *SOS* will require flexibility, adaptability, and an understanding of the interdependence between different management tools.

Finally, this study contributes to a better understanding of how LM tools can directly affect SOS issues in an industrial context, serving as an example of how to integrate methodologies such as SEM and SD to address complex industrial and sustainability problems. We hope that the implications of these findings may be valuable for practitioners and managers in the industry, as they offer insights into how LM methodologies influence SOS and provide guidance for decision-making to improve business practices and policies related to sustainability.

Limitations

LM integrates many tools for optimizing industrial processes; however, in this study, only four tools were related to *SOS* to create a more understandable model, which is a limitation because other LM tools must be analyzed. Additionally, data used to validate the SEM in this study were obtained from the MMI established by Ciudad Juarez (Mexico). Their particular characteristics, such as socioeconomic environment, labor culture, and relationship with the local community, can influence our findings. They may not be generalizable to other regions or countries in different contexts.

Future work

Future research will include ES and ECS and analyze the effects of these tools in generating sustainability. We will extend the research to other locations with significant maquiladora companies to compare and contrast the findings. This would allow us to evaluate whether the results obtained in Ciudad Juarez are consistent in other contexts or if there are significant differences. These strategies could focus on training programs, social responsibility policies, and improvements in working conditions, among other aspects.

Funding

José Roberto Díaz Reza is receiving a grant for his postdoctoral stay at the Universidad Autónoma de Ciudad Juárez under agreement 548515.

CRediT authorship contribution statement

José Roberto Díaz-Reza: Writing – review & editing, Writing – original draft, Funding acquisition, Conceptualization. **S. Hooman Mousavi:** Writing – review & editing, Formal analysis. **Cuauhtémoc Sánchez-Ramírez:** Writing – review & editing, Software, Methodology, Data curation, Conceptualization. **Jorge Luis García-Alcaraz:** Writing – review & editing, Supervision, Methodology, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

José Roberto Díaz-Reza reports financial support was provided by Consejo Nacional de Humanidades, Ciencias y Tecnologías (CONAHCYT). A database has been generated with the information obtained from the applied questionnaire, registered with property rights into the Public Registry of Copyrights in Mexico. This is done to protect the rights of the information, its confidentiality, and its use in future research. This statement is made in this section since it is not a patent but an intellectual property.

Data availability

Data will be made available on request.

Acknowledgements

The authors would like to thank all managers, engineers, and lean manufacturing project leaders in the Mexican maquiladora industry who responded to the survey. We hope that the findings of this study will facilitate decision making in their production lines.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jclepro.2024.141453.

References

Afum, E., Sun, Z., Agyabeng-Mensah, Y., Baah, C., 2021. Lean production systems, social sustainability performance and green competitiveness: the mediating roles of green technology adoption and green product innovation [Article]. J. Eng. Des. Technol. https://doi.org/10.1108/JEDT-02-2021-0099.

Agustiady, T.K., Cudney, E.A., 2018. Total Productive Maintenance. Total Quality Management & Business Excellence, pp. 1–8. https://doi.org/10.1080/14783363.2018.1438843.

Alarcón Bernal, S., Castillo, W., Mora Rubio, M., Vera Romero, A., 2014. Aplicación del pilar de mantenimiento autónomo de la metodología TPM en la línea 1 de producción de *CAPD de Fresenius Medical Cares SA* Universidad de La Sabana.

Alexander, L., Iskandar, I., 2023. Application of lean manufacturing in aluminum cable ladder manufacturing companies: case study at PT. Indra saputra triassic. Journal of Mechanical Civil and Industrial Engineering. https://doi.org/10.32996/jmcie.2023.4.1.2.

Amrani, A., Ducq, Y., 2020. Lean practices implementation in aerospace based on sector characteristics: methodology and case study. Prod. Plann. Control 31 (16), 1313–1335. https://doi.org/10.1080/09537287.2019.1706197.

Antosz, K., Pacana, A., 2018. Comparative analysis of the implementation of the SMED method on selected production stands. Teh. Vjesn. 25 (Suppl. 2), 276–282.

