



Relationship between lean manufacturing tools and their sustainable economic benefits

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Abstract

Traditionally, the isolated relationship of total preventive maintenance (TPM), quick setup (QS), overall equipment effectiveness (OEE), and one-piece flow (OPF) with economic sustainability (ESU) has been investigated; however, these lean manufacturing (LM) tools are implemented together into production systems, and traditional research does not report their relationships and interactions. To contribute to this gap, this paper integrates all those variables in a structural equation model (SEM), which are related by seven hypotheses that are validated using the partial least squares (PLS) technique using information from 176 responses to a questionnaire applied to the Mexican maquiladora industry. Additionally, a sensitivity analysis has been carried out to determine the probability of occurrence at high and low implementation levels for all variables when they occur in isolation, jointly and conditionally. Findings indicate that TPM is a precursor of QS and OEE, while QS is a precursor of OEE and OPF, OEE is a precursor of OPF and ESU, but also OPF is a precursor of ESU. The sensitivity analysis indicates that low levels of TPM are a risk for reaching adequate levels of OEE and QC, while low levels in OEE and OPF are a risk for reaching adequate ESU levels.

Keywords Lean manufacturing · TPM · OEE · Economic sustainability · Structural equation

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1 Introduction

In the era of the global market, manufacturing companies face various problems such as resource waste, material shortages, pollution, and environmental impact, which affect the cost of production [1]. To solve these problems, companies apply the lean manufacturing (LM) philosophy, which is a system of industrial work organization focused on improving the production system by eliminating activities that do not add value to the process or to the customer, including overproduction, long lead times, and product defect rate [2].

LM is a set of tools focused on different aspects of the production system. For example, there are basic tools associated with level production, visual management, process standardization, and long-term thinking; however, it has several pillars in which tools are associated with the material flow (just in time, takt time, pull system, Kanban, among others), quality assurance (total quality management, Gemba, continuous improvement), machines (total preventive maintenance, overall equipment effectiveness, poka-yoke, andon systems, Jidoka), and human factors (supplier

development, multifunctional workers, personnel selection, training, and education) [3].

The LM implementation generates many benefits, and one is cost reduction, which focuses on waste elimination, which impacts companies' economic sustainability (ESU) as it indirectly refers to reducing costs [4]. The relationship of LM with ESU in companies has been of academic and industrial interest; for example, Resta et al. [5] indicate that LM supports ESU if the objectives of the two are properly aligned, Rupasinghe and Wijethilake [6] point out that the supply chain and logistics of materials are one of the most benefited by LM, as they do not add value to the product, and finally, Jum'a et al. [7] indicate that the LM relationship is not only with ESU but also with social and environmental.

In the same way, some studies analyze some relationships of specific LM tools with ESU, such as TPM, TQM, and Jidoka [2], SMED [8], to name a few. However, many of the studies are very general when talking about the relationship between LM and others very specific, without focusing on a group of tools in one pillar in this production philosophy.

Also, it has been observed that many studies have been conducted in different countries, such as Brazil [9], Spain and Italy [10], Thailand [11, 12], Spain and Portugal [13], and India [14]. However, few studies have been carried out on this topic in Mexico, and those that exist are limited to analyzing isolated LM tools [8, 15]. However, the LM implementation implies that several tools are applied simultaneously in a production line and that there is a sequence and dependence between them; for example, OEE depends on the efficiency of the implemented TPM programs.

Specifically, in Mexico, few studies relate LM to economic, social, and environmental sustainability, even though Mexico has a long history in the manufacturing industry through the maquiladora program. A maquiladora company is a subsidiary of others established in other countries and characterized by labor-intensive assembly activities and state-of-the-art machinery and equipment in the production system [16].

Mexican maquiladora companies are characterized by importing raw materials and exporting finished products, they are established in the northern part of the country, given the proximity to the USA, and they obtain the benefit of low tariffs, taking advantage of the free trade agreements between Mexico, USA, and Canada, as well as the low wages and high level of training of human resources [17].

There are currently a total of 5192 maquiladora companies nationwide in Mexico, but 488 are located in Chihuahua state, and of these, 323 are in Ciudad Juárez, offering 339,499 direct jobs in that city [18]. Those values indicate the regional importance of this industrial sector and the need for research that relates the impact of the machines and LM tools applied and used in their production processes on the sustainability achieved.

Different studies have been found regarding the LM tools in different work environments in the MMI, like SMED [17]

and TPM [2]; however, those studies are analyzing the LM tool in isolated, and no studies have been found that relate and measure the effect of TPM, OEE, QS, and OPF on the economic sustainability. However, TPM is associated with ESU, as parts produced on poorly calibrated machines represent economic losses [19, 20], as well as SMED, which represents idle machines [21] and material flow [8]. Therefore, the following research question is established: What is the effect of TPM, OEE, QS, and OPF on the ESU in maquiladora companies in northern Mexico?

This paper aims to integrate into a single analysis the relationship of four LM tools (TPM, quick setup, OEE, and one-piece flow) associated with machinery installed in the production process with the ESU obtained by MMI established in Ciudad Juárez. Measuring the impact of these tools' activities on ESU will allow MMI managers to identify which activities are important according to their objectives and in which resources must be invested to achieve the correct implementation and correct deviations in poorly executed activities.

The contributions of this work are that it integrates four LM tools into a single analysis and associates them with ESU. Additionally, we report a sensitivity analysis based on conditional probabilities in which risks are explored for identifying high and low implementation scenarios in the LM tools. This analysis will allow managers and persons responsible for the LM implementation in the MMI to understand the risks incurred by not executing certain activities and the loss of sustainable benefits.

The rest of the article is distributed as follows: Sect. 2 reports a literature review, describes the LM tools and economic sustainability, and proposes and justifies the hypotheses for each relationship. Section 3 describes the methodology developed for this research, which consists of six steps. Section 4 describes the results obtained, characterizes the sample, validates the variables, presents the structural equation model results, performs a sensitivity analysis, and discusses the results. Finally, Sect. 5 describes the conclusions of the findings of this research.

2 Literature review and hypothesis

This section defines the LM tools and ESU studied in this research. It also provides a literature review that helps to indicate the relationship between them and helps to justify and establish the research hypotheses.

