ISBN: 978-628-96613-3-0. ISSN: 2414-6390. Digital Object Identifier: https://dx.doi.org/10.18687/LACCEI2026.1.1.823

Effect of gemba on muda and economic sustainability in the Mexican maquiladora industry

García Alcaraz, Jorge Luis [1]; Celis Gracia, Omar [2]; Mendoza Solis, Maribel [3,4]
[1] Universidad Autónoma de Ciudad Juárez, Mexico, *jorge.garcia@uacj.mx*
[2] *Universidad Autónoma de Ciudad Juárez, Mexico,* al232735@alumnos.uacj.mx
[3] Universidad Autónoma de Ciudad Juárez, Mexico, *maribel.mendoza@uacj.mx*
[4] Universidad Tecnológica de Ciudad Juárez, Mexico, *maribel_mendoza@utcj.edu.mx*

Abstract*– This article analyzes the relationships between Gemba (GEM), Muda identification (MUD), and Economic Sustainability (ECS) in the maquiladora industry in Ciudad Juárez (Mexico) using a structural equation model evaluated by partial least squares (PLS-SEM). Three hypotheses were proposed and validated using data from 834 responses to a questionnaire administered to managers, engineers, and supervisors. The results indicate that GEM has a direct effect on MUD (β=0.642, p<0.001), explaining 41.3% of its variance; GEM directly impacts ECS (β=0.296) and indirectly through MUD (β=0.260), generating a total effect of β=0.557; and MUD affects ECS (β=0.405, p<0.001). A probability-based sensitivity analysis indicated that the probability of high MUD given that high GEM had occurred was 63.9%, whereas the probability of obtaining high ECS given that high MUD had occurred was 61.1%. These results empirically validate the Toyota principle of genchi genbutsu and demonstrate that MUD partially mediates the relationship between GEM and ECS. The GEM→MUD and GEM→ECS relationships exhibited non-linear patterns (S-shaped and J-shaped, respectively), while MUD→ECS behaved linearly. Managers should prioritize GEM in the early stages of lean implementation, given its strongest marginal returns at lower maturity levels.

***Keywords*-- Gemba, Muda, Economic sustainability, Lean manufacturing, PLS-SEM.**

I. INTRODUCTION

Ciudad Juárez (Mexico) is an industrial center with a long history in the maquiladora industry and is home to one of the most dynamic sectors in Latin America. Currently, this sector faces challenges in balancing the operational efficiency required for production processes and economic sustainability [1]. Therefore, many companies have implemented the lean manufacturing (LM) philosophy to identify and eliminate processes that do not add value, and thus achieve operational excellence [2]. However, to date, traditional lean manufacturing tool (LMT) indicators have not identified all the economic, social, and environmental factors necessary for a comprehensive sustainability assessment [3].

In this context, there are two fundamental concepts in Toyota's production system for continuous improvement: Gemba Walking and Muda. Gemba (GEM) means "the real place" in Japanese and refers to the process of directly observing problems on the production line where the work is done, allowing supervisors and managers to identify anomalies, communicate with operators, and provide immediate feedback [4]. On the other hand, Muda (MUD) refers to the seven classic wastes identified by LM, such as overproduction, waiting, transportation, overprocessing, inventory, unnecessary movements, and defects, whose identification and elimination are at the core of LM philosophy [5]. Economic sustainability (ECS), on the other hand, is the organizational capacity to optimize available resources and minimize production costs, thereby increasing financial profitability through continuous improvement practices.

In this study, ECS is operationalized through seven items capturing cost awareness, process efficiency, resource optimization, profitability knowledge, supplier cost–benefit evaluation, innovation investment, and productivity monitoring (see Table 2). These items reflect both internal efficiency and external value-chain dimensions of economic performance.

LMTs are not implemented in isolation on production lines; rather, there is a relationship between them, and they present an associative logic. For example, GEM is a practice that allows management to obtain first-hand information about production processes, identify deviations or anomalies that do not generate value, and determine workers' training needs. This activity is in line with Toyota's principle of "going to see" (*Genchi genbutsu*), in which direct observation of the production process precedes waste identification [6]. For example, it has been proven that the implementation of Kaizen promotes GEM (β=0.667, p<0.001) and that many LMTs are directly related to sustainability indicators [4].

Waste elimination is the basis of all strategies or LMTs to ensure economic sustainability (ECS) through its principles [5]. Previous studies have shown that LMTs mediate the relationship between digital technologies and the economic performance of companies [7], explaining up to 59.7% of the variability in the latter. Likewise, Díaz-Reza, et al. [8] indicate that LMTs, such as Kaizen, GEM, and Whys, improve ECS because the root causes of anomalies are identified, and continuous improvement programs are implemented in response to deviations identified with GEM.

While prior studies have examined individual LMTs and sustainability, no study has simultaneously quantified the direct, indirect, and total effects of GEM on ECS through MUD as a mediator in the maquiladora context, nor has the non-linear behavior of these relationships been characterized. This gap limits the knowledge and understanding of how GEM practices and workplace tours can identify waste in manufacturing contexts and generate economic benefits. Therefore, the following question arises: What is the effect of GEM on MUD?

What is the effect of GEM on the ECS? What is the effect of MUD on ECS?

The following hypotheses are proposed: H_1: GEM has a direct and positive effect on the identification of MUD; H_2: GEM has a direct and positive effect on ECS; and H_3: MUD has a direct and positive effect on ECS. This study was conducted in the maquiladora sector, providing empirical evidence on how GEM and MUD promote ECS and reinforce the existing literature.

Similarly, from a practical perspective, the findings of this study will enable managers responsible for continuous improvement to understand how and to what extent GEM fosters capabilities for identifying waste, which ultimately translates into economic benefits. However, although the cross-sectional design limits temporal causal inference, the model provides associative evidence consistent with the theoretical sequence proposed by the TPS.

Following this introduction, Section 2 presents the theoretical framework and justifies the three hypotheses of the study. Section 3 describes the proposed methodology. Section 4 presents the results of the study. Section 5 discusses the implications of these findings. Section 6 presents the conclusions, limitations, and future research directions.

II. THEORETICAL FRAMEWORK AND HYPOTHESIS DEVELOPMENT

A. Toyota Production System and Sustainability

This study and the relationships between constructs are based on the philosophical framework of the Toyota Production System (TPS), given that the Toyota Way has been widely analyzed, as has its impact on the economic growth of companies that have applied it [6]. In addition, previous studies have shown that LMT implementation is a pillar of sustainability (economic, environmental, and social) for companies [1, 9]. Helleno, et al. [3] showed that integrating sustainable parameters with LMT is a conceptual method for evaluating and improving the efficiency of manufacturing processes. In addition, there are cases in which these constructs are linked. For example, Ghaithan, et al. [10] used a structural equation model to demonstrate that LMTs positively affect the sustainable performance of the plastics and petrochemical industries.

