The International Journal of Advanced Manufacturing Technology
https://doi.org/10.1007/s00170-026-18620-6

ORIGINAL ARTICLE

Mizusumashi as a precursor to the pull and pitch system: Empirical evidence using PLS-SEM

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Received: 26 February 2026 / Accepted: 23 June 2026

Abstract

Lean manufacturing integrates various tools to optimize production processes; however, the hypothesized influence relationships between Mizusumashi, the Pull system, and Pitch have been scarcely explored empirically. This study developed and validated a structural equation model based on partial least squares (PLS-SEM) to examine the direct and indirect interrelationships between these three fundamental constructs of the Toyota Production System. A total of 773 valid responses were collected using a content-validated questionnaire administered to operational and administrative personnel in the maquiladora industry in Ciudad Juárez, Mexico. The results confirmed the three proposed hypotheses ($p < 0.001$): Mizusumashi significantly influenced the Pull system ($\beta = 0.683$, ES $= 0.467$) and Pitch both directly ($\beta = 0.453$) and indirectly through the Pull system ($\beta = 0.259$), with a total effect of $\beta = 0.712$. The Pull system, acting as a mediator, also positively influenced Pitch ($\beta = 0.380$). The model explains 58.5% of the variance in Pitch with a Tenenhaus index (GoF $= 0.619$), which confirms its robustness. The sensitivity analysis based on conditional probabilities shows that when Mizusumashi operates at high levels, the probability of achieving an optimal Pitch is 60.6%, compared with 5.2% when the supply is deficient. These findings provide quantitative empirical evidence of the systemic integration of lean tools and offer criteria for managers to prioritize investments in internal supply systems as a critical antecedent of production synchronization.

Keywords Mizusumashi · Pull production system · Production synchronization · PLS-SEM · Lean manufacturing

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Published online: 29 June 2026

1 Introduction

Lean manufacturing (LM) is a methodology that facilitates the optimization of industrial processes and continuous improvement of productivity on production lines. LM originated in the Toyota Production System (TPS) and has evolved into a holistic approach that seeks to reduce waste and maximize customer value [1]. However, with the growing customization of products, many challenges are currently being faced, as this involves manufacturing small and highly varied batches, which require a frequent supply of parts in small quantities [2].

LM involves the integration of a set of tools that focus on planning, maintaining, and balancing the production. Mizusumashi (MIZ) is one such tool that facilitates the supply of components on production lines. It has been shown that the absence of this approach to defining MIZ operator routes can cause imbalances in workloads, leading to failures in the component supply process and, in turn, operator and machine downtime [3]. For example, the joint application of MIZ and e-Kanban has been shown to reduce inventory by 50% in production areas [4], but when integrated with 5 S, visual management, and Kanban, the MIZ reduced the time required to locate materials to be supplied by 70% [5].

Another LM is the Pull system (PUL), which functions as a made-to-order manufacturing environment in which production begins only after receiving the customer's order, facilitating the flow of materials [6]. The literature has identified 23 attributes of PULs, which are classified into design, stability, and control [7]. It has been found that hybrid systems integrating Kanban and CONWIP (CONstant Work In Progress) reduce work in progress by up to 26% and shorten cycle time by 16% [8], hence their practical significance.

Another important concept in LM is Pitch (PIT), the pace of production synchronized with customer demand, which is intrinsically linked to PUL, in which batches are produced at fixed intervals called PIT [9]. The joint implementation of Heijunka has shown increases of 63% and 39% in human and machine productivity, respectively [10]. Furthermore, synchronizing all activities with the pace of the capacity-constraining resource through PIT has been shown to generates high-impact results [11].

Despite the widespread adoption of lean principles, their core tools have largely been studied in isolation, and the empirical understanding of how MIZ, the PUL, and PIT interrelate remains limited. MIZ has been examined mainly through route design and milk-run optimization [2, 3], whereas the PUL has been characterized through its attributes rather than its antecedents [7], with internal material supply treated as a supporting activity rather than an object of study. Modelling that integrates Kanban systems with JIT has clarified JIT characteristics but has not established relationships between the variables [12]. Therefore, the joint behavior of the three constructs as a single chain has not been tested empirically with a confirmatory model.

This study addresses this gap by developing a structural equation model (SEM) that integrates the MIZ, PIT, and PUL variables and examines their direct and indirect interrelationships. The SEM assumes that the MIZ is an independent construct that directly affects the PUL and PIT, with the PUL acting as a mediator and the PIT as the dependent construct. The main objective was to develop and validate the model to quantify these effects, while a secondary objective was to examine its invariance through multigroup analysis across the respondent's position, seniority, industrial sector, company size, and department of assignment to determine whether the relationships are generalizable or subject to moderating conditions [7]. The PLS-SEM approach was adopted because it has been applied in similar studies to quantify the associations between advanced manufacturing technologies and PUL production systems [13].

1.1 Novelty and contribution of the research

Beyond filling this gap, the contribution of this study lies in quantifying the chain and separating the effect on PIT that travels directly from MIZ to the share mediated by the PUL. This decomposition repositions internal supply as a foundational antecedent that conditions both the functioning of the PUL and the stability of production PIT, rather than as a peripheral logistics function. The sensitivity and multigroup analyses extend this contribution by expressing the relationships in operational terms and testing their generalizability across respondent and organizational characteristics.

The second section presents the theoretical concepts and justifies the hypotheses. The third section reports the methodology used to achieve the objective. The fourth section presents the study results and discusses these issues. Finally, the fifth section presents the study conclusions.

2 Theoretical foundations

2.1 Toyota production system, Just-in-Time, and Theory of Constraints

This study analyzed the relationships between the constructs of the three theories. The first is TPS, the basis of LM, which establishes that production systems operate as integrated sets, in which the fundamental pillars of Just-in-Time (JIT) and Jidoka require the synchronization of multiple operational elements that facilitate the flow of materials [1]. In this context, JIT is an LM tool that allows manufacturing and delivering what is needed, when it is needed, and in the exact quantity [1]. The importance of this systemic perspective allows us to understand the associations between MIZ, PIT, and PUL, since TPS proposes that these do not function independently but rather integrate and complement each other to improve the effectiveness and functioning of production lines.

Finally, the Theory of Constraints (TOC) developed by Goldratt complements the theoretical framework by establishing that every production system has at least one constraint that limits its performance. For example, Baeza-Serrato [11] demonstrated that by identifying, optimizing, and protecting the capacity-limiting resource (CLR) and synchronizing all activities into a continuous flow, performance improves. Therefore, integrating LM principles and synchronous manufacturing provides a basis for understanding how the PUL generates demand signals that determine the production PIT.