2.1 Total productive maintenance (TPM)

In the current industrial scenario, wastage occurs due to faulty machines or machines running at a slower speed, leading to process bottlenecks, lower product quality, and

non-fulfillment of orders [22]. Total productive maintenance (TPM) is an LM tool used in industries to solve the above problems and increase financial savings.

TPM aims to improve the competitiveness of organizations and encompasses a structured approach to change the mindset of employees and involve all managers to maximize the overall effectiveness of production teams [23]. TPM optimizes equipment efficiency, breakdowns are reduced, and autonomy is promoted through maintenance prevention [24]. TPM also improves production integrity, which translates into increased quality and economic profits for the industry [11].

TPM has been of academic and scientific interest; for example, Chan et al. [25] report a case study in which it increases the productivity of a molding machine by 83%, increases the effectiveness of the equipment and the quality of the product, where there is also a change in the organizational culture and paradigm. For their part, Ribeiro et al. [26] implemented TPM to increase availability on a critical production line and indicated that the time between failures is decreased by 20%, repair time is reduced by 13%, and availability is increased by 1.2%, all of them impacting financial income for the companies.

2.2 Quick setup (QS)

To better respond to market demands, companies need to find strategies to make their processes more flexible and streamline machine setup activities to produce different parts in small batches, called rapid changeovers. Quick changeover is a technique to reduce setup or changeover times from one specific product manufacturing process to another and is commonly referred to as Single Minute Exchange of Die (SMED) [27]. Proper implementation of SMED will ensure greater flexibility to increase product range, improve product flow in the manufacturing area, decrease machine downtime, and increase financial income for companies [28].

The application of QS is of academic interest in different industrial sectors; for example, Ribeiro et al. [29] report the case of the electrical industry to reduce in-process inventories and cost reduction for product changes, while Tamás [30] focuses on combining it with simulation to evaluate different scenarios in production systems for dismissing idle time in machines, and Jain and Vaishya [31] indicate that its application has reduced setup time by 87.5% and increased equipment efficiency (OEE) by 4.7% in the SIM card manufacturing electronics industry, increasing operational and financial indexes.

In this research, it is assumed that if TPM is applied to all machines, they will be clean, there will be a system of warnings when they fail, the reviews will be periodic by the operators, and that will facilitate the carrying out of QS, since it

is not required to search for materials, review maintenance logs, among others [28]. In addition, the permanent cleaning of the machines by the operators makes it easier for the tooling to be in place and easily accessible to the maintenance staff, which avoids wasting time on these activities when a product change is made [32], and the machines remain idle for less time. In that sense, it is concluded that TPM guarantees machine availability and its application implies continuous improvements leading to a better application of QS [28]. In this sense, the following hypothesis is proposed:

H_1 : TPM has a direct and positive effect on quick setup.

2.3 OEE (OEE)

Overall equipment efficiency (OEE) is a function of equipment availability, throughput efficiency, and quality and is often used as a metric for TPM [33] as it has a direct impact on the improvement of the overall performance of production equipment [24] and originated in the framework of lean management with the introduction of TPM [30]. OEE is the product of availability rate, throughput rate, and quality rate, where availability rate is the time the equipment is running versus the time the equipment could have been running; throughput rate is the quantity produced during the running time versus the potential quantity produced at the designed speed of the equipment, while the quality rate is defined as the ratio of the number of good products produced versus the total quantity of products produced [28].

OEE applications in the industry have several reports, as they help to understand the robustness of the production system. For example, Costa and Lopes [34] indicate that OEE boosts productivity, reduces costs, and increases sales and financial indexes in the automotive sector, whereas Purwanto and Jaqin [35] associated it with productivity in the tire industry and finally, Cercós et al. [36] associate OEE with the environmental impacts of production processes.

In TPM, the performance of a production system is measured with the OEE index, as it integrates the throughput rate, availability, and quality rate, which are measures of equipment losses [37], and all of them can be associated with economic indexes. By performing preventive maintenance activities such as cleaning, adjusting lubrication, performing small maintenance operations, and monitoring quality and performance, OEE levels increase dramatically in short periods, thereby increasing efficiency and productivity and decreasing overall defectiveness [38], which represent financial savings. Therefore, the following hypothesis is proposed.

H₂: TPM has a direct and positive effect on OEE.

However, OEE integrates the availability of machines and equipment into its calculation, so downtimes due to product changes must be fast [39], and this can be solved by the application of QS [39], although there may be many other factors (Junior et al., 2022). For Haddad et al. [40], in the case of the QS, having machines and a clean space facilitates quick changeovers and increases machine availability levels by decreasing downtime, which in turn increases OEE levels and economic savings, so the following hypothesis is proposed:

H₃: Quick setup has a direct and positive impact on OEE.

2.4 One-piece flow (OPF)

In the ideal LM environment, the product flows through the manufacturing process piece by piece, carried along by the downstream operations, as all operations progress at the same rate [41]. This LM environment is supported by pull, takt time, and Kanban systems to control the flow of materials in the right quantity and time and to manufacture only the strictly necessary products [42]. Thus, one-piece flow refers to moving one piece at a time between operations within a work cell.

Manufacturing with a one-piece flow discipline allows for short lead times, rapid response to changing market requirements, adequate levels of in-process inventory (WIP), and reduced downtime [43], which translates into increased productivity and reduced wastage [44] because men and machines are up and running (Ioana et al., 2020).

However, the OEE implementation eliminates six losses associated with breakdown, downtime, setup, speed, throughput, and scrap during manufacture [45], representing financial savings. In other words, OEE reflects the effectiveness of a process by manufacturing quality parts in the planned time and in the right quantity, which implies the speed of the production flow [46]. Therefore, it is associated with one-piece flow, and the following hypothesis is proposed:

H₄: OEE has a direct and positive effect on one-piece flow

Purwanto and Jaqin [35] state that applying the one-piece flow philosophy in a production system requires great flexibility and agility in the production system, and a quick setup can help in these two aspects, i.e., one must be sure to respond quickly to customers and have several alternatives to do so. In addition, the materials depend a lot on machines and tools, which also integrate TPM, but simulations should always be carried out to find out what is needed. Sun and Du [43] indicate that simulations should always be carried

out to know the scenarios of the production processes before implementing OPF and increase financial possibilities, where variables associated with layout, machine availability, or OEE, among others, should be included. Therefore, the following hypothesis is proposed.

H₅: Quick setup has a direct and positive effect on quick setup.