B. Gemba→Muda Relationship

Managers and workers who practice gemba walking develop the ability to distinguish between activities that generate value and those that are wasteful. Previous studies have shown that the relationships between kaizen and GEM improvement programs are solid and have strong coefficients. This indicates that working directly on production lines facilitates the identification of opportunities for improvement [9]. In addition, interactions between engineers or supervisors and workers integrate them into the problem-solving process.

Some studies have shown that if direct observation of problems on production lines is not carried out, waste may remain invisible to management and cannot be effectively eliminated, as management is responsible for providing resources to workers. For example, Díaz-Reza, et al. [8] reported that the use of tools such as Gemba and 5 Whys improves sustainability by identifying waste using techniques that allow the root problem in the production lines to be established. Therefore, the following hypothesis is proposed:

H_1: Gemba Walking has a direct and positive effect on the identification of Muda in the manufacturing industry.

C. Relationship between Gemba and economic sustainability

Given that GEM focuses on managers and engineers personally visiting the production line, the anomalies they identify, and resolve are likely to have an economic impact. Previous studies have shown through SEM that continuous improvement tools, such as GEM, promote savings and provide economic benefits to companies. For example, Figueroa, et al. [9] indicated that managers should frequently visit production lines to seek information to support their decisions and learn about operators' perspectives, which will allow them to save and optimize resources.

García-Alcaraz, et al. [1] indicated that continuous improvement programs implemented on production lines, which include direct observation of the line, achieve greater integration of workers in problem-solving to minimize costs and increase employees' sense of belonging, morale, and commitment. In addition, Naeemah and Wong [11] conducted a systematic review of the impacts of LMTs, such as GEM, and concluded that economic aspects were the most analyzed, particularly cost reduction and the reduction of losses owing to poor quality. Therefore, this study proposes the following hypothesis:

H2: Gemba has a direct and positive effect on economic sustainability in the manufacturing sector.

D. Relationship between Muda Identification and Economic Sustainability

This relationship is perhaps the most studied, given that the focus of waste identification is to improve economic indicators, as supported by several studies. For example, Papetti, et al. [12] proposed the Muda index as a quantitative indicator, demonstrating that less than 20% of the resources consumed during the production process generate value (80% can be considered waste in any form) and that 20% is capable of keeping the company profitable.

Sadiq, et al. [2] report reductions of 26% in delivery time and 39% in value-added time through LM frameworks to identify waste. They propose identifying MUDs, as their identification and subsequent reduction deliver ECS. Khakpour, et al. [13] have proposed a step-by-step method to improve the sustainability of manufacturing processes, indicating that resource consumption and waste can be reduced with proper analysis, with positive effects on ECS. Therefore, the following hypothesis is proposed:

H_3: The identification of Muda has a direct and positive effect on Economic Sustainability in the manufacturing industry.

E. Proposed Conceptual Model

Based on the hypotheses proposed above, this study proposes a structural equation model that examines the associative relationships between GEM, MUD, and ECS (Figure 1). The SEM proposes that GEM is an antecedent that encourages and promotes the identification of waste or MUD in production lines (H_1) and that it influences ECS (H_2), while MUD has a direct effect on ECS (H_3) and is also a mediator in the relationship between GEM and ECS. MUD is hypothesized as a partial mediator: GEM influences ECS both directly (H_2) and indirectly through MUD ($H_1 \times H_3$).

Although other lean manufacturing tools—such as 5S, SMED, and Kanban—may interact with GEM and MUD in practice, this study deliberately focuses on the GEM→MUD→ECS chain to maintain model parsimony and isolate the specific contribution of direct observation practices to waste identification and economic performance. The potential moderating or complementary role of these tools on the proposed relationships is acknowledged as a promising avenue for future research

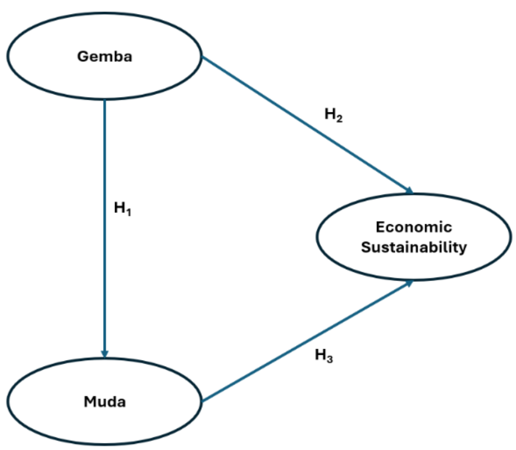

Fig. 1 Proposed hypotheses

III. METHODOLOGY

A. Design and application of a questionnaire

GEM, MUD, and ECS have been investigated in isolation; therefore, a literature review was conducted to identify items that adequately described these concepts. Items were originally sourced in English from García-Alcaraz, et al. [4], (GEM, 5 items), Fercoq, et al. [14] (MUD,5 items), and Hosen, et al. [5] and Figueroa, et al. [9] (ECS, 7 items). A back-translation protocol (English→Spanish→English) was applied by two bilingual researchers to ensure semantic equivalence.

However, these studies come from other countries and contexts and were often conducted many years ago and were in English. Therefore, content validation was performed using Aiken's V method for clarity [15] and Lawshe's method for relevance [16] by a group of judges comprising six academics and eleven engineers working in the manufacturing industry. After two rounds with the judges, a final questionnaire was determined where the Aiken's V coefficients ranged from 0.82 to 0.96 (threshold ≥ 0.75), and Lawshe's CVR values ranged from 0.64 to 1.00, confirming content validity for all retained items. The final questionnaire consists of two sections: the first obtained demographic data, and the second obtained ratings of the items on a Likert scale.

The questionnaire was administered to managers, engineers, and supervisors working in the manufacturing industry in Ciudad Juárez (Mexico) and remained open from March 12 to June 12, 2025. Contact information was obtained from the manufacturing industry directory maintained by INDEX Juárez. A total of 2,381 emails were sent to potential respondents with a link to the questionnaire hosted on Google Forms platform. Two reminders were sent after 15 days, and if no response was received, the case was excluded from the study.