2.2 Mizusumashi: The logistics operator in lean systems

The MIZ, sometimes known as a "water spider," is a fixed-route logistics operator that supplies components to production lines [2]. The MIZ is vital in contexts involving customized products with small and highly varied batches, which require a recurring supply of parts in small quantities with high efficiency.

Although MIZ offers balancing advantages, problems have been reported when it is inadequate. For example, Ribeiro et al. [3] indicated that without a method for defining routes, imbalances in workloads are generated, leading to supply failures and downtime for both humans and machines. For their part, Sousa [14] identified specific problems, including component disorganization, picking inefficiencies, imbalances, and poor signage, all of which cause supply delays. Miwa et al. [12] developed a module-based modeling scheme that integrates double-card Kanban systems with MIZ, demonstrating that it is possible to represent systems comprising multiple parts, production lines, suppliers, and fixed-route MIZ, and that their benefits should be analyzed in detail.

2.3 Pull system: Principles and attributes

PUL operates as a made-to-order manufacturing environment, where production begins only after receiving the customer's order, which confirms demand [15]. Gayer et al. [7] developed a holistic method for evaluating PUL, identifying 23 attributes divided into three groups: design, stability, and control. The authors reported that occasional violations of PUL principles can be legitimate and not necessarily detrimental to performance, highlighting their contextual nature.

Despite advances in Industry 4.0, digital Kanban and CONWIP systems have not been widely adopted, and traditional systems remain the preferred options [16]. Ongkowijoyo et al. [17] reported a 13% improvement in supply chain metrics through the application of the Kanban system to implement the PUL.

2.4 Pitch and Heijunka: Synchronized production rhythm

PIT represents a production rhythm that is synchronized with customer demand. Cunha Neto et al. [9] established that PIT is intrinsically linked to PUL, in which batches of any product are produced at fixed intervals called PIT. Gupta and Kumar [10] demonstrated that the implementation of Heijunka led to improvements, with increases of 63% and 39% in human and machine productivity, respectively, by establishing a Heijunka flow at all levels to ensure effective PUL, values that are attractive to managers.

2.5 Justification of Hypotheses

Hypothesis 1. Mizusumashi → Pull System The first hypothesis states that MIZ has a direct and positive effect on PUL. This relationship is based on JIT Theory, which states that production should be carried out by delivering the right materials in the right quantity at the right time [1]. The MIZ physically executes the PUL signals and responds to Kanban cards to replenish points of use. Matos et al. [4] demonstrated this relationship by reporting that the combination of MIZ and e-Kanban reduced the inventory in the production area by 50%. Pombal et al. [5] reported 70 improvements in material location times and 50 improvements in replenishment times by integrating Kanban and MIZ into a production line. Finally, Ramos et al. [18] explicitly recognized the operational interrelationship between MIZ and JIT/Kanban systems in their lean manufacturing simulation platform, leading to the following hypothesis:

> **H_1**. Mizusumashi has a direct and positive effect on the pull system.

Hypothesis 2. Mizusumashi → Pitch The second hypothesis proposes that the MIZ has a direct and positive effect on PIT. This relationship is based on the Continuous Flow Theory of TPS, which states that the flow of materials must be continuous and synchronized with the pace of production. The MIZ maintains a constant supply of components at regular intervals [2]. Without an efficient MIZ, the PIT cannot remain stable because the lines stop owing to a lack of materials. This hypothesis is based on Ribeiro et al. [3], who provided evidence that the absence of a systematic method for MIZ routes directly affects the production place. Pereira et al. [19] demonstrated that optimizing the MIZ system allowed employees to perform all tasks within the stipulated *takt time*, thus evidencing the direct relationship between MIZ efficiency and PIT maintenance. Thus, the following hypothesis is proposed:

> **H_2**. Mizusumashi had a direct and positive effect on the production pitch.

Hypothesis 3. Pull System → Pitch The third hypothesis proposes that PUL has a direct positive effect on PIT. This relationship is based on the Theory of Constraints and principles of synchronized manufacturing. The PUL, based on actual customer demand, establishes the signals that determine the pace at which the production line should operate. Baeza-Serrato [11] demonstrated that by synchronizing all activities to the pace of the RRC, high-impact results are obtained, showing that the production control system determines the PIT. Cunha Neto et al. [9] explicitly established that PIT is intrinsically linked to PUL. Gupta and Kumar [10] provided direct empirical evidence by demonstrating that the transition to PUL, through Heijunka, resulted in substantial productivity improvements. Finally, Cheng et al. [8] demonstrated that hybrid Kanban-CONWIP systems can reduce WIP (Work in Process) by up to 26% and shorten cycle time by 16%, confirming the influence of PUL on production pace. Thus, the following hypothesis is proposed:

> **H_3**. The Pull system has a direct and positive effect on the production pitch.

Figure 1 presents the proposed structural model with the three hypotheses evaluated using PLS-SEM.

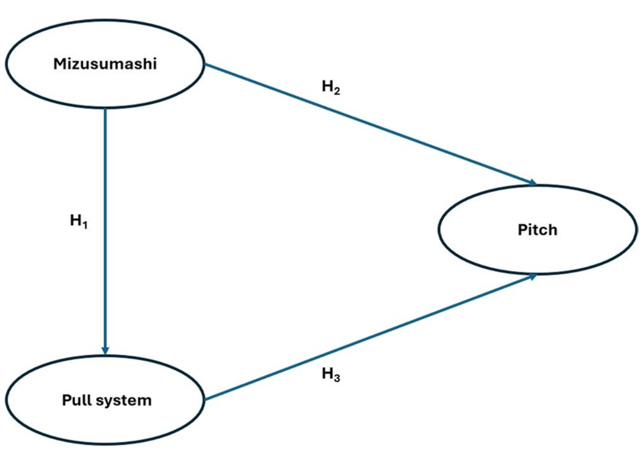

Fig. 1 Proposed PLS-SEM

3 Methodology

3.1 Creation of a questionnaire

This study relates MIZ, PUL, and PIT; therefore, it is necessary to know the items that comprise them. Therefore, a search was conducted for previous studies in which the three constructs had been used to identify those that included them. In this case, the items were obtained from the following sources: MIZ [2, 5, 12, 20]; PUL [7, 21, 22]; and PIT [9–11].

These items were derived from studies conducted in different geographical, cultural, and social environments; therefore, content validation was conducted by judges comprising five academics and six managers working in the industry. To improve the clarity of the items, Aiken's V method [23] was used, and Lawshe's method [24] was used for relevance. After two rounds of judging, a final questionnaire was developed and authorized by the Institutional Research Ethics Committee to ensure compliance with the Declaration of Helsinki.