2.5 Economic sustainability

Sustainability is a process that aims to find a balance between the environment and the use of natural resources. Humanity has degraded natural resources, and now necessary to seek and plan their consumption to ensure their existence in future generations, and it includes three important pillars, social, economic, and environmental [47]. The integration of these three pillars is often referred to as the triple bottom line (TBL) in industry and government. However, in this study, we only analyze the impact of LM tools on the ESU.

ESU uses different strategies to employ, safeguard, and maintain human and material resources optimally, to create a responsible and beneficial balance, sustainable in the long term, through recovery and recycling, which should be a permanent industrial practice [8], and to achieve these objectives, and LM tools are applied.

The relationship of LM with sustainability has been investigated, both generally and specifically. In general terms, Shafiq and Soratana [48] indicate that LM implementation represents an economic investment that managers do not want to risk; however, they point out that the main problem is ESU preparation. Specifically, García-Alcaraz et al. [15] relate 8 LM tools to Mexican maquiladora companies' industrial sustainability and indicate that ESU requires high investments and LM.

Changes in manufacturing processes occur in response to improvement programs in which LM is applied, resulting in reductions in production cost, reduced product development time, energy consumption, inventory, rejects, and reprocesses, which directly influence the company's economic sustainability [49].

One of the LM tools that benefit ESU the most is OEE, as it integrates three important aspects, such as the level of availability of machines, no downtime due to lack of maintenance, and thus no delays in on-time order deliveries [50]. For their part, Chikwendu et al. [37] state that implementing OEE will improve product quality and reduce equipment breakdowns, downtime, accident rates, excess inventory, and scrap and defects.

Another pillar is the quality obtained from the production process because when this is higher, rework of defective parts, complaints and rejections of products by customers,

warranty validations, and order cancellations are reduced, affecting companies economically [51]. Therefore, the following hypothesis is proposed:

H₆: OEE has a direct and positive effect on economic sustainability.

However, having high availability of machines and equipment in the production system, these are flexible and can be quickly adapted to make changes so that only what is required is produced. In that case, more market coverage with satisfied customers will be available [52]. Likewise, if the OPF is achieved, then this indicates that the high flexibility of the production system allows for smaller or even more customized production batches and special customer service, as indicated by Ioana et al. [44] in the automotive industry. In other words, the application of OPF allows it to serve more customers, improve customer satisfaction, and therefore increase the total sales and revenues of the companies, so the following hypothesis is proposed.

H₇: One-piece flow has a direct and positive effect on economic sustainability.

Figure 1 indicates the relationships between variables graphically set out as hypotheses.

3 Methodology

This section describes each of the steps carried out to develop this research, and a summary of the main steps and their development is shown in Fig. 2.

3.1 Development of the questionnaire

The information must be collected from the regional industry to validate the hypotheses in Fig. 1, so a questionnaire

is designed through a literature review in different databases. The final questionnaire is divided into three sections. The first section asks for demographic data such as gender, respondent’s position, experience, and the industry sector in which they work. The second section looks at the LM tools; in this case, 207 questions (items) are divided into 35 LM tools. The third section comprises 27 questions (items) divided into three different types of sustainability (social, environmental, and economic). However, in this research, only the relationships between total productive maintenance (TPM), quick setup (QS), overall equipment effectiveness (OEE), one-piece flow (OPF), and economic sustainability (ESU) are analyzed.

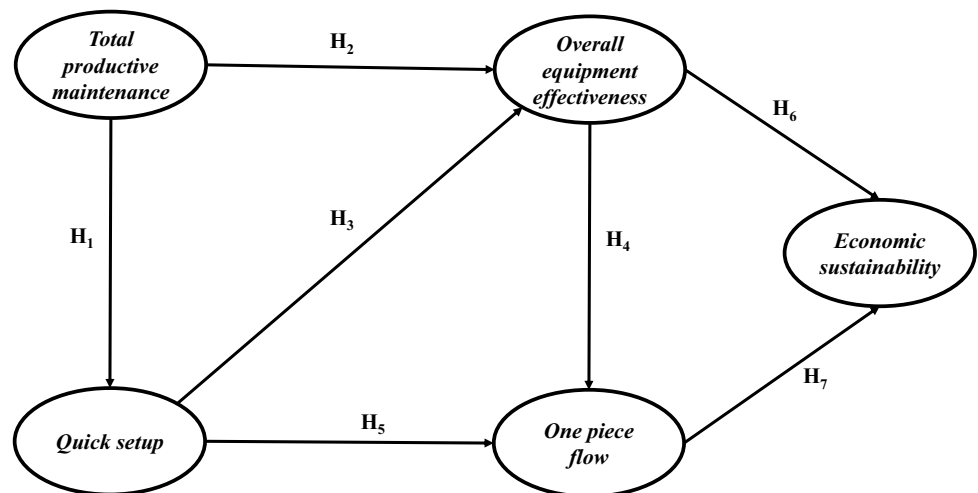
The questionnaire is validated by expert judgment (5 academics and 5 managers) to adapt it to the environment in which it is applied. A 5-point Likert scale is used to answer the questions, where 1 means strongly disagree, 2 means agree, 3 means neither agree nor disagree, 4 means agree, and 5 means strongly agree. A final version of the questionnaire is given as supplementary material.

3.2 Obtaining information

Due to the restrictions generated by the COVID-19 health crisis, the application of the questionnaire was carried out on the Google forms platform, where the three questions sections were loaded and programmed as mandatory to avoid missing values. The application period is from 15 January 2022 to 15 April 2022. The identification of the sample is done with the help of the Asociación de Maquiladoras A.C. Index Juárez. The sample comprises managers, engineers, and supervisors to guarantee experience in implementing LM.