To assess nonresponse bias, early respondents (first tercile, $n = 278$) were compared with late respondents (third tercile, $n = 278$) on all construct means using independent-samples Mann–Whitney U tests; no significant differences were found ($p > 0.05$ for all constructs).

B. Data cleaning

In this study, three activities were performed to clean the data before analysis. First, missing values were identified; a total of 22 values (0.15% of all data points) were missing and replaced with the item median, a conservative imputation strategy appropriate for ordinal Likert-scale data [17]. Second, extreme values were detected by standardizing item scores; 32 values with $|z| > 3$ were replaced by the item median. Third, uncommitted respondents were identified by computing the standard deviation of each case across all items; 55 cases with $SD < 0.5$ were discarded, yielding a final sample of 834 valid responses. To verify that these preprocessing decisions did not bias the results, a sensitivity check was conducted by re-estimating the model without any imputation (listwise deletion); the path coefficients remained within the original 95% confidence intervals, confirming robustness.

Because all constructs were measured via the same self-report questionnaire, common method bias (CMB) was addressed through both procedural and statistical remedies. Procedurally, respondent anonymity was guaranteed, items were distributed across different questionnaire sections, and construct-specific instructions were provided to reduce consistency motifs [18].

Full collinearity variance inflation factors (VIFs) for all constructs were below 3.3 (see Table 3), indicating the absence of common method bias according to the Kock [19] threshold. Additionally, the Harman's single-factor test was conducted: an unrotated exploratory factor analysis of all 17 items yielded a first factor explaining 37.49% of total variance (below the 50% threshold), suggesting that CMB does not pose a serious threat to the results.

C. Construct validation

The variables were refined according to several indices proposed by Kock [19], such as R^2 and adjusted R^2 for parametric predictive validity, Cronbach's alpha and composite reliability index for internal validity, average extracted variance (AVE > 0.5) for convergent validity, variance inflation indices to measure collinearity, and Q^2 to measure non-parametric predictive validity. In addition, construct bias and Jarque-Bera normality tests are reported to justify the use of the partial least squares (PLS-SEM) approach rather than the variance approach (CB-SEM).

Furthermore, discriminant validity was evaluated using three complementary criteria: (1) item factor loadings and cross-loadings to verify that each indicator loads highest on its intended construct, (2) the Fornell-Larcker criterion, confirming that the square root of each construct's AVE exceeds its correlations with other constructs [20], and (3) the Heterotrait-Monotrait ratio of correlations (HTMT), with all values below the 0.85 conservative threshold [21]. Detailed tables for these three assessments are provided as supplementary material at: http://doi.org/10.6084/m9.figshare.32051937.

D. Structural equation model

To validate the relationships between GEM, MUD, and ECS, a structural equation model (SEM) was used with the partial least squares (PLS) approach, which is recommended when constructs do not have a normal distribution. All SEM parameters were evaluated at a 95% confidence level using WarpPLS V.8 software.

The validated constructs were integrated into the SEM for evaluation. The algorithm used to evaluate the input model was PLS Regression, as it minimizes collinearity and does not require data normality [22]. The algorithm used to evaluate the output model was Warp3, which allows for the identification of nonlinear relationships and reduces the coefficients, making them more realistic. The resampling method was Stable3 [23].

In the SEM, several global indices were evaluated before being interpreted, such as the Average Path Coefficient (APC) to determine the average validity of the path coefficients, the Average R-squared (ARS) and Average Adjusted R-squared (AARS) to measure the overall predictive validity, average block VIF (AVIF), and average full collinearity VIF (AFVIF) to measure collinearity, and the Tenenhaus index (GoF) as a measure of the fit of the data to the model [19].

The hypotheses were validated using direct effects. For each relationship between the constructs, the standardized coefficient β was estimated using PLS as a measure of dependence. To measure its statistical significance, the null hypothesis H0: $\beta = 0$ was tested against the alternative hypothesis H1: $\beta \neq 0$. If $\beta=0$ is demonstrated, it is concluded that there is no relationship between the constructs; if $\beta \neq 0$ is demonstrated, it is concluded that there is a relationship [22]. In addition, for each β, the confidence interval and effect size (ES) are reported as a measure of the variance explained by the independent construct on the dependent construct.

For each direct effect, a graph of unstandardized values (on an ordinal scale) is reported to observe the behavior and values of β at different levels of LMT implementation and to observe whether there are any non-normal trends in the data.

In this study, GEM exerted an indirect effect on the ECS through MUD, which has also been reported. However, the total effect between GEM and ECS is the sum of the direct and indirect effects, which has also been reported [19]. Statistical significance tests are also reported for both types of effects.

E. Sensitivity analysis

WarpPLS v.8 software allows conditional probabilities to be calculated for different levels of implementation of LMTs and ECS, which can be low (-) or high (+). This study reports three probabilities: 1. The probabilities of finding a construct at its high or low level in isolation, 2. The probability that two related constructs will appear in a combination of high or low occurrences, and 3. The probability that the dependent construct will occur at its high or low level, given that the independent construct has occurred at its high or low level [19].

IV. RESULTS

A. Sample and items

Of the 893 initial responses, only 22 missing values were identified in the total cells (replaced with median). Item standardization identified 32 outlier values (|z| > 3), replaced with the median. Case standardization removed 55 uncommitted respondents (SD<0.5), yielding 834 usable cases containing responses from 482 men and 352 women. Table 1 illustrates the respondents' years of experience and job positions, showing that engineers (387) and supervisors (295) led the positions, while those with 2-3 years (358) and 3-5 years (235) of experience responded the most.

TABLE 1
YEARS AND EXPERIENCE OF RESPONDENTS

Position	2-3 years	3-5 years	5-10 years	>10 years	Total
Manager	47	41	31	33	152
Engineer	195	105	38	49	387
Supervisor	116	89	53	37	295
Total	358	235	122	119	834

Table 2 presents the median and interquartile range (IQR) of the 17 items in the constructs, ordered from lowest to highest based on the median.