The questionnaire contained two sections: the first collected demographic data on the respondents and the companies they worked for, while the second collected responses to items from the three latent variables analyzed, which were answered on a 5-point Likert scale [25].

3.2 Application of the questionnaire

The questionnaire was administered in the manufacturing industry in Ciudad Juárez (Mexico), a city in the north of the country that is characterized by its long history in this sector, as there are currently 318 companies of this type [26], all of which have production lines that require supplies, calculate PIT, and use the PUL. In addition, administrative and operational personnel from these companies are easily accessible for interviews.

The questionnaire was administered online using Google Forms and remained open from May 15 to August 15, 2025. A total of 2,328 emails were sent to potential respondents, including a link to the online questionnaire. As an eligibility requirement, only personnel with at least one year of experience in their current position were invited to respond, ensuring that every participant had sufficient familiarity with the supply, PUL, and PIT dynamics of their production lines. If no response was received after two weeks, up to two reminders were sent every two weeks inviting them to participate. If no response was received, the case was dismissed from the study.

3.3 Data cleansing

On August 15, 2025, a database containing the survey responses was downloaded. However, before being analyzed, the following data cleaning activities were performed: first, extreme values were identified through a standardization process for each of the items in the second section of the questionnaire, where values greater than 3 in absolute value were considered outliers and replaced by the median [27]; second, missing values were identified and replaced by the median of each item (this activity was only performed if the number of missing values in each case was less than 10%) [28]; third, non-engaged respondents were identified by standardizing each case, where values greater than 0.5 were excluded from the analysis.

3.4 Validation of constructs and descriptives

Before integrating the constructs into the SEM, a validation process was conducted according to the indices proposed by Kock [29]. For predictive parametric validation, $R^2$and adjusted R^2 were used, which should be greater than 0.2; for internal validation, the composite reliability index and Cronbach's alpha index were used, which should be greater than 0.7; for convergent validity, the average extracted variance (AVE) was used, which should be greater than 0.5; to measure collinearity within the latent variables, variance inflation indices were used, which should be less than 3.3; finally, for non-parametric predictive validity, Q^2 was used, which must be greater than zero and with values similar to R^2.

With the cleaned database, descriptive statistics for the sample were obtained using cross-tabulations for the first section of the questionnaire (demographic data only). For the second section, the median was obtained as a measure of central tendency and the interquartile range as a measure of dispersion, given that the information was obtained on an ordinal scale [30].

3.5 Structural equation model

The associations between the constructs were validated using a structural equation model (SEM) with a partial least squares (PLS) approach, given that the information was obtained on an ordinal scale, which is recommended when normality is not present or the samples are very small [31]. Sarstedt et al. [31] recently used this approach to model supply chains and material flows, and García-Alcaraz et al. [22] used it in the manufacturing industry. PLS-SEM evaluation was performed in WarpPLS v.8 software, where the PLS-Regression algorithm was used to evaluate the input model [32], while the Warp3 algorithm was used to evaluate the output model [33] and resampling by Stable3, as they allow the identification of nonlinear relationships and the confidence intervals of the parameters are more accurate [34].

3.5.1 Model efficiency indices

Before interpreting the model, the constructs were validated according to the indices proposed by Kock [29], such as the average path coefficient (APC), Average R-squared (ARS), and average adjusted R-squared (AARS) to measure predictive validity. These parameters were associated with a p-value of less than 0.05, since all analyses were performed with a confidence level of 95%. To measure collinearity between constructs, the average block VIF (AVIF) and average full collinearity VIF (AFVIF) were used, which must be less than 3.3. Finally, the Tenenhaus GoF index (GoF) is reported as a measure of the fit of the data to the model, and its minimum value must be 0.36. It is important to mention that AVIFs were used in this study as a measure of the common method bias problem.

3.5.2 Direct effects

To validate the three proposed hypotheses, direct effects between the constructs were used [29]. Using PLS, a standardized β-parameter was calculated to measure the association between the constructs. To calculate the statistical significance of this parameter, a hypothesis test was performed, with H_0: $\beta = 0$ versus the null hypothesis H_1: $\beta \neq 0$ with a confidence level of 95%.

If $\beta=0$, it was concluded that there was no relationship between the constructs analyzed; however, if $\beta\neq0$, it was concluded that there was a relationship, regardless of its sign. For each direct effect, the effect size (ES) is reported as a measure of the variance explained by the independent construct in the dependent construct. For the two dependent constructs in the model, the value of $R^2$is reported as a measure of the variance explained in the dependent construct by the independent constructs. Finally, a 95% confidence interval was reported for each parameter β.

To determine whether the sample size was adequate for SEM, the inverse square root and exponential gamma tests were used, which are based on the minimum statistically significant value of β in the model.

3.5.3 Indirect effects and total effects

In this model, the PUL construct acted as a mediator between the MIZ and PIT constructs; therefore, an indirect effect was estimated. As with the direct effects, a β parameter was calculated, and the same statistical significance tests were performed. Finally, the total effect between the

MIZ and PIT constructs was reported, integrating direct and indirect effects. For each of these effects, the effect size was also reported, as well as a 95% confidence interval for the β-parameter.

3.5.4 Sensitivity analysis

This study reports three probabilities that can be obtained from the WarpPLS 8.0 software [35], which are as follows:

1. The probability that a construct will occur at its low or high level of implementation, independently or in isolation.
2. The probability that two constructs associated with a hypothesis will occur in a combination of low and high implementation levels.
3. The conditional probability of the dependent construct occurring at a low or high level, given that the independent construct has occurred at a low or high level.

A low implementation level of the constructs is considered when associated with a standardized value less than -1, while a high implementation level is associated with a standardized value greater than 1.

3.5.5 Multigroup analysis

The sample analyzed had several demographic characteristics among the respondents; therefore, a multigroup analysis was performed, comparing the β coefficients for the subgroups and determining whether there were statistical differences [36]. The grouping variables used were respondents' position (operational vs. administrative), length of service (less than two years vs. two years or more, or novices vs. experts), industrial sector (automotive, electronics/electrical, and others), company size (small vs. large), and department of assignment (production vs. others).

The Satterthwaite method was used for the statistical comparison of β between groups, which is robust when subgroup sizes are different and the homogeneity of variances between them cannot be assumed [36]. In addition, the method adjusts the degrees of freedom based on the variances of each subgroup, generating conservative and reliable estimates compared with the pooled standard error method.