All potential respondents were contacted via email, inviting them to participate and attaching the link to the survey. They were given 10 days to respond to the email and answer the questionnaire; if in that time they did not get a response, then

Fig. 1 Proposed model



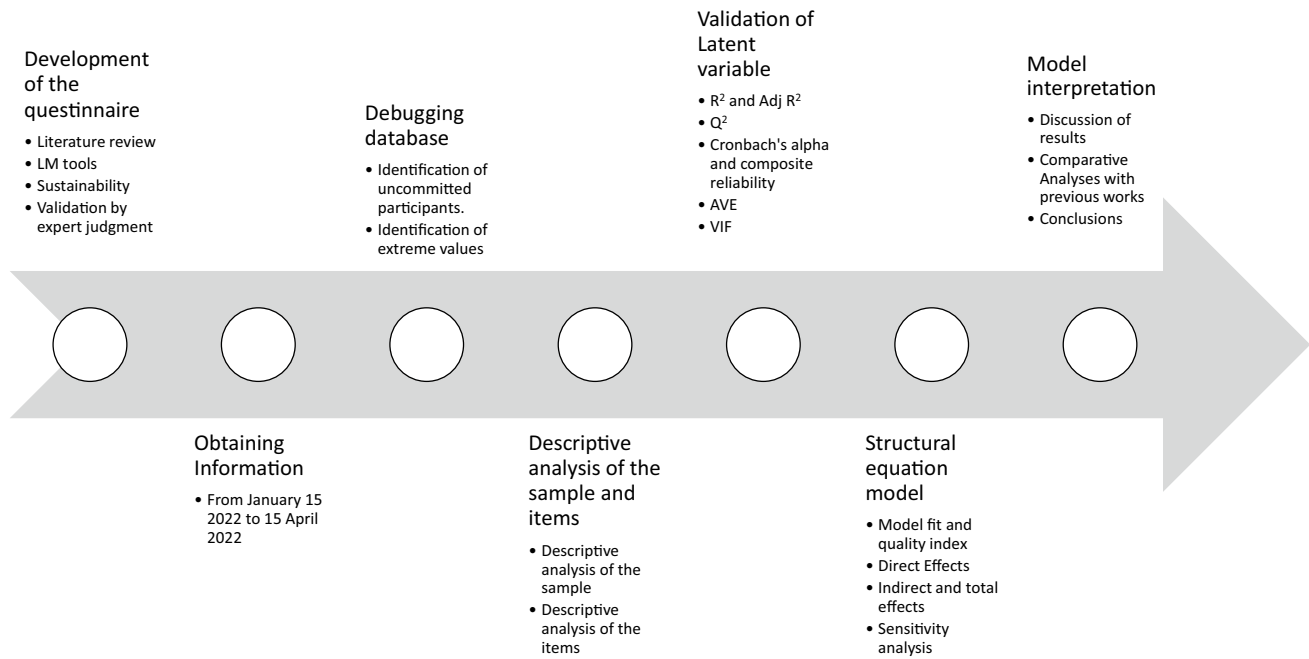


Fig. 2 Methodology

a reminder was sent, and they were given another 10 days, and if they did not respond once more, that case was discarded.

3.3 Debugging the database

Once the period for the questionnaire application was over, the data was downloaded into an Excel file from the Google Forms platform, and then the data was debugged using SPSS 25® software according to the following task [53]:

- The standard deviation for each questionnaire (excluding demographic information) is calculated to identify disengaged participants when answering the questionnaire. Suppose the standard deviation is less than 0.5. In that case, the questionnaire is eliminated as it does not show much dispersion in the data and indicates that the respondent gave almost always the same answers (low commitment), which is difficult to do in a questionnaire containing many questions.
- The items in the latent variables are standardized, i.e., the standard deviation of each item is obtained, and each value in the item is divided by this. Standardized values with an absolute value greater than 4 are considered extreme and replaced by the mean.

3.4 Descriptive analysis of the sample and items

Cross tables were used to summarize the demographic information obtained (industrial sector, experience, sex, and position held). For the descriptive analysis of the items,

the median for grouped midpoints was used as a measure of central tendency since assessments are on an ordinal Likert-type scale. High median values indicate that the activities of each of the LM tools are carried out, and low median values indicate that these activities are not carried out.

In addition, the interquartile range (IQR, difference between third and first quartile) was used as a measure of dispersion. High values in the IQR indicate a high dispersion of responses and that there was no consensus among respondents regarding the item's median value. On the other hand, low values in the IQR indicate a consensus among responders.

3.5 Validation of latent variables

To validate the four latent variables related to LM tools (TPM, QS, OPF, and OEE) and ESU, we use the validation indices proposed by Kock [54] shown in Table 1, where the first column indicates the type of validation it measures, the second column illustrates the index used, and the third column indicates the cut-off values.

It is important to mention that the validation indices were obtained iteratively since, frequently, the elimination of an item in a latent variable increased it, so the number of items reported in the survey differs from those integrated into the model.

3.6 Structural equation modeling

Once the latent variables pass the validation process, they are integrated into the model, and the partial least

Table 1 Validation indices of the latent variables

Test	Coefficient	Acceptable values
Parametric predictive validity	R^2 and Adj R^2	≥ 0.02
Non-parametric predictive validity	Q^2	≥ 0.02 and similar to R^2
Internal validity	Cronbach’s alpha and composite reliability	≥ 0.70
Convergent validity	Average variance extracted	≥ 0.50
Collinearity	Variance inflation factor	≤ 5 ; ideally ≤ 3.3

squares-structural equation modeling technique (PLS-SEM) integrated into WarpPLS 7.0 software is used to evaluate all hypotheses in Fig. 1. PLS-SEM is chosen because it can efficiently process small sample data without assuming normal distribution in data and that they are obtained on a Likert scale [55]. In addition, PLS-SEM is efficient at estimating parameters, which translates into high levels of statistical power, indicating that it will generate a specific and significant relationship when it is significant in the population [56].

Before interpreting the results from the structural equation model, we review the model quality indices proposed by Kock [54] and shown in Table 2, where the first column indicates the index, the second column the validation type, and the third column the desired cut-off values.

Three effects on the relationships between hypotheses are assessed in the model with 95% confidence and are indicated below.

3.6.1 Direct effects

The direct effects between variables are used to validate the proposed hypotheses [57]. These are measured using a standardized β value (change in the dependent latent variable due to a one-unit change in the independent latent variable) and associated with a p -value. To test statistical significance, we test the null hypothesis $H_0: \beta=0$ versus the alternative hypothesis $H_1: \beta \neq 0$. If it is shown that $\beta=0$ statistically, then it is concluded that there is no relationship between the variables, but if it is shown that $\beta \neq 0$, then it is concluded that there is a relationship between the variables, regardless of the sign.

In addition, we report the effect size (ES) for each direct effect, which is the amount of variance explained by each independent variable in the dependent variable. This index

is especially important when several dependent variables explain the dependent variable, and the R^2 value is the sum of all the ES in the dependent variable.