TABLE 2
ITEMS, THEIR MEDIAN, AND IQR

GEM3. I receive immediate feedback when there are problems in my work	3.959	2.033
GEM5. I feel comfortable discussing problems with my supervisors	3.736	2.259
GEM4. Management is aware of the real problems that we face daily.	3.723	2.152
GEM1. My supervisor regularly observes my work in the area.	3.717	2.171
GEM2. Managers ask me about problems and suggestions during their visits to the field.	3.478	2.215
MUD5. I understand which activities are wasteful and which ones add value.	4.259	1.638
MUD2. I actively look for ways to eliminate unnecessary motion.	4.051	1.771
MUD1. I identify and report activities that do not add value to my work.	4.045	1.876
MUD4. I minimize waiting times in my work areas.	4.034	1.754
MUD3. I avoid producing more than what is necessary at my station.	3.935	1.991
ECS4. I am aware of how my actions directly impact the company's profitability.	4.127	1.811
ECS2. I identify and report opportunities to improve the efficiency of my work processes.	4.019	1.927
ECS1. I optimize material use to avoid waste and reduce operating costs.	4.015	1.959
ECS7. Monitoring efficiency and productivity indicators in my area of responsibility	3.986	2.121
ECS3. Participating in initiatives that seek to reduce costs without compromising quality	3.878	2.090
ECS6. I contribute to innovation projects that generate economic value for the organization.	3.822	2.228
ECS5. I evaluate suppliers and materials by considering long-term cost-benefit criteria.	3.782	2.274

B. Validation of constructs

Table 3 illustrates the indices for validating the constructs and the desired cutoff value. It can be seen that R^2 and adjusted R^2 in the dependent constructs are greater than 0.2, indicating sufficient parametric predictive validity; Cronbach's alpha and the composite reliability index are greater than 0.7, indicating internal validity; the average extracted variance is greater than 0.5, indicating sufficient convergent validity; the inflation indices are less than 3.3 and indicate the absence of collinearity.

For its part, Q^2 has values similar to R^2 indicating sufficient non-parametric predictive validity, while the bias values, although negative, are within range. Finally, Jarque-Bera normality tests indicate that the constructs are not normal, justifying the PLS-SEM approach instead the CB-SEM.

Please see the supplementary material with raw data, Fornell-Larker criterion for discriminant analysis, factor loadings, and HTMT values with confidence interval at http://doi.org/10.6084/m9.figshare.32051937.

TABLE 3
CONSTRUCT VALIDATION INDICES

Indexes	GEM	MUD	ECS	Best if
R-squared	-	0.413	0.406	0.200
Adjusted R-squared	-	0.412	0.405	>0.200
Composite reliability	0.922	0.928	0.948	>0.700
Cronbach's alpha	0.894	0.903	0.949	>0.700
Average variances extracted	0.704	0.720	0.765	>0.500
Full collinearity VIFs	1.841	1.977	1.680	<3.300
Q-squared	-	0.413	0.407	>0
Skewness	-0.491	-0.841	-0.640	[-1, 1]
Normal-JB	No	No	No	Yes
Normal-RJB	No	No	No	Yes

C. Structural equation model

The model was evaluated, and its efficiency indices were as follows:

- Average path coefficient (APC)=0.448, P<0.001
- Average R-squared (ARS)=0.409, P<0.001
- Average adjusted R-squared (AARS)=0.408, P<0.001
- Average block VIF (AVIF)=1.703, ideally <= 3.3
- Average full collinearity VIF (AFVIF)=1.832, ideally <= 3.3
- Tenenhaus GoF (GoF)=0.547, large >= 0.36

These values indicate that the model was sufficiently robust, with predictive validity and absence of collinearity, and that the data fit the model, as illustrated in Figure 2. The minimum value of β was found in the GEM→ECS relationship and was 0.296; therefore, it was used to calculate the sample size, which was 71 using the inverse square root method and 58 using the exponential gamma method. However, the sample size was 834; therefore, this criterion was satisfied. Readers can see the raw data, full model outputs, factor loadings, Fornell-Larcker criterion matrix and the HTMT reports with a confidence interval as supplementary material at: http://doi.org/10.6084/m9.figshare.32051937.

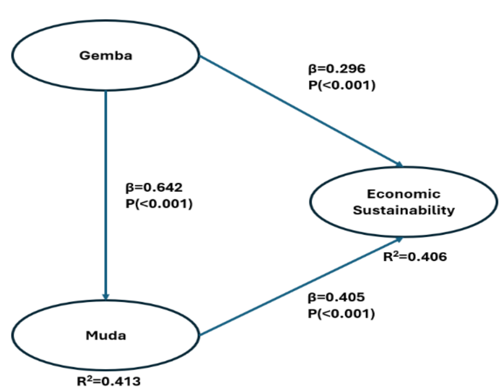

Fig. 2 Evaluated model

Table 4 illustrates the direct effects of the relationships between constructs, the associated p-value, the effect size as a measure of explained variance, the 95% confidence interval, and the conclusion. These results indicate that the three proposed hypotheses are accepted and that the strongest relationship exists between GEM and MUD, indicating the importance of conducting production line tours to identify waste (MUD), which has the greatest impact on ECS (0.405) compared to GEM (0.296).

TABLE 4
HYPOTHESIS VALIDATION

Hypothesis	β(p-value)	ES	Confidence interval		Decision
			LCI	UCI	
H_1. GEM→MUD	0.642(<0.001)	0.413	0.579	0.706	Supported
H_2. GEM→ECS	0.296(<0.001)	0.165	0.230	0.362	Supported
H_3. MUD→ECS	0.405(<0.001)	0.241	0.340	0.470	Supported

In this study, GEM had an indirect effect on ECS through MUD, which was statistically significant with β=0.260 (P<0.0001) and explained up to 14.5% of its variance, giving a total effect for these two constructs of β=0.557 (P<0.0001), explaining up to 31% of its variance. Table 5 illustrates these effects, effect sizes, and 95% confidence intervals.

TABLE 5
INDIRECT AND TOTAL EFFECTS

	Indirect effect	Total effect	
	GEM	GEM	MUD
MUD		0.642 (P<0.0001) ES=0.413 (0.577, 0.707)	
ECS	β=0.260 (P<0.0001) ES=0.145 (0.213, 0.307)	0.557 (P<0.0001) ES=0.310 (0.492, 0.622)	0.405 (P<0.0001) ES=0.241 (0.340, 0.470)

D. Sensitivity analysis

Table 6 presents a probability-based sensitivity analysis. For each construct, the high (+) and low (-) levels of occurrence in isolation, jointly in a combination of their levels (&), and the conditional probabilities (IF) are indicated. *GEM occurred at a high level (GEM+) in 17.6% of cases and at a low level (GEM−) in 20.0% of cases*. Similarly, GEM+ and MUD+ could occur together in 11.3% of cases, but the probability of MUD+ occurring given that GEM+ has occurred is 0.639, indicating that it occurs in 63.9% of cases. A more in-depth discussion of these values and their industrial implications is presented in the discussion section.