For each multigroup comparison, the β coefficients of each subgroup, the difference between coefficients (Δβ), the associated p-value, and the 95% confidence interval for the differences were reported. Differences with $p < 0.05$ or those that did not include zero in the confidence interval were considered significant.

4 Results and discussion

4.1 Sample descriptives

A total of 788 valid responses were collected from the Google Forms platform, but 4 were discarded because they did not give their consent and were blank, 5 because they had more than 10% missing values, and 6 because they came from uncommitted respondents, leaving 773 responses for analysis. Of the total, 412 were men and 334 were women. A total of 317 respondents were classified as novices, with one to fewer than two years of experience, and 456 as experts, with two or more years of experience. Regarding their roles, 560 held operational positions (operators or technicians), and 213 held administrative positions (engineers, supervisors, and managers). Similarly, 364 responses were identified from companies in the automotive sector, 165 from the electronics/electrical sector, and 244 from other sectors (medical, plastics, and machining). However, 586 were considered large because they had more than 250 employees, and 187 were considered small because they had fewer than 250 employees.

4.2 Descriptive analysis of the items

Table 1 presents the first and third quartiles (Q1, Q3), median, and interquartile range (IQR) for each item, grouped by construct and ordered by descending median. Moderately high ratings were observed for the 15 items evaluated, with medians ranging from 3.674 to 4.168 on a Likert scale. In relation to the MIZ construct, item MIZ1 ("A specific person is responsible for bringing materials to my station") had the highest median (4.168), while MIZ3, which refers to uninterrupted operational continuity, reported the lowest value (3.755) with an IQR of 2.079, indicating heterogeneity in the respondents' answers.

For the PUL construct, the item medians were more tightly clustered (3.674–4.030), with PUL4, which refers to containers or visual signals, standing out. However, PUL1 had the widest IQR (2.394) of all the items analyzed, indicating a lack of consensus regarding when a production run should be started based on an emitted signal. The PIT construct had the most stable and consistent medians. For example, PIT4, which refers to synchronization with specific production rhythms, had a median of 4.134 and the lowest IQR (1.838) in the entire model analyzed, indicating uniformity in the respondents' perception of production synchronization.

Figure 2 complements Table 1 by displaying each item as an interquartile box with its median; within every construct, the items are arranged in descending order of their median. All distributions lie clearly above the neutral point, and the

Table 1 Descriptive analysis of items: quartiles, median, and interquartile range

Items	Q1	Median	Q3	IQR
PUL4. I have containers or signals that indicate when I should produce	2.740	4.03	4.831	2.091
PUL3. The next process "pulls" the work from my station.	2.85	4.011	4.801	1.951
PUL5. I never produce more than the next process can use.	2.72	4.007	4.819	2.099
PUL2. I do not manufacture parts without a specific order for the next process.	2.67	3.987	4.802	2.132
PUL1. I only produce when I receive a signal that my product is required.	2.27	3.674	4.664	2.394
MIZ1. A specific person was responsible for bringing materials to my station.	3.03	4.168	4.908	1.878
MIZ5. I always have the necessary materials without excess inventory.	2.85	4.008	4.795	1.945
MIZ4. The supplier follows a fixed and scheduled route.	2.87	4.002	4.771	1.901
MIZ2. I receive materials at regular and predictable intervals.	2.82	3.968	4.777	1.957
MIZ3. I do not have to interrupt my work to search for materials.	2.58	3.755	4.659	2.079
PIT4. My work is synchronized with specific production rhythms.	3.04	4.134	4.878	1.838
PIT2. I know when I must complete specific production batches.	2.97	4.105	4.864	1.900
PIT3. I have production goals for short time intervals.	2.93	4.057	4.847	1.917
PIT1. I understand the time intervals for moving products on my line	2.77	4.009	4.802	2.032
PIT5. I received regular feedback on my adherence to the pitch.	2.65	3.932	4.761	2.111

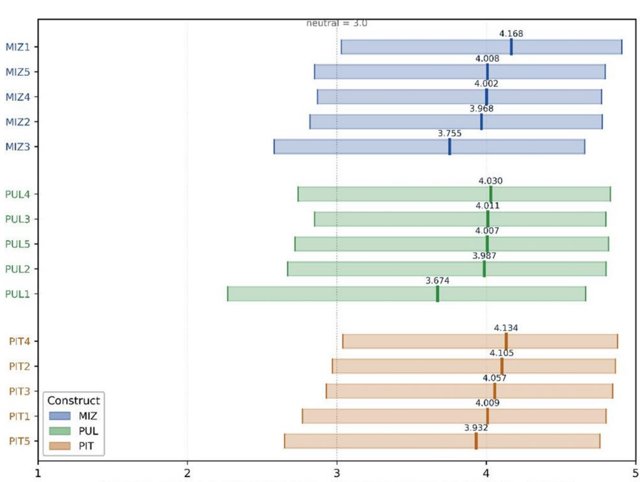

Fig. 2 Median and interquartile range (Q1–Q3) of the questionnaire items by construct

Table 2 Construct validation indices

Index	PUL	MIZ	PIT	Better if
R^2	0.467		0.585	> 0.2
Adjusted R^2	0.466		0.584	> 0.2
Composite reliability	0.919	0.926	0.946	> 0.7
Cronbach's alpha	0.889	0.899	0.929	> 0.7
Average extracted variance	0.694	0.713	0.779	> 0.5
Full collinearity VIF	2.210	2.365	2.391	< 3.3
Q^2	0.467		0.585	> 0
Normal JB	No	No	No	

boxes are left-skewed, indicating a concentration of high-agreement responses. The widest dispersion corresponds to PUL1, whose first quartile drops to 2.27, whereas the PIT items show the most compact boxes, consistent with the greater consistency of the synchronization item.

4.3 Validation of latent variables and model

Table 2 illustrates the psychometric properties of the constructs, and the last column indicates the recommended cutoff value. Regarding parametric predictive validation, the R^2 coefficients for PUL (0.467) and PIT (0.585) indicate that the model explains 46.7% and 58.5% of the dependent constructs, respectively. Similarly, the Q^2 values are greater than zero and similar to those of R^2, indicating non-parametric predictive validity.

Regarding internal consistency, the composite reliability (0.919–0.946) and Cronbach's alpha (0.889–0.929) exceed the critical value of 0.7, indicating sufficient reliability of the constructs. Regarding convergent validity, the AVE values ranged from 0.694 to 0.779, which were greater than 0.5, indicating that the items captured the variance of the constructs to which they related. Similarly, the VIFs are less than 3.3 (2.210–2.391), which allows us to rule out problems of multicollinearity and common method bias. Finally, the Jarque-Bera test shows the absence of multivariate normality, which justifies the use of PLS-SEM as the model estimation technique rather than CB-SEM.