3.6.2 Indirect and total effects

An indirect effect occurs when the influence of an antecedent variable (X) on the effect variable (Y_2) is mediated by an intervening variable (Y_1), called the mediator [58]. This effect has at least two segments, and in this paper, we report only the sum of indirect effects, their p -value, and effect size, given that it can be using two, three, four, or more segments.

Finally, the total effects obtained from the sum of direct and indirect or mediating effects are reported. For the sum of indirect effects and total effects, the same hypothesis test is performed for the standardized β value with a confidence level of 95%.

3.6.3 Sensitivity analysis

PLS analysis uses standardized data, so it is possible to obtain meaningful probabilities for managers and decision-makers as they provide insight into different scenarios of occurrence and risks [54]. This article reports the estimated values for each of the following scenarios:

- The probability of finding the latent variables independently at their high levels, indicating that LM activities are performed adequately, or ESU benefits are obtained ($Z > 1$), and for low levels or the scenario where LM activities are not performed adequately or ESU benefits are not obtained ($Z < -1$), where Z represents a standardized latent variable.

Table 2 Model quality and fit indices

Index	Validation	Acceptable value
Average path coefficient (APC)	Predictive	$p < 0.05$
Average R -squared (ARS) and average Adjusted R -squared (AARS)	Predictive	$p < 0.05$
Average block VIF (AVIF)	Collinearity	Acceptable if ≤ 5 , ideally ≤ 3.3
Average full collinearity VIF (AFVIF)	Collinearity	Acceptable if ≤ 5 , ideally ≤ 3.3
Tenenhous GoF (GoF)	Data model fit	≥ 0.36

Table 3 Respondents' positions and industry sector

Industrial sector	Job position			Total
	Manager	Engineer	Supervisor	
Automotive	20	28	21	69
Electrical/electronics	18	31	10	59
Logistics	8	10	5	23
Machining	7	5	0	12
Rubber	3	5	0	8
Aeronautics	4	1	0	5
Total	60	80	36	176

- The probability of the variables occurring simultaneously in any combination of their scenarios. The possible combinations are $P(Z > 1) \cap P(Z > 1)$, $P(Z > 1) \cap P(Z < -1)$, $P(Z < -1) \cap P(Z > 1)$, and $P(Z < -1) \cap P(Z < -1)$.
- The conditional probability of the dependent variable occurring in a scenario (high or low) given that the independent variable has occurred in a scenario (high or low). The combinations are as follows: $P(Z > 1)/P(Z > 1)$, $P(Z > 1)/P(Z < -1)$, $P(Z < -1)/P(Z > 1)$, and $P(Z < -1)/P(Z < -1)$.

4 Results

A continuación, se describen los resultados obtenidos con la realización de esta investigación (The results obtained from this research are described below.).

4.1 Sample descriptions

A total of 192 responses were obtained at the end of the questionnaire application period; however, 16 were excluded because the respondent did not meet the inclusion criteria, belonged to commercial departments, and

were very different from the production process or LM, and this appends because there was not an updated email registered in IMMEX, and only 176 were analyzed. From that valid sample size, 75 were women, and 101 were men. The positions held are illustrated in Table 3, where it can be seen that engineers and plant supervisors implementing LM were the most common respondents, and the most common sector surveyed was automotive and electrical/electronics.

4.2 Validation of variables and their descriptives

Table 4 indicates the validation indices for each model's latent variables. The first row indicates the number of items before (B) and after (A) the latent variables were validated, some of which have been removed to increase reliability. The reported index values refer to the latent variables after the validation process, and it is observed that all of them meet the cut-off values established in the methodology and illustrated in the last column, i.e., the variables have sufficient predictive, internal, convergent validity and there are no collinearity problems, so they are integrated into the model.

Furthermore, the last row indicates that none of the latent variables has a normal distribution according to the Jarque–Bera algorithm, which justifies using the partial least squares approach.

Table 5 illustrates the median and interquartile range of items remaining in the latent variables after the validation process, which are ordered in descending order. In general, it is observed that all activities or items that remain after the validation process are almost always implemented, as the median value is greater than four, including the benefits reported in the ESU. Similarly, the IQR is a low value and indicates consensus among respondents regarding the mean value of the items.

Table 4 Validation process

Index	TPM		QS		OEE		OPF		ESU		Best if
	B	A	B	A	B	A	B	A	B	A	
Items					5				5		
<i>R</i> -squared			0.541		0.598		0.665		0.418		> 0.2
Adjusted <i>R</i> -squared			0.538		0.593		0.661		0.411		> 0.2
Composite reliability	0.931		0.930		0.935		0.923		0.938		> 0.7
Cronbach alpha	0.902		0.887		0.907		0.895		0.912		> 0.7
AVE	0.772		0.815		0.782		0.705		0.792		> 0.5
Full collinearity IVF	2.755		2.643		3.409		3.120		1.741		< 5
<i>Q</i> -squared			0.539		0.595		0.664		0.419		> 0.2
Jarque–Bera normality	No		No		No		No		no		

B before validation, *A* after validation

Table 5 Descriptive analysis

TPM	Median	IQR
We dedicate regular inspections to keeping the machines in operation	4.23*	1.48
We have a daily maintenance sound system to prevent machine failures	4.09*	1.71
Operators are trained to keep the machines in operation	4.11*	1.67
We highlight the excellent maintenance system as a strategy to achieve quality compliance	4.13*	1.58
QS		
Some working groups seek to make model changes more efficient and reduce preparation times	4.32*	1.37
Machines and tools facilitate rapid changeovers	4.29*	1.47
The procedure for model changes is standardized	4.29*	1.48
OEE		
Is the production department highly productive?	4.25*	1.44
Is the production target met on time, and does it always meet the required quality?	4.17*	1.44
No significant stops in the production process?	4.16*	1.56
No waste in the production process?	4.08*	1.66
OPF		
Is a production batch only produced if you have the customer's purchase order?	4.34*	1.38
Is only the specific quantity requested by the customer produced?	4.29*	1.42
Is production at a particular job based on the demand for its subsequent job?	4.28*	1.35
Are workstations making good use of the pull system?	4.27*	1.53
Is the Kanban system used to authorize production?	4.21*	1.51
ESU		
Reduction of production costs	4.39*	1.30
Reduction of administrative penalties for environmental mishaps	4.35*	1.35
Reduction of energy costs	4.32*	1.35
Reduction of waste treatment costs	4.32*	1.38
Reducing the costs of rejects and reworks	4.24*	1.44