V. DISCUSSION OF RESULTS

A. Univariate analysis

The GEM items had low medians (3.478–3.959), especially those related to the questions asked during the visit, indicating that more interaction with operators is needed. In addition, the IQRs were high (2.033–2.259), suggesting heterogeneity when performing GEM tours and requiring greater standardization.

TABLE 6
SENSITIVITY ANALYSIS

			GEM		MUD	
			+	-	+	-
			0.176	0.200	0.200	0.157
MUD	+	0.200	&=0.113 IF=0.639	&=0.011 IF=0.054		
	-	0.157	&=0.000 IF=0.000	&=0.103 IF=0.515		
ECS	+	0.231	&=0.106 IF=0.599	&=0.014 IF=0.072	&=0.122 IF=0.611	&=0.002 IF=0.015
	-	0.181	&=0.005 IF=0.027	&=0.089 IF=0.443	&=0.007 IF=0.036	&=0.095 IF=0.603

In relation to MUD, the items have medians in the range of 3.935 to 4.259, where MUD5 is related to understanding which activities are wasteful and which do not add value, suggesting that managers, engineers, and supervisors have the knowledge and experience to identify waste in the process. This construct also had the lowest IQRs (1.638–1.991), indicating a greater consensus among respondents.

Finally, the ECS items indicate intermediate medians (3.782–4.127), where ECS4, "I am aware of how my actions directly impact the company's profitability," has the highest value (Mdn=4.127). However, items related to the supplier evaluation process (ECS5) and innovation projects (ECS6) had the lowest medians and greatest dispersion.

B. Relationship between Gemba and Muda (H_1)

The results indicate that GEM has a direct effect on MUD with β=0.642 (p<0.001), which is the relationship with the largest β and explains 41.3% of its variance, supporting the premise that the practice of direct observation of problems on production lines is associated with the identification of waste. The confidence interval [0.579, 0.706] reinforces the robustness of the results, indicating a strong relationship.

The probabilities of the sensitivity analysis complement this direct effect, as the conditional probability P(MUD+|GEM+)=0.639 indicates that when GEM is implemented at high levels, there is a 63.9% probability that MUD will also reach high levels. However, P(MUD-|GEM-)=0.515 indicates that the absence of GEM is associated with low waste identification in 51.5% of cases.

The relationship between GEM and MUD is not linear (Figure 3), since at low levels of GEM (1.49–1.80). At low GEM levels (1.49–1.80), the marginal effect β ranges from 0.93 to 0.78, indicating that initial GEM efforts yield the highest marginal gains in MUD identification. As GEM increases to intermediate levels, β decreases to 0.57, suggesting diminishing marginal returns (not a decrease in MUD, but a slower rate of increase). At high GEM levels, β recovers to 0.78, indicating a second acceleration phase. This S-shaped pattern implies that early GEM adoption is highly productive for MUD detection, followed by a plateau, and then renewed benefits at advanced maturity.

The findings of this study are consistent with those of García-Alcaraz, et al. [4] , who indicate that Kaizen affects Gemba (β=0.667), and with those of Figueroa, et al. [9] , who reported that the relationships between continuous improvement tools had high coefficients. Furthermore, from the perspective of Ohno [24], these results confirm the principle that problems can only be identified in *genchi genbutsu*, which underpins the Toyota philosophy.

From a theoretical perspective, the S-shaped pattern observed contributes to organizational learning theory by providing empirical evidence of stage-dependent knowledge acquisition [25]. The initial high-β phase reflects rapid experiential learning, where novel shop-floor observations generate substantial new waste-related knowledge. The subsequent plateau is consistent with the concept of competency traps [25], in which routinized observation practices yield fewer novel insights. The second acceleration phase at high GEM levels suggests that organizations that persist beyond this plateau develop higher-order learning capabilities—such as pattern recognition across production lines—that reignite MUD identification. This three-stage dynamic has not been previously documented in lean manufacturing research.

In practice, GEM findings are operationalized through structured information flows: observations are documented in standardized walk reports, prioritized using Pareto analysis, and translated into corrective-action projects tracked via operational indicators such as defect rates, cycle-time deviations, and first-pass yield. These mechanisms convert shop-floor observations into measurable MUD reductions.

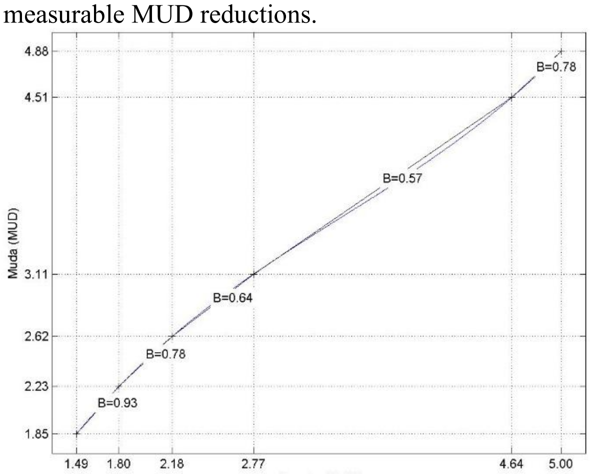

Fig. 3 GEM→MUD relationship

The results of this relationship imply that managers should institutionalize tours of their production lines as a routine rather than a sporadic practice that allows them to hear about problems from operators. Furthermore, observing that the greatest impact occurs in the initial stages of implementation, companies that do not yet practice these tours should prioritize them to develop the skills required to identify MUD with the help of their operational staff.

C. Relationship between Gemba and economic sustainability (H_2)

The results indicate that GEM has a direct effect on the ECS with β=0.296 (p<0.001) and ES=0.165. However, there is an indirect effect through MUD with β=0.260 (p<0.001) and ES=0.145, which is equivalent to the direct effect (0.296), supporting the hypothesis that MUD acts as a partial mediator in this relationship. This generated a total effect of GEM on ECS of β=0.557 (p<0.001), explaining 31% of its variance, which almost doubled the direct effect. When comparing the total effect size, it was concluded that 46.7% of this was channeled through the identification of MUD in the production system.

The probabilities of the sensitivity analysis show that P(ECS+|GEM+)=0.599, indicating that high GEM implementation generates economic benefits in 59.9% of cases. Conversely, P(ECS-|GEM-)=0.443 indicates that poor GEM increases the possibility of not achieving economic goals by 44.3% of the time. This difference in conditional probabilities (0.599 vs. 0.443) indicates that GEM can generate more economic benefits than negative scenarios, which may be due to operators' interventions to resolve identified problems.