The variables were integrated into the model, and the overall fit indices confirmed their validity and robustness of the model. In this case, the average trajectory coefficient indicates that the relationships between the constructs are statistically significant (APC = 0.510, $p < 0.001$), while the ARS (0.526) and AARS (0.525) values are associated with $p < 0.001$, indicating that the model explains approximately 52.5% of the variance in the endogenous constructs. In addition, the AVIF (1.882) and AFVIF (2.322) indices are less than 3.3, which allows us to rule out problems of collinearity and common method bias. Finally, the Tenenhaus index (GoF = 0.619) was greater than 0.36, which was established as the minimum cutoff value. The evaluated model is illustrated in Fig. 3, and the indices are as follows:

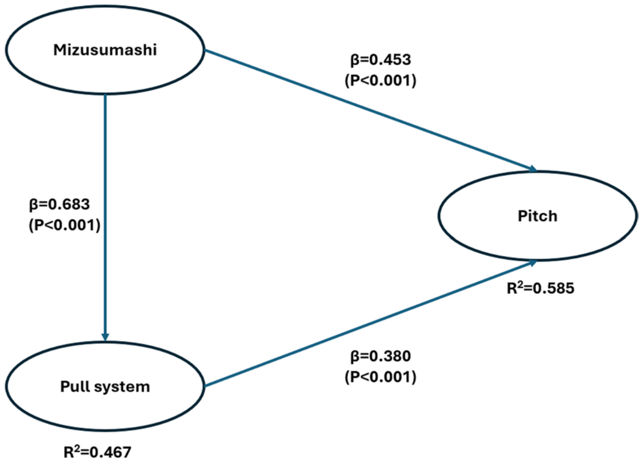

Fig. 3 Model evaluated

Table 3 Discriminant validity: Fornell–Larcker criterion

MIZ	MIZ	PUL	PIT
	0.850		
PUL	0.697	**0.835**	
PIT	0.718	0.693	**0.887**

The diagonal elements (in parentheses) are the square roots of the AVE; the off-diagonal elements are the correlations between the constructs. Discriminant validity is supported when the diagonal value exceeds the off-diagonal values in the row and column

- Average path coefficient (APC) = 0.505, $P<0.001$.
- Average R-squared (ARS) = 0.526, $P<0.001$.
- Average adjusted R-squared (AARS) = 0.525, $P<0.001$.
- Average block VIF (AVIF) = 1.882, ideally <= 3.3.
- Average full collinearity VIF (AFVIF) = 2.322, ideally <= 3.3.
- Tenenhaus GoF (GoF) = 0.619, large >= 0.36.

Discriminant validity was assessed using three complementary criteria, all of which were met. Table 3 shows the Fornell–Larcker criterion, which confirms the discriminant validity of the constructs, as the square root of the AVE of each construct (0.850 for MIZ, 0.835 for PUL, and 0.887 for PIT) is greater than its correlation with any other construct, the largest of which was 0.718 between MIZ and PIT; each construct shares more variance with its indicators than with the remaining ones. The inspection of structure loadings and cross-loadings pointed in the same direction, as each indicator loaded more strongly on the construct it was supposed to measure, with loadings ranging from 0.801 to 0.911, than on any other construct.

Additionally, the heterotrait–monotrait ratio of correlations (HTMT) was checked as a more stringent criterion for discriminant validity. The complete set of ratios, significance values, and confidence intervals are available in the Supplementary Material. The three ratios were 0.760, 0.775, and 0.783, which are all below the conventional cut-off of 0.90, with p-values lower than 0.001, and the 90% confidence intervals excluded the value of one in all cases. The agreement of these criteria confirms that MIZ, PUL, and PIT are empirically distinct constructs.

Table 4 Direct effects

Hypothesis	β (LCI-UCI)	ES	Conclusion
H_1. MIZ→PUL	0.683 ($P<0.001$) (0.617, 0.749)	0.467	Supported
H_2. MIZ→PIT	0.453 ($P<0.001$) (0.386, 0.520)	0.323	Supported
H_3. PUL→PIT	0.380 ($P<0.001$) (0.312, 0.448)	0.262	Supported

Table 5 Total effects

To:	From:	
	MIZ	PUL
PUL	β = 0.683 ($P<0.001$) (0.617–0.749) ES = 0.467	
PIT	β = 0.712 ($P<0.001$) (0.645–0.778) ES = 0.508	β = 0.380 ($P<0.001$) (0.312–0.448) SE = 0.262

Figure 3 shows that the lowest β was 0.380 in the relationship between PUL and PIT; therefore, it was used to calculate the sample size for this study. The results indicate that the inverse square root method requires 43 responses, while the gamma-exponential method requires only 30, allowing us to conclude that this requirement is met, since the sample size was 773 responses (see Supplementary Material with graphs).

4.4 Model analysis

Table 4 illustrates the direct effects between the constructs measured through β, the associated p-values for statistical significance, effect sizes (ES), and 95% confidence intervals. According to the p-value, the three proposed hypotheses are accepted, and it is observed that the most robust relationship is MIZ→PUL with β = 0.683 in H_1, where MIZ explains up to 46.7% of the variance in PUL, while the MIZ→PIT relationship is modest with β = 0.453 and has an effect size of 32.3%; and finally, in the PUL→PIT relationship with β = 0.380, PUL explains up to 26.2% of the variance in PIT. None of the confidence intervals for the β parameters included zero, confirming the stability of the estimates.

In this model, PUL serves as a mediator between MIZ and PIT; therefore, there is an indirect effect between these constructs of β = 0.259 ($P<0.001$) and ES = 0.185, which is statistically significant. Therefore, Table 5 was constructed with the total effects, integrating the indirect effects.