Arshad Ali, A., Mahmood, A., Ikram, A., Ahmad, A., 2020. Configuring the drivers and carriers of process innovation in manufacturing organizations. Journal of Open Innovation: Technology, Market, and Complexity 6 (4), 154. https://doi.org/10.3390/joitmc6040154.

Attri, R., Singh, B., Mehra, S., 2017. Analysis of interaction among the barriers to 5S implementation using interpretive structural modeling approach [Article]. Benchmarking 24 (7), 1834–1853. https://doi.org/10.1108/BIJ-07-2016-0110.

Bai, K., Zang, L., Brown, E.D., 2016. Ability of a low-dimensional model to predict geometry-dependent dynamics of large-scale coherent structures in turbulence. Phys. Rev. https://doi.org/10.1103/physreve.93.023117.

Bevilacqua, M., Ciarapica, F.E., De Sanctis, I., Mazzuto, G., Paciarotti, C., 2015. A through an integration of lean practices: a case study from pharmaceutical sector. Assemb. Autom. 35 (1), 22–34. https://doi.org/10.1108/AA-05-2014-035.

Burawat, P., 2019. The relationships among transformational leadership, sustainable leadership, lean manufacturing and sustainability performance in Thai SMEs manufacturing industry [Article]. Int. J. Qual. Reliab. Manag. 36 (6), 1014–1036. https://doi.org/10.1108/IJQRM-09-2017-0178.

Cañas, J., Coronado, R., Gilmer, R., 2011. Maquiladora downturn: structural change or cyclical factors? Int. Bus. Econ. Res. J. https://doi.org/10.19030/iber.v3i8.3712.

Chadha, R., Singh, A., Kalra, J., 2012. Lean and queuing integration for the transformation of health care processes. Clin. Govern. Int. J. 17 (3), 191–199. https://doi.org/10.1108/14777271211251309.

Chand, G., Shirvani, B., 2000. Implementation of TPM in cellular manufacture. J. Mater. Process. Technol. 103 (1), 149–154. https://doi.org/10.1016/S0924-0136(00)00407-6.

Correia Pinto, G.F., José Gomes da Silva, F., Octávio Garcia Fernandes, N., Carla Barros Casais, R., Baptista da Silva, A., Jorge Vale Carvalh, C., 2020. Implementing a maintenance strategic plan using TPM methodology. International Journal of Industrial Engineering and Management 11 (3), 192–204.

De Vries, H., Van der Poll, H.M., 2018. Cellular and organisational team formations for effective Lean transformations. Production & Manufacturing Research 6 (1), 284–307. https://doi.org/10.1080/21693277.2018.1509742.

Delgado-Maciel, J., Cortés-Robles, G., Sánchez-Ramírez, C., García-Alcaraz, J., Méndez-Contreras, J.M., 2020. The evaluation of conceptual design through dynamic simulation: a proposal based on TRIZ and system Dynamics [Article]. Comput. Ind. Eng. 149 https://doi.org/10.1016/j.cie.2020.106785. Article 106785.

Díaz-Reza, J.R., García-Alcaraz, J.L., Figueroa, L.J.M., Vidal, R.P.i., Muro, J.C.S.D., 2022a. Relationship between lean manufacturing tools and their sustainable economic benefits. Int. J. Adv. Des. Manuf. Technol. 123 (3), 1269–1284. https://doi.org/10.1007/s00170-022-10208-0.

Díaz-Reza, J.R., García-Alcaraz, J.L., Martínez-Loya, V., Blanco-Fernández, J., Jiménez-Macías, E., Avelar-Sosa, L., 2016. The effect of SMED on benefits gained in maquiladora industry [Article]. Sustainability 8 (12). https://doi.org/10.3390/su8121237. Article 1237.

Díaz-Reza, J.R., García Alcaraz, J.L., Morales García, A.S., 2022b. Best Practices in Lean Manufacturing - A Relational Analysis. Springer. https://doi.org/10.1007/978-3-030-97752-8.

Eldardiry, Z., El-Dardiry, M.A., Nada, O.A., 2021. A Conceptual Framework for Reducing Changeover Time in Batch Production Facilities.