The J-shaped GEM→ECS pattern (Figure 4) suggests three maturity zones: (1) an initiation zone (GEM ≈ 1.5–2.1) where modest investments yield moderate returns (β ≈ 0.35); (2) a consolidation plateau (GEM ≈ 2.1–4.0) where β drops to 0.29, indicating that incremental GEM effort produces diminishing economic returns—firms should not abandon GEM at this stage; and (3) an advanced zone (GEM > 4.0) where β rises to 0.45, reflecting a threshold beyond which institutionalized GEM practices unlock significant economic benefits. Managers should target at least the advanced zone to maximize ECS returns.

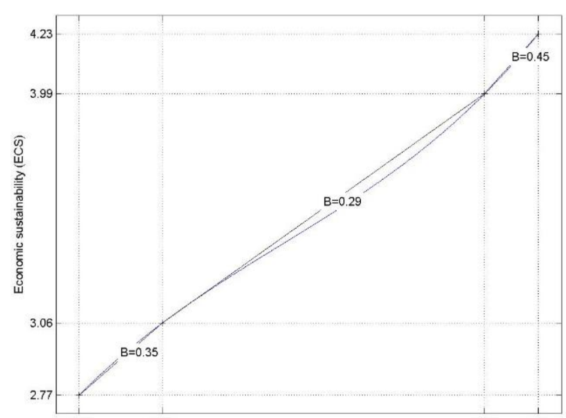

Fig. 4 GEM→ECS relationship

Theoretically, this J-shaped pattern extends the dynamic capabilities framework [26] by suggesting that the *sensing* function of GEM (direct observation) requires sustained organizational investment before it translates into economic value. The consolidation plateau ($\beta \approx 0.29$) may reflect an intermediate stage in which firms have developed sensing routines but have not yet built the *seizing* mechanisms—such as systematic action protocols and resource reallocation processes—needed to convert observations into economic outcomes. The acceleration at high GEM levels indicates that once these complementary mechanisms are in place, the economic returns of GEM increase substantially. This threshold behavior challenges the implicit linear assumptions in existing lean–sustainability models.

These findings are consistent with Figueroa, et al. [9], who recommend that managers adopt a supervisory approach based on the work carried out on the production floor to support economic growth decisions. Buhaya and Metwally [7] also indicate that LM practices explain up to 59.7% of the variance in ECS, which is comparable to the total effect obtained in this study, of which 31% came from GEM. Finally, García Alcaraz, et al. [27] reported that continuous improvement programs that include GEM generate greater organizational commitment from employees, which minimizes waste and reduces costs.

The results of this relationship imply that managers should analyze not only the direct benefits obtained from the improvements made, but also the indirect benefits through the waste identified, reduced, or eliminated. In other words, the path to ECS through GEM walks is twofold, as they obtain economic benefits from the information obtained directly from the production lines and indirectly from the waste identified.

In quantitative terms, a one-point increase on the GEM Likert scale is associated with a total increase of 0.557 points in ECS, combining the direct path ($\beta = 0.296$) and the indirect path through MUD ($\beta = 0.260$). For managers, this means that advancing GEM practices from an intermediate implementation level (e.g., 3.0) to a high level (e.g., 4.0) is associated with an improvement of approximately half a scale point in perceived economic sustainability—equivalent to shifting a typical plant's ECS perception from "neutral" toward "agree" on cost-efficiency, profitability awareness, and resource optimization items. This reinforces the business case for sustained investment in structured shop-floor observation programs.

D. Relationship between Muda and economic sustainability

The findings indicate that MUD has a direct and positive effect on ECS with $\beta=0.405$ ($p<0.001$) and explains 24.1% of its variance, being the second strongest effect in the model, but the strongest in ECS, as GEM explains only 16.5%. This result indicates the importance of creating and developing capabilities to identify waste in production lines in the manufacturing industry, as waste elimination is the general principle of LM.

The sensitivity analysis indicates that $P(ECS+|MUD+)=0.611$, indicating that industries that can identify their waste can achieve economic benefits in 61.1% of cases, which is the highest value in the model. However, $P(ECS-|MUD-)=0.603$ indicates that industries with little capacity to identify waste in their production lines will experience financial problems in 60.3% of cases. This symmetry in values indicates that MUD can generate benefits for companies, but it can also prevent negative results of a similar magnitude.

Figure 5 illustrates a linear relationship between MUD and ECS, with $\beta=0.44$ constant across the MUD range (1.00–4.96). This linearity indicates that each unit increase in MUD identification produces proportional and predictable economic returns without diminishing returns or saturation thresholds. Unlike the nonlinear relationships of GEM→MUD (H_1) and GEM→ECS (H_2), the MUD→ECS relationship allows managers to accurately estimate the expected economic benefits of their waste reduction initiatives.

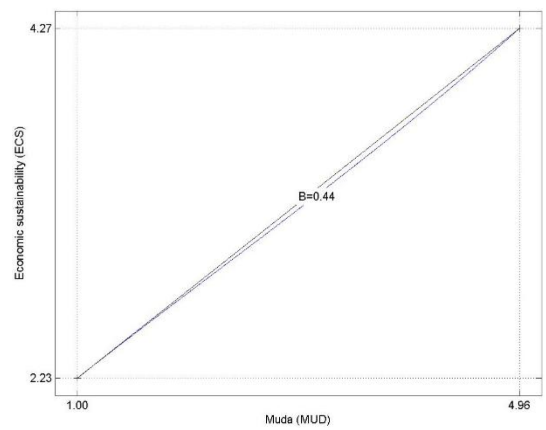

Fig. 5 MUD→ECS relationship

From a theoretical standpoint, the strict linearity of MUD→ECS contrasts sharply with the non-linear patterns of H1 and H2 and carries a distinct theoretical implication: waste identification operates as a *proportional value-generating mechanism* that is not subject to the learning dynamics or maturity thresholds observed in GEM-related paths. This suggests that, within the dynamic capabilities framework [26], MUD functions as an *operational capability* whose economic returns are direct and predictable, whereas GEM operates as a higher-order *dynamic capability* subject to developmental stages. This asymmetry between operational and dynamic capabilities in the lean context has not been previously documented and offers a new lens for theorizing lean maturity progression.