Table 6 presents the results of the sensitivity analysis. In this study, high levels of implementation in the constructs are represented by the sign "+" and low levels by "-", while

Table 6 Probability-based sensitivity analysis

			MIZ		PUL	
			+	-	+	-
			0.220	0.173	0.232	0.162
PUL	+	0.232	&=0.132 IF = 0.600			
	-	0.162	&=0.003 IF = 0.012	&=0.107 IF = 0.619		
PIT	+	0.211	&=0.133 IF = 0.606	&=0.009 IF = 0.052	&=0.131 IF = 0.564	&=0.005 IF = 0.032
	-	0.182	&=0.004 IF = 0.018	&=0.182 IF = 0.657	&=0.006 IF = 0.028	&=0.105 IF = 0.648

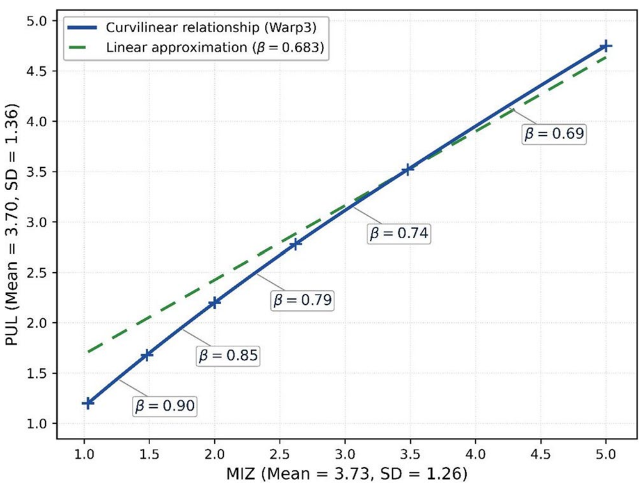

Fig. 4 MIZ→PUL relationship

the probabilities of occurrence in isolation are found in the third row and column for both levels, the joint probabilities are indicated by the sign "&", and the conditional probabilities by "IF". Thus, for example, the probability of MIZ occurring at a high level (MIZ+) in isolation is 0.220, but the probability of MIZ occurring at a low level (MIZ-) is 0.173. Similarly, the probability of MIZ + and PUL+ occurring together (P(MIZ+∩PUL+)) was 0.132, whereas the probability of PUL+ occurring given that MIZ + had occurred (P(PUL+|MIZ+)) was 0.600. More in-depth analyses and their implications are provided in the discussion of the results.

4.5 Analysis of Hypothesis H1: Mizusumashi → Pull System

This hypothesis proposes that the MIZ influences PUL, and the model evaluation indicates that this was the most robust relationship, with β = 0.683 (95% CI: 0.617–0.749) and an effect size of 0.467, indicating that the MIZ explains up to 46.7% of the variance in PUL. Sensitivity analysis showed that when MIZ+ occurs, PUL + can occur in 60% of cases, indicating a strong relationship between these constructs. However, when MIZ is poorly implemented, PUL implementation levels may be obtained in 61.9% of cases, representing an operational risk due to a lack of supply that compromises the flow of all materials.

Figure 4 illustrates the relationship between MIZ and PUL through a marginal effect that decreases smoothly as the internal supply matures. The slope is steepest at the lowest levels of supply, where β reaches 0.90 in the MIZ range close to 1.03–1.48, and then declines in successive steps to 0.85, 0.79, and 0.74 as MIZ rises through the intermediate range, settling at 0.69 once supply approaches its highest levels, above an MIZ of roughly 3.48. The absence of a turning point indicates a concave but monotonic pattern rather than an inverted U, so that every additional improvement in internal supply continues to strengthen the PUL although by a progressively smaller margin.

This progression defines two operating regions with distinct managerial implications. While internal supply remains irregular, each improvement in route definition and replenishment discipline yields a large gain in the functioning of the PUL because dependable material availability is the precondition on which kanban signaling and made-to-order flow rest. This is the high-yield stage typical of plants that still operate with non-standardized routes. As supply becomes reliable and shortages grow rare, the marginal contribution of further logistic refinement diminishes, because the operation of the PUL is then governed increasingly by its own design, stability, and control attributes. Nevertheless, the relationship remains strong across the entire range, with β never falling below 0.69, which indicates that internal supply continues to sustain the PUL even at high maturity instead of becoming negligible. Therefore, the largest gains accrue early, and the systematization of supply, once achieved, must be maintained as a stable foundation rather than treated as a one-off intervention.

The analysis of this relationship coincides with Matos et al. [4], who indicated that the application of MIZ and E-kanban achieved a 50% reduction in inventory, as well as with Pombal et al. [5], who mentioned 70% improvements in location times when kanban and MIZ were integrated simultaneously. However, there are differences with Gayer et al. [7], who pointed out that occasional violations of PUL principles may not affect material flow performance; however, in our study, the results indicate a high dependency on the PUL principle. This discrepancy may be due to the contextual environments of the studies, as Gayer et al. [7] conducted their study in multiple industrial sectors, while ours focuses solely on the manufacturing industry.

These results have managerial implications, indicating that investments in the MIZ should precede and accompany the implementation of the PUL. Therefore, establishing fixed, scheduled routes for suppliers and delivery schedules to ensure that materials are available without excess is recommended. Finally, note that the probability of success in PUL when MIZ operates efficiently was 0.600, indicating that it is successful 60% of the time, which helps justify economic investments in training and standardization of logistics routes within production lines.

4.6 Analysis of Hypothesis H2: Mizusumashi → Pitch

This hypothesis proposes that MIZ has an effect on PIT, which was β = 0.453 with ES = 0.323, indicating that it explains 32.3% of its variance; however, there is an indirect effect through PUL, which was β = 0.259 with SE = 0.185, resulting in a total effect of β = 0.712 with an ES = 0.508. In other words, the MIZ can directly and indirectly explain up to 50.8% of the variance in the PIT. The decomposition of this variance indicates that 63.6% of the total effect was direct, while 36.4% was indirect through the mediator PUL.

The analysis of conditional probabilities shows asymmetries that must be analyzed; for example, P(PIT+|MIZ+) = 0.606 indicates that efficient implementation of routes through the MIZ can generate PIT + 60.6% of the time. However, P(PIT+|MIZ −) = 0.052 indicates that the absence of MIZ prevents the presence of PIT, as

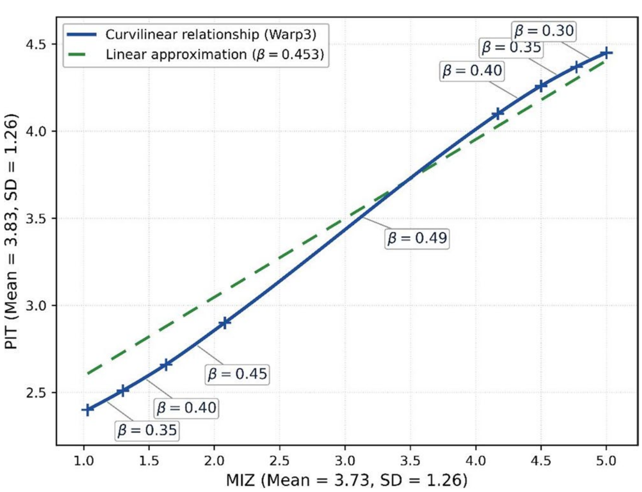

Fig. 5 MIZ→PIT relationship

the probability is almost zero. On the other hand, P(PIT-|MIZ-) = 0.657 confirms the above, since the presence of MIZ- can lead to PIT- in 65.7% of cases, indicating a lack of synchronization in the production system.