*The median has been calculated using group midpoints

4.3 Structural equation modeling

Before interpreting the model, the efficiency indices of the model are reviewed, which indicate that there are strong relationships between the variables in general; since the p -value of APC is less than 0.05, there is predictive validity since the p -values of ARS and AARS are less than 0.05, there are no collinearity problems since AVIF and AFVIF is less than 3.3, and finally, the data have a good fit to the model since GoF is greater than 0.36. The indices are:

- Average path coefficient (APC) = 0.446, $p < 0.001$
- Average R -squared (ARS) = 0.556, $p < 0.001$
- Average adjusted R -squared (AARS) = 0.551, $p < 0.001$
- Average block VIF (AVIF) = 2.293, acceptable if ≤ 5 , ideally ≤ 3.3
- Average full collinearity VIF (AFVIF) = 2.734, acceptable if ≤ 5 , ideally ≤ 3.3
- Tenenhaus GoF (GoF) = 0.655, small ≥ 0.1 , medium ≥ 0.25 , large ≥ 0.36

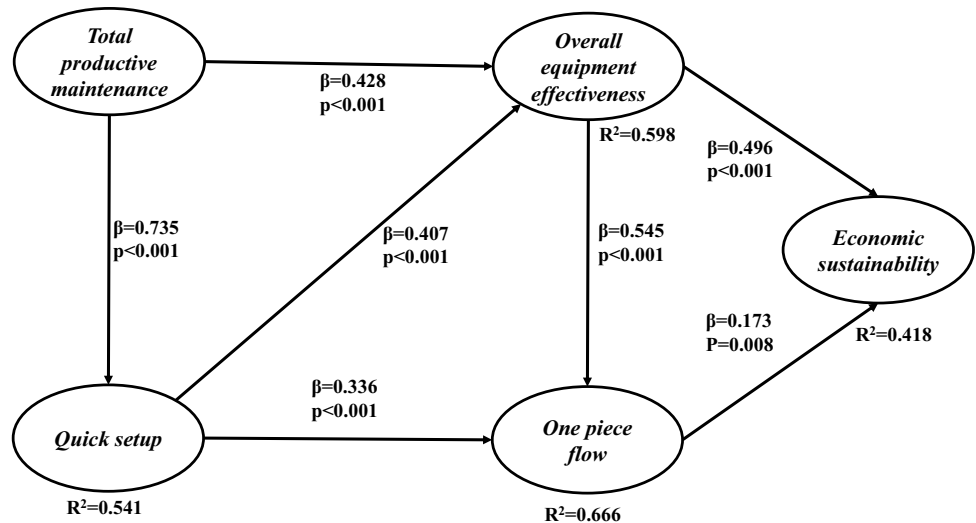
Figure 3 illustrates the model evaluated, where a standardized β -value and the associated p -value are observed for each relationship between hypotheses and an R -squared value for the dependent variables. In general terms, it is observed that all hypotheses are accepted with up to 99% confidence, as the p -values are less than 0.001.

4.3.1 Direct effects

The direct effects validate the hypotheses put forward. Table 6 illustrates a summary of these, where conclusions are given based on the p -value associated with the standardized β -value of each relationship. It is concluded that all are accepted at the established confidence level.

Figure 3 also shows that the dependent variables are explained by more than one independent variable. Table 7 illustrates the effect size, where this value is decomposed to identify which of these is the most important based on the variance explained.

Fig. 3 Evaluated model



4.3.2 Sum of indirect effects and total effects

Table 8 illustrates the indirect and total effects sum, the associated *p*-value, and the effect size. According to the *p*-values associated with the standardized β -value, it is concluded that the sum of indirect effects and total effects is statistically significant. The maximum indirect effect exists between TPM and OPF, which is through QS and OEE as mediating variables and has a value of 0.643; however, there are two total effects with large values, and they are in the relationships between TPM and QS, which is equal to the direct effect and that between TPM and OEE, with 0.735 and 0.727, respectively.

4.4 Sensitivity analysis

Table 9 presents a sensitivity analysis for each hypothesis in Fig. 1. High scenarios are represented by “+” and low by “-”; thus, TPM+ represents a high level of TPM and QS- indicates a low level of QS. In addition, we report the probability of the latent variables occurring in isolation, jointly and is represented by “&” and the conditional probability of the dependent variable occurring given that the independent variable has occurred and is represented by “IF.”

Table 6 Validation of hypotheses

Hypothesis	Relation	β	<i>p</i> -value	Conclusion
H ₁	TPM → QS	0.725	<0.001	Accept
H ₂	TPM → OEE	0.428	<0.001	Accept
H ₃	QS → OEE	0.407	<0.001	Accept
H ₄	OEE → OPF	0.545	<0.001	Accept
H ₅	QS → OPF	0.336	<0.001	Accept
H ₆	OEE → ESU	0.496	<0.001	Accept
H ₇	OPF → ESU	0.173	=0.008	Accept

5 Discussion of results

This section discusses the results found in the SEM and the sensitivity analysis.

5.1 Regarding the structural equation model

Uno de los objetivos de este artículo era cuantificar la relación que tienen las herramientas de LM TPM, SMED, OEE y QS entre ellas y con ESU, lo cual se ha podido realizar mediante el SEM (The main research goal of this article was to quantify the relationship that LM TPM, SMED, OEE and QS tools have with each other and with ESU, which has been done using SEM.).