These findings are consistent with those of previous studies. For example, Hosen, et al. [5] indicated that MUD elimination should be the main component of strategies to ensure ECS. Papetti, et al. [12] indicate that less than 20% of the resources consumed generate value, which shows that there is much room for economic improvement through the identification and elimination of waste. In more practical contexts, Sadiq, et al. [2] reported reductions of 26% in delivery time and 39% in value-added time, confirming that the identification of Muda is an effective economic lever for improving efficiency.

These results help managers justify the investments required for training processes and electronic systems that enable the identification of the seven classic wastes in production systems. Furthermore, the linearity of the relationship implies that there is no "ceiling" on benefits; that is, the more sophisticated the ability to identify waste, the greater the economic return. However, metrics and indicators must be established to monitor the identification of Muda, given its direct and predictable impact on organizational profits.

VI. CONCLUSIONS

A. *Summary of findings*

These findings represent associative evidence from a cross-sectional design and should not be interpreted as definitive proof of temporal causality. This study analyzed the associative relationships between Gemba, Muda identification, and economic sustainability in the maquiladora industry in Ciudad Juárez, Mexico, using a structural equation model evaluated with PLS-SEM. The PLS-SEM evaluation confirmed the three proposed hypotheses: H_1 demonstrates that GEM has a direct effect on MUD with $\beta=0.642$ ($p<0.001$), explaining 41.3% of its variance.

This result empirically validates the Toyota principle of *genchi genbutsu*, which indicates that direct observation of production lines is crucial for developing capabilities to identify waste. In H_2, GEM has a direct effect on ECS ($\beta=0.296$) and an indirect effect through MUD ($\beta=0.260$), generating a total effect of $\beta=0.557$, which explains 31% of the variance in ECS. This result indicates that MUD is a partial mediator between these constructs and is responsible for 47% of the total effects.

Finally, H_3demonstrates that MUD has a direct effect on ECS ($\beta=0.405$, $p<0.001$), which is greater than the direct effect of GEM, and confirms that the ability to identify waste is the most direct strategy for achieving ECS.

B. *Theoretical contributions*

This study advances lean manufacturing theory in three ways that go beyond confirming known relationships. First, it provides the first simultaneous quantification of the direct, indirect, and total effects within the GEM→MUD→ECS chain, revealing that 47% of GEM's total effect on ECS is channeled through waste identification. This mediating architecture was theorized but never empirically decomposed in prior work, and it extends the dynamic capabilities framework [26]] by showing that GEM functions as a sensing routine whose economic value is largely realized through MUD as a seizing mechanism. Second, the non-linear patterns identified—S-shaped for GEM→MUD and J-shaped for GEM→ECS—contribute to organizational learning theory by providing empirical evidence of stage-dependent returns: rapid initial learning, a consolidation plateau consistent with competency traps [25], and a second acceleration phase reflecting higher-order learning.

These patterns challenge the implicit linearity assumption prevalent in lean–sustainability models. Third, the contrast between non-linear behavior (H1, H2) and strict linearity in MUD→ECS suggests that waste identification operates as a proportional value-generating mechanism regardless of maturity level, whereas the observation practices that feed it are subject to learning dynamics. This asymmetry has not been previously documented and has implications for how lean maturity models are conceptualized.

C. *Practical contributions*

Managers can benefit from the results of this study, as they suggest that: (1) Gemba programs should be institutionalized as a systematic practice, especially in companies with LMT implementation; (2) economic performance indicators should consider direct and indirect effects; and (3) training is required to identify waste, whose elimination generates proportional and predictable economic returns.

D. *Limitations and future research*

This study has some limitations that should be considered. First, the research was conducted in the maquiladora industry in Ciudad Juárez, limiting its generalizability to other contexts; Second, the cross-sectional design prevents the establishment of definitive temporal causality; therefore, longitudinal studies are required to strengthen associative inferences. Third, the data were obtained from self-reports, which could introduce social desirability bias. Fourth, the model considers only three constructs; other lean tools could moderate the relationships studied. Building on these limitations, several avenues for future research are proposed.

Fifth, future studies should integrate objective plant-level data (e.g., OEE, scrap rates, cycle times) to triangulate self-report perceptions and strengthen external validity. Sixth, the inclusion of additional LMTs (5S, SMED, Kanban) as moderating variables could clarify boundary conditions under which GEM→MUD→ECS effects are amplified or attenuated. Seventh, a longitudinal panel design—measuring GEM, MUD, and ECS at multiple time points—would enable stronger temporal-causal inferences and address the cross-sectional limitation acknowledged herein.

To address these limitations, the following future research directions are proposed: (1) replicate the model in different industrial sectors and geographic regions; (2) implement longitudinal panel designs to evaluate temporal evolution of relationships and enable stronger causal inferences; (3) integrate moderating constructs related to company size, lean maturity, and additional LMTs (5S, SMED, Kanban); (4) triangulate with objective plant-level data (OEE, scrap rates, cycle times) to strengthen external validity; and (5) perform multilevel analyses to examine differences between hierarchical levels.

References

[1] J. L. G. García-Alcaraz, A. S. Morales-García, J. R. Díaz-Reza, E. Jimenez, C. Javierre, and J. Blanco-Fernández, "Effect of lean manufacturing tools on sustainability: the case of Mexican maquiladoras," *Environmental Science and Pollution Research,* Article vol. 29, no. 26, pp. 39622–39637, 2022, doi: 10.1007/s11356-022-18978-6.

[2] S. Sadiq, M. S. Amjad, M. Z. Rafique, S. Hussain, U. Yasmeen, and M. A. Khan, "An integrated framework for lean manufacturing in relation with blue ocean manufacturing - A case study," *Journal of Cleaner Production,* Article vol. 279, 2021, Art no. 123790, doi: 10.1016/j.jclepro.2020.123790.

[3] A. L. Helleno, A. J. I. de Moraes, and A. T. Simon, "Integrating sustainability indicators and Lean Manufacturing to assess manufacturing processes: Application case studies in Brazilian industry," *Journal of Cleaner Production,* Article vol. 153, pp. 405–416, 2017, doi: 10.1016/j.jclepro.2016.12.072.

[4] J. L. G. García-Alcaraz, Y. Baez-Lopez, J. Limon-Romero, J. B. Fernández, J. R. D. Reza, and D. Tlapa, "The complex pathways to social sustainability: Quantifying the effects of Kaizen and Gemba in the maquiladora industry," *Results in Engineering,* Article vol. 28, 2025, Art no. 107862, doi: 10.1016/j.rineng.2025.107862.