Figure 5 illustrates the nonlinear relationship between the MIZ and PIT. The slope rises from β = 0.35 at low MIZ levels to a maximum of β = 0.49 in the intermediate range (MIZ ≈ 2.08–4.17) and then declines to β = 0.30 at the highest levels, describing an inverted-U pattern in the marginal effect rather than a constant one. This pattern defines three operating regions with distinct managerial meanings. While MIZ remains low, modest improvements in internal supply yield progressively larger gains in PIT, the high-yield stage typical of plants that still operate with irregular replenishment and unstandardized routes of supply. The effect peaks in the intermediate range, where materials arrive reliably and line interruptions become infrequent, so that replenishment improvements exert their maximum influence on the production rhythm; this band represents the point of greatest operational return. Beyond MIZ ≈ 4.17, the effect weakens because once routes are standardized and shortages are rare, the constraints on synchronization shift to other factors such as machine reliability, workforce balancing, setup times, and bottleneck capacity.

Therefore, the practical reading is one of diminishing marginal returns, which suggests a sequence for lean investment: supply is stabilized first through fixed routes and replenishment schedules; effort is then concentrated on the intermediate range, where synchronization gains are largest; and resources are redirected towards PUL refinement, Heijunka, and bottleneck management once internal supply reaches maturity.

The results of this study coincide with Pereira et al. [19], who, by optimizing the MIZ system, ensured that employees completed all tasks within the scheduled takt time, and with Kock [36], who indicated that the absence of MIZ routes negatively impacts the pace of production lines. Similarly, the conceptual work of Gil-Vilda et al. [2] on frequent but small-quantity supplies to promote production efficiency is empirically supported in this study.

However, our study differs from Baeza-Serrano [11], who emphasized synchronization with the capacity-limiting resource (CLR) as a determinant prior to PIT. Our study suggests that logistics supply has a comparable or greater effect, which may be because a poorly implemented MIZ often becomes the RRC of the production system, limiting its pace regardless of the capacity of the available workstations.

Considering these results, managers must recognize that the MIZ has a direct and indirect effect (through PUL) on PIT; therefore, they must monitor supplier performance indices and production synchronization metrics, always establishing feedback systems between the PIT obtained and the MIZ routes. Similarly, they should invest in both channels (direct and indirect) to maximize the benefit, as the total effect can explain up to 50% of the variance in PIT, allowing us to establish that improvements in the MIZ should be a high-return strategy that optimizes production flow.

4.7 Analysis of Hypothesis H3: Pull System → Pitch

This hypothesis proposes that PUL has a direct effect on PIT, and the results indicate that β = 0.380 with ES = 0.262; that is, PUL explains up to 26.2% of the variance in PIT. However, PIT is also influenced by the MIZ (ES = 0.323), so the total variance explained is 0.585, which is equivalent to the value of R2. The probability analysis shows that P(PIT+|PUL+) = 0.564, which confirms that PUL helps to maintain synchronized PIT 56.4% of the time; however, P(PIT-|PUL-) = 0.648 indicates that the absence of PUL leads to low PIT levels and a lack of synchronization 64.8% of the time. In addition, it can be seen that P(PIT+|PUL-) = 0.032, confirming that the absence of PUL is not associated with high PIT. The comparison of P(PIT+|PUL+) = 0.564 and P(PIT+|MIZ+) = 0.606 indicates that MIZ has a greater impact on PIT than PUL.

Figure 6 illustrates the relationship between PUL and PIT through a marginal effect that declines steadily as the PUL consolidates. The slope is largest where the PUL is least developed, with β close to 0.45 in the PUL range of 1.11–1.99, and falls in regular steps to 0.40, 0.36, and 0.31 as PUL increases, reaching 0.27 at the highest levels, above a PUL of approximately 4.44. As in the MIZ–PUL relationship, the decline is smooth and monotonic, which points to diminishing marginal returns without a turning point: each additional advance in the PUL keeps improving PIT, but by an increasingly smaller amount.

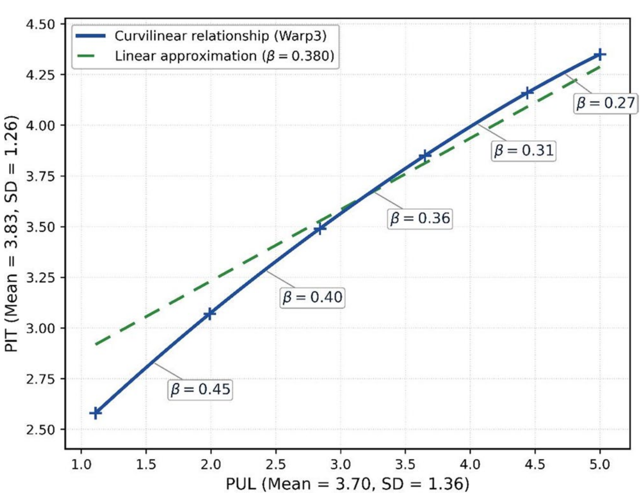

Fig. 6 PUL→PIT relationship

This progression defines two operating regions, analogous to those observed for the internal supply. Where the PUL is still incipient, introducing its basic mechanisms, such as empty-container signals, demand-driven replenishment, and work-in-progress limits, produces large gains in the regularity of production PIT because the system is moving from an environment of overproduction and erratic flow towards one paced by downstream demand; this is the stage of greatest operational return. As the PUL consolidates, additional refinement yields progressively smaller improvements in PIT because synchronization becomes less constrained by the PUL mechanisms themselves and more by factors such as machine reliability, setup times, workforce balancing, and the capacity-limiting resource. The persistence of a positive slope across the range nonetheless confirms that a well-functioning PUL continues to contribute to a stable PIT even at advanced levels, although its weight relative to internal supply remains the smaller of the two, consistent with the comparison of conditional probabilities reported above.

The results of this study align with Cunha Neto et al. [9], who established an intrinsic link between PIT and PUL, as well as with García-Alcaraz et al. [21], who reported improvements of 63% in human productivity and 39% in machines through the transition to PUL using Heijunka. Similarly, they align with Cheng et al. [8], who reported reductions of 26% in WIP and 16% in cycle time through hybrid Kanban-CONWIP systems, confirming that the PUL influences production time metrics. However, Lanouari et al. [16] indicate that digital Kanban and CONWIP systems have not been widely adopted despite advances in Industry 4.0. However, our findings, obtained in a context where traditional systems predominate, suggest that the effectiveness of PUL over PIT does not depend exclusively on digitization.