Emamisaleh, K., Taimouri, A., 2021. Sustainable supply chain management drivers and outcomes: an emphasis on strategic sustainability orientation in the food industries. Indepen. J. Manag. Prod. 12 (1), 282–309.

Espinoza-Huamash, M., Arana-Hurtado, I., León-Chavarri, C., 2022. Maintenance management model to increase availably in a metalworking SME applying TPM, SMED and PDCA. In: Proceedings of the LACCEI International Multi-Conference for Engineering. Education and Technology.

García-Alcaraz, J.L., Morales García, A.S., Díaz-Reza, J.R., Jiménez Macías, E., Javierre Lardies, C., Blanco Fernández, J., 2022. Effect of lean manufacturing tools on sustainability: the case of Mexican maquiladoras. Environ. Sci. Pollut. Control Ser. 29 (26), 39622–39637. https://doi.org/10.1007/s11356-022-18978-6.

Garcia-Garcia, G., Singh, Y., Jagtap, S., 2022. Optimising changeover through lean-manufacturing principles: a case study in a food factory. Sustainability. https://doi.org/10.3390/su14148279.

García Alcaraz, J.L., Morales García, A.S., Díaz Reza, J.R., Blanco Fernández, J., Jiménez Macías, E., Puig I Vidal, R., 2022. Machinery lean manufacturing tools for improved sustainability: the Mexican maquiladora industry experience [article]. Mathematics 10 (9). https://doi.org/10.3390/math10091468. Article 1468.

Ghaithan, A., Khan, M., Mohammed, A., Hadidi, L., 2021. Impact of industry 4.0 and lean manufacturing on the sustainability performance of plastic and petrochemical organizations in Saudi Arabia. Sustainability 13 (20), 11252.

Ghaithan, A.M., Alshammakhi, Y., Mohammed, A., Mazher, K.M., 2023. Integrated impact of circular economy, industry 4.0, and lean manufacturing on sustainability performance of manufacturing firms. Int. J. Environ. Res. Publ. Health. https://doi.org/10.3390/ijerph20065119.

Gholami, H., Jamil, N., Zakuan, N., Saman, M.Z.M., Sharif, S., Awang, S.R., Sulaiman, Z., 2019. Social value stream mapping (Socio-VSM): methodology to societal sustainability visualization and assessment in the manufacturing system. IEEE Access 7, 131638–131648. https://doi.org/10.1109/ACCESS.2019.2940957.

Grineski, S.E., Collins, T.W., Aguilar, M.d.L.R., 2015. Environmental injustice along the US–Mexico border: residential proximity to industrial parks in Tijuana, Mexico. Environ. Res. Lett. 10 (9), 095012.

Gupta, A.K., Garg, R., 2012. OEE improvement by TPM implementation: a case study. International Journal of IT, Engineering and Applied Sciences Research 1 (1), 115–124.

Gupta, S., Jain, S.K., 2015. An application of 5S concept to organize the workplace at a scientific instruments manufacturing company. International Journal of Lean Six Sigma 6 (1), 73–88. https://doi.org/10.1108/IJLSS-08-2013-0047.

Haddad, T.H., Shaheen, B.W., Németh, I., 2021. Improving overall equipment effectiveness (OEE) of extrusion machine using lean manufacturing approach. Manufacturing Technology. https://doi.org/10.21062/mft.2021.006.

Heaton, A., Abdelazim, A., 2021. The Most Important Cog in the Machine: Business Analysis and 5S Implementation in an Engineering Company.

Heravi, G., Kebria, M.F., Rostami, M., 2021. Integrating the production and the erection processes of pre-fabricated steel frames in building projects using phased lean management. Eng. Construct. Architect. Manag. 28 (1), 174–195. https://doi.org/10.1108/ECAM-03-2019-0133.

Hernández-Nieto, R.A., 2002. Contributions to Statistical Analysis. Universidad de Los Andes.

Husgafvel, R., Pajunen, N., Virtanen, K., Paavola, I.-L., Päällysaho, M., Inkinen, V., Heiskanen, K., Dahl, O., Ekroos, A., 2015. Social sustainability performance indicators–experiences from process industry. Int. J. Sustain. Eng. 8 (1), 14–25.