For the relationship TPM → QS in H₁, it can be concluded that the activities performed within the TPM positively influence the QS, since when the first variable increases its standard deviation in one unit, the second one goes up by 0.725 and explain 54.1% of its variance. Our findings agree with Suryaprakash et al. [28], who mention that TPM ensures machine availability, contributing to SMED implementation. However, TPM also contributes to OPF and ESU indirectly, as it has indirect effects of 0.643 and 0.474, respectively, which is in agreement with Samadhiya and Agrawal [59] and Durán and Durán [60], who mention that well-calibrated machines represent less rework, waste, and idle time, which translates into economic savings. Thus, managers should seek a high availability of their machines and equipment, as

Table 7 Decomposition of R² into effect sizes

	TPM	QS	OEE	OPF	R ²
QS	0.541				0.541
OEE	0.308	0.29			0.598
OPF		0.241	0.425		0.666
ESU			0.316	0.102	0.418

Table 8 Sum of indirect effects and total effects

	Sum of indirect effects			Total effects			
	TPM	QS	OEE	TPM	QS	OEE	OPF
QS				$\beta=0.735$ ($p<0.001$) EN=0.545			
OEE	$\beta=0.299$ ($p<0.001$) EN=0.215			$\beta=0.727$ ($p<0.001$) EN=0.523	$\beta=0.407$ ($p<0.001$) EN=0.290		
OPF	$\beta=0.643$ ($p<0.001$) EN=0.464	$\beta=0.221$ ($p<0.001$) EN=0.159		$\beta=0.643$ ($p<0.001$) EN=0.464	$\beta=0.557$ ($p<0.001$) ES=0.400	$\beta=0.545$ ($p<0.001$) ES=0.435	
ESU	$\beta=0.474$ ($p<0.001$) EN=0.239	$\beta=0.300$ ($p<0.001$) EN=0.158	$\beta=0.096$ ($p=0.034$) EN=0.061	$\beta=0.474$ ($p<0.001$) EN=0.239	$\beta=0.300$ ($p<0.001$) ES=0.158	$\beta=0.592$ ($p<0.001$) ES=0.378	$\beta=0.176$ ($p<0.001$) ES=0.102

this represents the possibility of carrying out more production orders at a lower cost.

Regarding the relationship TPM → OEE in H₂, it is concluded that TPM has a direct and positive effect on OEE because when the first variable increases its standard deviation, the second one goes up by 0.428 units and explains 30.8 of its variance. However, TPM also has an indirect effect on OEE of 0.299 units through QS, giving a total effect of 0.727 units. The above indicates that if proper maintenance is applied to machines and equipment, the availability and quality of the products generated will increase; furthermore, OEE is a metric of TPM, hence its high correlation. Our findings are consistent with Chiarini [38] and Jain et al. [33], who mentions that by performing preventive maintenance activities and controlling quality and performance, OEE percentages will increase.

For the relationship QS → OEE in H₃, QS has a direct and positive effect on OEE because when the first variable increases its standard deviation by one unit, the second one goes up by 0.407 units and explains 29% of its variance. However, also QS indirectly affects ESU through OEE and OPF with 0.300 units. These findings indicate that when a QS program is in place, the availability of machines and tools increases. As a consequence, the OEE goes up, and all it translates into higher revenue. These results agree with Jebaraj Benjamin et al. [61], who report a 2% increase in OEE due to QS implementation. Similar results were reported by Bhade and Hegde [62] and Pinto et al. [63], who indicate a 10% and 90% increase in OEE by applying QS, respectively.

Table 9 Sensitivity analysis

	Probability	TPM +	TPM –	QS +	QS –	OEE +	OEE –	OPF +	OPF –
		0.176	0.148	0.239	0.136	0.193	0.148	0.142	0.136
QS +	0.239	&=0.125 IF=0.710	&=0.001 IF=0.077						
QS –	0.136	&=0.000 IF=0.000	&=0.097 IF=0.654						
OEE +	0.193	&=0.144 IF=0.645	&=0.006 IF=0.038	&=0.114 IF=0.476	&=0.000 IF=0.000				
OEE –	0.148	&=0.000 IF=0.000	&=0.085 IF=0.577	&=0.006 IF=0.024	&=0.091 IF=0.667				
OPF +	0.142	&=0.097 IF=0.548	&=0.000 IF=0.000	&=0.108 IF=0.452	&=0.000 IF=0.000	&=0.119 IF=0.618	&=0.000 IF=0.000		
OPF –	0.136	&=0.000 IF=0.000	&=0.097 IF=0.607	&=0.006 IF=0.024	&=0.097 IF=0.708	&=0.000 IF=0.000	&=0.102 IF=0.692		
ESU +	0.244	&=0.097 IF=0.548	&=0.023 IF=0.143	&=0.125 IF=0.524	&=0.011 IF=0.080	&=0.114 IF=0.588	&=0.006 IF=0.038	&=0.091 IF=0.640	&=0.006 IF=0.042
ESU –	0.119	&=0.000 IF=0.000	&=0.063 IF=0.393	&=0.006 IF=0.024	&=0.063 IF=0.440	&=0.000 IF=0.000	&=0.068 IF=0.468	&=0.000 IF=0.000	&=0.068 IF=0.500

Concerning the OEE \rightarrow OPF relationship in H_4 , it is concluded that OEE has a direct and positive effect on OPF, because when the first variable increases its standard deviation by one unit, the second one goes up by 0.545 units and explains 42.5% of its variance. It indicates that with the high availability and performance of machines that manufacture quality products, the OPF is guaranteed. Our findings agree with Acevedo Robles [46], who indicates that OEE reflects the effectiveness of a process in manufacturing quality parts in the planned time and in the right quantity, which implies the speed of the production flow.

For the QS \rightarrow OPF relationship in H_5 , it is concluded that QS has a direct and positive effect on OPF because when the first variable increases its standard deviation in one unit, the second one goes up by 0.336 units and explains 24.1% of its variance. In addition, QS indirectly affects OPF through OEE of 0.221 units, giving a total effect of 0.557 units. This indicates that the implementation of QS increases the flexibility of the production system, which allows the batch size to be reduced and continuous. This result agrees with Rodríguez-Méndez et al. [64], which report improving model changeover times and delivering diversified products in small batches.

In the OEE \rightarrow ESU relationship in H_6 , it is concluded that OEE has a direct and positive effect on ESU because when the first variable increases its standard deviation by one unit, the second one goes up by 0.496 units and explains 31.6% of its variance. In addition, OEE has an indirect effect on ESU of 0.096 units through OPF, giving a total effect of 0.592 units. This means that a high percentage of machine availability, throughput, and quality in products facilitates ESU through a reduction in production costs, energy consumed, rejects, wastage, and, above all, government administrative penalties. This result agrees with Wan Mahmood et al. [65], who indicate that OEE leads to higher energy efficiency, labor efficiency, lower production costs, and customer satisfaction.

Finally, for the relationship OPF \rightarrow ESU in H_7 , it is concluded that OF has a direct and positive effect on ESU because when the first variable increases its standard deviation by one unit, the second increases it by 0.173 units and explains 10.2% of its variance. This means that OPF allows more personalized products for specific customers, with small production batches that allow for variety, representing higher sales and economic income because the company is attending more markets.