[5] M. I. Hosen, S. R. Tushar, M. F. B. Alam, and M. Syduzzaman, "Strategies for economic sustainability: An empirical study on Muri, Mura, and Muda in the readymade garment sector," *Green Technologies and Sustainability,* Article vol. 3, no. 1, 2025, Art no. 100115, doi: 10.1016/j.grets.2024.100115.

[6] M. Palhau, J. C. de Sá, P. Da Silva Ávila, J. Dinis-Carvalho, C. Rodrigues, and G. Santos, "Toyota Way – the Heart of TPS and its Impact on Sustainable Company Growth," *Quality Innovation Prosperity,* Article vol. 28, no. 3, pp. 23–45, 2024, doi: 10.12776/qip.v28i3.2073.

[7] M. I. Buhaya and A. B. M. Metwally, "The Interplay Between Digital Technologies and Sustainable Performance: Does Lean Manufacturing Matter?," *Sustainability (Switzerland),* vol. 16, no. 22, 2024, Art no. 10002, doi: 10.3390/su162210002.

[8] J. R. Díaz-Reza, J. L. G. García-Alcaraz, A. J. Gil-López, and A. Realyvásquez-Vargas, "Lean manufacturing tools as drivers of social sustainability in the Mexican maquiladora industry," *Computers and Industrial Engineering,* Article vol. 196, 2024, Art no. 110516, doi: 10.1016/j.cie.2024.110516.

[9] L. J. M. Figueroa *et al.*, "Measuring Impact of Lean Manufacturing Tools for Continuous Improvement on Economic Sustainability," *Journal of Systems Science and Systems Engineering,* Article vol. 33, no. 4, pp. 452–474, 2024, doi: 10.1007/s11518-023-5588-2.

[10] A. Ghaithan, M. Khan, A. Mohammed, and L. A Hadidi, "Impact of industry 4.0 and lean manufacturing on the sustainability performance of plastic and petrochemical organizations in saudi arabia," *Sustainability (Switzerland),* Article vol. 13, no. 20, 2021, Art no. 11252, doi: 10.3390/su132011252.

[11] A. J. Naeemah and K. Y. Wong, "Positive impacts of lean manufacturing tools on sustainability aspects: a systematic review," (in English), *J. Ind. Prod. Eng.,* Article vol. 39, no. 7, pp. 552–571, 2022, doi: 10.1080/21681015.2022.2041742.

[12] A. Papetti, R. Menghi, G. Di Domizio, M. Germani, and M. Marconi, "Resources value mapping: A method to assess the resource efficiency of manufacturing systems," *Applied Energy,* Article vol. 249, pp. 326–342, 2019, doi: 10.1016/j.apenergy.2019.04.158.

[13] R. Khakpour, A. Ebrahimi, and S. Saghiri, "How to assess and improve the triple bottom line (TBL) in manufacturing processes: a real case in home appliance manufacturing," *International Journal of Lean Six Sigma,* Article vol. 14, no. 7, pp. 1456–1491, 2023, doi: 10.1108/IJLSS-09-2022-0202.

[14] A. Fercoq, S. Lamouri, and V. Carbone, "Lean/Green integration focused on waste reduction techniques," *Journal of Cleaner Production,* Article vol. 137, pp. 567–578, 2016, doi: 10.1016/j.jclepro.2016.07.107.

[15] L. R. Aiken, "Three Coefficients for Analyzing the Reliability and Validity of Ratings," *Educational and Psychological Measurement,* vol. 45, no. 1, pp. 131–142, 1985, doi: 10.1177/0013164485451012.

[16] C. H. Lawshe, "A quantitative approach to content validity," *Personnel Psychology,* vol. 28, no. 4, pp. 563–575, 1975, doi: 10.1111/j.1744-6570.1975.tb01393.x.

[17] N. Reunanen, T. Räty, and T. Lintonen, "Automatic optimization of outlier detection ensembles using a limited number of outlier examples," *International Journal of Data Science and Analytics,* vol. 10, no. 4, pp. 377–394, 2020, doi: 10.1007/s41060-020-00222-4.

[18] P. M. Podsakoff, S. B. MacKenzie, J.-Y. Lee, and N. P. Podsakoff, "Common method biases in behavioral research: A critical review of the literature and recommended remedies," *Journal of Applied Psychology,* vol. 88, no. 5, pp. 879–903, 2003, doi: 10.1037/0021-9010.88.5.879.

[19] N. Kock, *WarpPLS user manual: Version 8.0*. Laredo, TX, USA: Scriptwarp, 2025.

[20] C. Fornell and D. F. Larcker, "Evaluating Structural Equation Models with Unobservable Variables and Measurement Error," *Journal of Marketing Research,* vol. 18, no. 1, pp. 39–50, 1981, doi: 10.2307/3151312.

[21] J. Henseler, C. M. Ringle, and M. Sarstedt, "A new criterion for assessing discriminant validity in variance-based structural equation modeling," *Journal of the Academy of Marketing Science,* vol. 43, no. 1, pp. 115–135, 2015/01/01 2015, doi: 10.1007/s11747-014-0403-8.

[22] N. Kock, "Using WarpPLS in E-collaboration Studies: An Overview of Five Main Analysis Steps," *Int. J. e-Collab.,* vol. 6, no. 4, pp. 1–11, 2010, doi: 10.4018/jec.2010100101.

[23] N. Kock, "Advanced mediating effects tests, multi-group analyses, and measurement model assessments in PLS-based SEM," *International Journal of e-Collaboration (IJeC),* vol. 10, no. 1, pp. 1–13, 2014, doi: 10.4018/ijec.2014010101.

[24] T. Ohno, *Toyota Production System: Beyond large-scale production*. Portland, OR, USA: Productivity Press., 1988.

[25] D. A. Levinthal and J. G. March, "The myopia of learning," *Strategic Management Journal,* vol. 14, no. S2, pp. 95–112, 1993, doi: https://doi.org/10.1002/smj.4250141009.

[26] D. J. Teece, "Explicating dynamic capabilities: the nature and microfoundations of (sustainable) enterprise performance," *Strategic Management Journal,* vol. 28, no. 13, pp. 1319–1350, 2007, doi: https://doi.org/10.1002/smj.640.

[27] J. L. García Alcaraz, A. S. Morales García, J. R. Díaz Reza, J. Blanco Fernández, E. Jiménez Macías, and R. Puig I Vidal, "Machinery Lean Manufacturing Tools for Improved Sustainability: The Mexican Maquiladora Industry Experience," (in English), *Mathematics,* Article vol. 10, no. 9, 2022, Art no. 1468, doi: 10.3390/math10091468.