Index, 2023. Statistical Information Monthly - Employment Information of IMMEX Companies Ciudad Juarez. https://indexjuarez.com/wp-content/uploads/2023/06/23-de-Junio-2023.pdf.

Index, J., 2022. Industria manufacturera de exportación: Panorama General. https://indexjuarez.com/wp-content/uploads/jesusmartinez/Maquila%20overview.pdf.

Ioana, A.D., Maria, E.D., Cristina, V., 2020. Case study regarding the implementation of one-piece flow line in automotive company. Procedia Manuf. 46, 244–248. https://doi.org/10.1016/j.promfg.2020.03.036.

Iranmanesh, M., Zailani, S., Hyun, S.S., Ali, M.H., Kim, K., 2019. Impact of lean manufacturing practices on firms' sustainable performance: lean culture as a moderator [Article]. Sustainability 11 (4). https://doi.org/10.3390/su11041112. Article 1112.

Ireland, F., Dale, B.G., 2001. A study of total productive maintenance implementation. J. Qual. Mainten. Eng. 7 (3), 183–192. https://doi.org/10.1108/13552510110404495.

Ishijima, H., Eliakimu, E., Mshana, J.M., 2016. The "5S" approach to improve a working environment can reduce waiting time: findings from hospitals in Northern Tanzania. The TQM Journal.

Jiménez, M., Romero, L., Domínguez, M., Espinosa, M.d.M., 2015. 5S methodology implementation in the laboratories of an industrial engineering university school. Saf. Sci. 78, 163–172. https://doi.org/10.1016/j.ssci.2015.04.022.

Jit Singh, B., Khanduja, D., 2010. SMED: for quick changeovers in foundry SMEs. Int. J. Prod. Perform. Manag. 59 (1), 98–116. https://doi.org/10.1108/17410401011006130.

Kara, A., 2018. Escaping mediocre-quality, low-productivity, low-performance traps at universities in developing countries: a human capital-based structural equation model with system-dynamics simulations [Article]. Kuram ve Uygulamada Egitim Bilimleri 18 (3), 541–559. https://doi.org/10.12738/estp.2018.3.0255.

Khalfallah, M., Lakhal, L., 2021. The impact of lean manufacturing practices on operational and financial performance: the mediating role of agile manufacturing. Int. J. Qual. Reliab. Manag. 38 (1), 147–168.

Kiefer, C., Lemmerich, F., Langenberg, B., Mayer, A., 2022. Subgroup discovery in structural equation models. Psychol. Methods.

Kock, N., 2021a. WarpPLS User Manual: Version 6.0. ScriptWarp Systems, Laredo, TX.

Kock, N., 2021b. WarpPLS User Manual: Version 7.0. ScriptWarp Systems, Laredo, TX.

Kock, N., Hadaya, P., 2018. Minimum sample size estimation in PLS-SEM: the inverse square root and gamma-exponential methods. Inf. Syst. J. 28 (1), 227–261.

Kumar, V., Kumar, V., Chaikittisilp, S., Tan, K.H., 2018. The effect of lean methods and tools on the environmental performance of manufacturing organisations. Int. J. Prod. Econ. https://doi.org/10.1016/j.ijpe.2018.03.030.

Langhelle, O., 1999. Towards Sustainable Development: on the Goals of Development-And the Conditions of Sustainability. Springer.

Longoni, A., Cagliano, R., 2015. Cross-functional executive involvement and worker involvement in lean manufacturing and sustainability alignment. Int. J. Oper. Prod. Manag. 35 (9), 1332–1358. https://doi.org/10.1108/IJOPM-02-2015-0113.

Marín, A.F., Casado, L.R., Gómez, M.E.L., Tarín, M.L.B., 2013. Implantación del sistema de calidad 5s en un centro integrado público de formación profesional. Rev. Electrón. Interuniv. Form. del Profr. 16 (2), 147–161.