5.2 Regarding the sensitivity analysis

Sensitivity analysis is important because it allows one to know on a probabilistic basis how one variable may favor another or how it may be or represent a risk, so managers

need to be aware of these scenarios to be able to make decisions.

TPM contributes in the maquiladora industry to more flexible processes by facilitating rapid changeovers because if managers ensure the correct TPM + implementation, they can guarantee 71.0% to achieve QS +. On the contrary, TPM – is a risk for managers, given that it is possible in 65.4% to achieve a QS –. However, it is observed that it is not possible that by having a TPM + and QS – cannot be achieved; furthermore, TPM – is not associated with QS +, which indicates that the investments that managers in the maquiladora industry make in their maintenance programs will always give them greater agility and flexibility in their production processes by making rapid changes.

Furthermore, ensuring proper execution of TPM + activities will help to ensure high levels of machine availability and performance, as well as good product quality through high overall equipment efficiency or OEE +, because TPM + ensures OEE + in 64.5%. Conversely, a TPM – can generate OEE – by 57.7%, representing a risk for managers, as it represents broken machines and, therefore, much idle time or low-quality products, which lowers the OEE index. Furthermore, it is observed that TPM + is not associated with OEE – and that TPM – will never generate an OEE +, as the probabilities are null or almost null.

It is observed that QS + since it is associated with the speed with which changes are made in the production system favors OEE + by 47.6%; however, a QS – can generate an OEE – by 66.7%, which represents a great risk for managers, affecting the flexibility and agility of the production system. Moreover, it is observed that the efforts made to achieve QS + will always be beneficial since the probability of generating OEE – is only 2.4% and that QS – is never associated with an OEE +. Thus, managers should seek to make rapid changes to increase the availability of their machines and not affect OEE rates.

QS is also associated with OPF, and it is observed that QS + favors the occurrence of OPF + by 45.2%, which indicates that rapid changes give flexibility and agility to the production system, allowing the acceptance of small and highly customized production batches. However, QS – favors OPF – by 70.8%, which represents a risk for the manager, as they will not be able to have agility and flexibility. Moreover, it is observed that QS + is very poorly associated with OPF –, as it is linked with only 2.4% and QS – is never associated with OPF +.

OEE + represents agility and speed of the production system and favors the occurrence of 61.8% OPF +, i.e., small batches, which are sought after by managers. However, an OEE – can generate 69.2% of OPF –, which indicates the absence of flexibility. Furthermore, it is observed that OEE + is not associated with OPF – or that OEE – is

not associated with OPF +, as the conditional probabilities are zero. The above indicates that high levels of equipment availability, with quality and calibration, will give agility and efficiency to the machines, improving their return on investment and is the gateway to Industry 4.0.

Finally, it is of great interest to analyze the impact of LM tools on ESU since, although there is no direct relationship, it is possible to obtain a conditional probability through indirect effects. Of the four LM tools analyzed, if these are presented in their high scenario (TPM +, QS +, OEE +, and OPF +), it is observed that they can generate ESU in 54.8%, 52.4%, 58.8%, and 64.0%, respectively, so it is OEE + that has the highest level of influence, which may be because it has a direct effect. However, low levels of LM tools (TPM –, QS –, OEE –, and OPF –) can generate ESU – in 39.3%, 44.4%, 46.8%, and 50%, respectively, with OPF having the highest effect, which may be due to the lack of flexibility and customization of products.

6 Conclusions

This research aimed to quantify the relationship between LM tools associated with machine tending and material flow and the ESU of MMIs. After analyzing 176 responses to a questionnaire applied to this industry sector in Ciudad Juarez, Mexico, the following conclusions can be drawn:

All seven hypotheses posed were statistically significant according to the direct effects; however, the highest relationship is TPM → QS, indicating that implementing maintenance programs facilitates rapid changes in the MMI and the lowest relationship was OPF → ESU, indicating that small batches are an antecedent of the firm's revenues.

However, when analyzing the total effects, it is observed that the TPM → OEE ratio is the highest in the model due to the indirect effect through QS. The above allows us to conclude the importance of TQM as a dependent variable since it is the direct and indirect of QS, OEE, and OPF and ESU.

From Fig. 3, it can be concluded that OEE is a variable that has a highest direct impact than OPF on ESU, which indicates that managers in the IMM should focus on achieving OEE in their production lines, as it ensures quality products, high machine availability and calibration, and high overall performance.

Sensitivity analysis also allows us to conclude very interesting things, and in this case, although some variables do not have a direct relationship, they do have an indirect relationship, and a probability of occurrence has been calculated. The first is that levels of TPM + always facilitate the occurrence of other variables, such as QS +, OEE +, OPF +, and ESU +. In addition, when TPM – occurs, there is also a risk that these variables will

occur at low levels, so managers should focus on achieving adequate levels of TPM.

Moreover, when TPM + occurs, the presence of low levels of the other tools and ESU is low or non-existent, i.e., investments in TPM always yield results that managers will appreciate. Similarly, when TPM – occurs, there are no high levels of the other variables, including ESU. This situation is similar for QS and OEE.

Since ESU is the response variable in the model, all probabilities have been calculated, and in line with what was observed in the direct and total effects, here high levels of OPF is the one that most favors the occurrence of ESU +, indicating that respondents consider it important to have certain levels of customization in the products they manufacture; i.e., for better ESU, it is necessary to have a customer focus. Similarly, OPF – is the highest risk variable for ESU, followed by OEE, as this index integrates product quality.

7 Limitations and future research

Unfortunately, this research was carried out when access to companies in Ciudad Juárez was restricted due to the COVID-19 pandemic, which caused a low response from potential respondents, resulting in a low sample size. Considering that we already have controlled access to some companies, the following is envisaged for future work:

- To conduct the study again in 2024 to perform a longitudinal analysis and analyze the differences and evolution of implementing the LM and ESU tools.
- Apply the survey to other cities and states to conduct comparative analyses since Ciudad Juarez is characterized by maquiladora companies from the USA, and Tijuana, for example, are more from China and South Korea, so the cultural approach must be very different.

The survey consisted of 25 LM tools and three pillars of sustainability (environmental, social, and economic), so further analysis with different tools is being planned.

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Declarations

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Consent to participate No applicable.

Consent for publication No applicable.

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