Mohandes, S.R., Kineber, A.F., Abdelkhalek, S., Kaddoura, K., Elsayed, M., Hosseini, M. R., Zayed, T., 2022. Evaluation of the critical factors causing sewer overflows through modeling of structural equations and system dynamics [Article]. J. Clean. Prod. 375 https://doi.org/10.1016/j.jclepro.2022.134035. Article 134035.

Muraliraj, J., Kuppusamy, S., Zailani, S., Santha, C., 2020. Lean, Six Sigma and its influence on potential and realized absorptive capacity [Article]. International Journal of Lean Six Sigma 11 (1), 84–124. https://doi.org/10.1108/IJLSS-03-2018-0020.

Nahmens, I., Ikuma, L.H., Garcia, T., 2011. Getting Organized across the Hospital with 5S. Lean Six Sigma for the Healthcare Enterprise CRC Press, UK.

Olawumi, T.O., Chan, D.W., 2018. A scientometric review of global research on sustainability and sustainable development. J. Clean. Prod. 183, 231–250.

Ondra, P., 2022. The impact of single minute exchange of die and total productive maintenance on overall equipment effectiveness. Journal of Competitiveness. https://doi.org/10.7441/joc.2022.03.07.

Ortega del Castillo, R., 2019. *Implementación de una estrategia de producción esbelta para la mejora del flujo de materiales de un proceso de ensamble en una empresa manufacturera* ORTEGA DEL CASTILLO. RICARDO.

Papetti, A., Gregori, F., Pandolfi, M., Peruzzini, M., Germani, M., 2020. A method to improve workers' well-being toward human-centered connected factories. Journal of Computational Design and Engineering. https://doi.org/10.1093/jcde/qwaa047.

Peron, M., Alfnes, E., Sgarbossa, F., 2021. Best Practices of Just-In-Time 4.0: Multi Case Study Analysis, 2021. Advanced Manufacturing and Automation X, Singapore.

Piercy, N., Rich, N., 2015. The relationship between lean operations and sustainable operations. Int. J. Oper. Prod. Manag. 35 (2), 282–315. https://doi.org/10.1108/IJOPM-03-2014-0143.

Posada, J.G.A., 2007. Interacción y conexiones entre las técnicas 5s, SMED y Poka Yoke en procesos de mejoramiento continuo. Tecnura 10 (20), 139–148.

Putri, N.T., Fatrias, D., Simbolon, S.R.R., 2022. 5S implementation to minimize waste in bread production process (case study: madani bakery). In: Global Conference on Sustainable Manufacturing.

Randhawa, J.S., Ahuja, I.S., 2017. Evaluating impact of 5S implementation on business performance. Int. J. Prod. Perform. Manag. 66 (7), 948–978. https://doi.org/10.1108/IJPPM-08-2016-0154.

Ribeiro, I.M., Godina, R., Pimentel, C., Silva, F.J.G., Matias, J.C.O., 2019. Implementing TPM supported by 5S to improve the availability of an automotive production line. Procedia Manuf. 38, 1574–1581. https://doi.org/10.1016/j.promfg.2020.01.128.
Ribeiro, M.A.S., Santos, A.C.O., de Amorim, G.d.F., de Oliveira, C.H., da Silva Braga, R. A., Netto, R.S., 2022. Analysis of the implementation of the single minute exchange of die methodology in an agroindustry through action research. Machines 10 (5), 287.
Rockow, Z.R., Ross, B.E., Black, A.M.B., 2019. Review of methods for evaluating adaptability of buildings. Int. J. Build. Pathol. Adapt. https://doi.org/10.1108/ijbpa-01-2018-0013.
Rupasinghe, H.D., Wijethilake, C., 2021. The impact of leanness on supply chain sustainability: examining the role of sustainability control systems. Corp. Govern. https://doi.org/10.1108/CG-06-2020-0217 [Article].
Samadhiya, A., Agrawal, R., Garza-Reyes, J.A., 2023. Investigating the influence of total productive maintenance key success factors on the social sustainability dimension of manufacturing SMEs. Benchmark Int. J. https://doi.org/10.1108/BIJ-05-2022-0287. *ahead-of-print*(ahead-of-print).
Senthil Kumar, K.M., Akila, K., Arun, K.K., Prabhu, S., Selvakumar, C., 2022. Implementation of 5S practices in a small scale manufacturing industries. Mater. Today: Proc. 62, 1913–1916. https://doi.org/10.1016/j.matpr.2022.01.402.
Shahriar, M.M., Parvez, M.S., Islam, M.A., Talapatra, S., 2022. Implementation of 5S in a plastic bag manufacturing industry: a case study. Cleaner Engineering and Technology 8, 100488. https://doi.org/10.1016/j.clet.2022.100488.
Singh, J., Singh, H., Singh, I., 2018. SMED for quick changeover in manufacturing industry–a case study. Benchmark Int. J. 25 (7), 2065–2088.
Takele, K., Zewotir, T., Ndanguza, D., 2023. A combined model of child malnutrition and morbidity in Ethiopia using structural equation models. Sci. Rep. 13 (1), 471.
Tang, S., Ng, T., Chong, W., Chen, K., 2016. Case study on lean manufacturing system implementation in batch printing industry Malaysia. MATEC Web Conf 70, 05002. https://doi.org/10.1051/matecconf/20167005002.
Toki, G.F.I., Ahmed, T., Hossain, M.E., Alave, R.K.K., Faruk, M.O., Mia, R., Islam, S.R., 2023. Single Minute Exchange Die (SMED): a sustainable and well-timed approach for Bangladeshi garments industry. Cleaner Engineering and Technology 12, 100592. https://doi.org/10.1016/j.clet.2022.100592.
Tsarouhas, P., 2007. Implementation of total productive maintenance in food industry: a case study. J. Qual. Mainten. Eng. 13 (1), 5–18. https://doi.org/10.1108/13552510710735087.
ul Haq, S., Boz, I., 2020. Measuring environmental, economic, and social sustainability index of tea farms in Rize Province, Turkey [Article]. Environ. Dev. Sustain. 22 (3), 2545–2567. https://doi.org/10.1007/s10668-019-00310-x.
Vaddula, B.R., Yalla, S., Gonzalez, M.A., 2015. An efficient and more sustainable one-step continuous-flow multicomponent synthesis approach to chromene derivatives. Journal of Flow Chemistry. https://doi.org/10.1556/1846.2015.00015.
Velazquez, L., Munguia, N., Zavala, A., Esquer, J., Will, M., Delakowitz, B., 2014. Cleaner production and pollution prevention at the electronic and electric Mexican maquiladora. Manag. Environ. Qual. Int. J. 25 (5), 600–614.
Veres, C., Marian, L., Moica, S., Al-Akel, K., 2018. Case study concerning 5S method impact in an automotive company. Procedia Manuf. 22, 900–905. https://doi.org/10.1016/j.promfg.2018.03.127.
Vieira, T., Sá, J.C., Lopes, M.P., Santos, G., Félix, M.J., Ferreira, L.P., Silva, F.J.G., Pereira, M.T., 2019. Optimization of the cold profiling process through SMED. Procedia Manuf. 38, 892–899. https://doi.org/10.1016/j.promfg.2020.01.171.
Vital, J.C.M., Lima, C.R.C., 2020. Total productive maintenance and the impact of each implemented pillar in the overall equipment effectiveness. International Journal of Engineering and Management Research. https://doi.org/10.31033/ijemr.10.2.17.
Vo, B., Kongar, E., Suárez Barraza, M.F., 2019. Kaizen event approach: a case study in the packaging industry. Int. J. Prod. Perform. Manag. 68 (7), 1343–1372. https://doi.org/10.1108/IJPPM-07-2018-0282.
Wang, D.-s., Li, A.-z., 2013. A case study on one-piece-flow production mode designing. In: International Asia Conference on Industrial Engineering and Management Innovation (IEMI2012) Proceedings: Core Areas of Industrial Engineering.
Zhang, Y., 2022. Modelling the lexical complexity of homogenous texts: a time series approach. Qual. Quantity 57 (3), 2033–2052. https://doi.org/10.1007/s11135-022-01451-4.