These results imply that, in practice, the implementation of PUL systems must be accompanied by other mechanisms that enable production lines to synchronize. Therefore, it is recommended to use containers and signals that indicate when they are empty to avoid wastage. However, subsequent production processes must emit clear demand signals to avoid overproduction through strict WIP. When reviewing the probability results, it can be seen that an ideal PIT can be obtained 56.4% of the time when the PUL is adequate; however, when the PUL fails or is poorly implemented, the probability drops to only 3.2%. This difference helps justify investments in training that enable a PUL production system and visual infrastructure using Kanban signals.

Figure 7 combines the three relationships in a plot that shows the evolution of the local effect β across the ranges of each predictor. The comparison shows that the supply driven paths behave differently: both the MIZ→PUL and

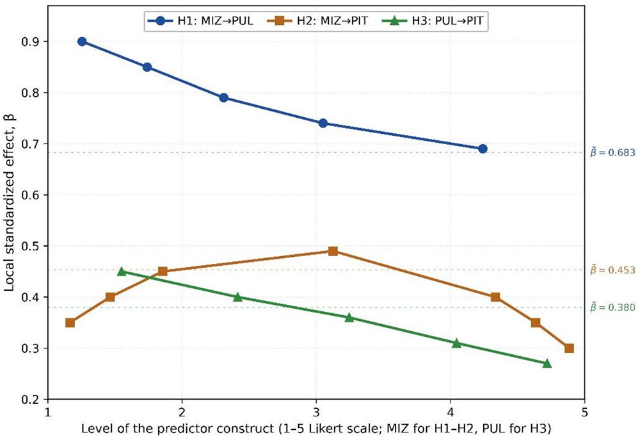

Fig. 7 Combined view of the three hypotheses: evolution of the local standardized effect (β) across the range of predictor construct

Table 7 Summary of the multigroup analysis

Grouping	Groups compared	*N* per group	Significant difference	Main finding
Position	Operational vs. Administrative	560 vs. 213	No	Invariance between hierarchical levels
Seniority	Novice vs. Experts	317 vs. 456	No	Consistent perception independent of experience
Industrial sector	Automotive/Electronics/Other	364/165/244	Yes (MIZ→PIT)	Electronics differs significantly from other sectors
Company size	Large vs. Small	586 vs. 187	No	Scalable structural relationships
Department	Production vs. Others	496 vs. 277	No	Invariance between functional areas

PUL→PIT paths show diminishing marginal returns, with β monotonically decreasing with the maturity of the predictor, while the MIZ→PIT path displays an inverted-U shape that peaks at an intermediate level of internal supply. In all three cases, the local coefficient deviates from the constant value a linear specification would imply (dashed lines), further confirming the appropriateness of the nonlinear Warp3 estimation.

4.8 Multigroup analysis

Due to space constraints, the complete results of the multigroup analysis are reported as supplementary material, so only a description of each category is provided. Table 7 summarizes the analysis of the five categories analyzed, the groups compared, the size of each group, the significant differences, and the interpretation.

4.8.1 Respondent's position

In this category, operational staff ($n = 560$) were compared with administrative staff ($n = 213$), and no significant differences were found in the three relationships analyzed ($p > 0.05$). The MIZ→PUL effect was greater among administrative staff ($\beta = 0.761$) than among operational staff ($\beta = 0.650$), but the difference ($\Delta\beta = 0.111$) was not statistically significant ($p = 0.119$). Similarly, the PUL→PIT relationships indicated comparable coefficients between the groups ($\beta = 0.393$ vs. $\beta = 0.349$, $p = 0.569$). These results indicate that the respondents' perception of the relationships between MIZ, PUL, and PIT is homogeneous, regardless of the hierarchical level. Therefore, invariance between hierarchical levels is demonstrated, indicating that training programs related to lean manufacturing can be designed in a unified manner without differentiation by position, thereby optimizing the resources allocated to training and education.

4.8.2 Seniority

The analysis indicated that no significant differences were found between novice employees with one to fewer than two years of experience ($n = 317$) and experts with two or more years of experience ($n = 456$). The differences between the coefficients are minimal in all relationships: MIZ→PUL ($\Delta\beta = 0.045$, $p = 0.496$), PUL→PIT ($\Delta\beta = 0.004$, $p = 0.955$), and MIZ→PIT ($\Delta\beta = 0.011$, $p = 0.870$). This result indicates that the perception of MIZ-PUL-PIT relationships is not influenced by work experience, as it shows that novices quickly integrate into the operational dynamics of a lean system. This may be due to the observable and tangible nature of the MIZ and the use of PUL visual signals on production lines. These results allow us to conclude that an understanding of lean manufacturing tools is quickly acquired on the job, indicating that managers can rely on the perceptions of novice employees to identify problems in material flow.

4.8.3 Industrial sector

This sector was the only one in which a statistically significant difference was found, which was in the MIZ→PIT relationship for the electronics/electrical ($\beta = 0.318$) and other ($\beta = 0.523$) sectors, with $\Delta\beta = 0.206$ ($p = 0.028$). However, the relationship between the automotive ($\beta = 0.470$) and electronics ($\beta = 0.318$) sectors is very close to being different, as $\Delta\beta = 0.152$ ($p = 0.083$). Furthermore, in this grouping, the electronics sector has the lowest coefficient in the MIZ→PIT relationship but the highest in PUL→PIT ($\beta = 0.462$), suggesting that PIT depends more on PUL than on MIZ or direct supply in this sector or that this sector has greater standardization of electronic components with short production cycles. Therefore, it is concluded that the industrial sector moderates the MIZ→PIT relationship, which implies that lean implementation strategies should be applied on a sectoral basis, thereby strengthening the PUL of the electronics sector.

4.8.4 Company size

In this grouping, no significant difference was found between large companies with more than 250 employees ($n = 586$) and small companies with fewer than 250 ($n = 187$) for any relationship between constructs. Although the MIZ→PIT effect was greater in small companies ($\beta = 0.521$ vs. $\beta = 0.416$), the difference ($\Delta\beta = 0.105$) was not significant ($p = 0.174$). In this grouping, it is interesting to note that large companies have a greater PUL→PIT effect ($= 0.407$ vs. $\beta = 0.334$), indicating that formal PUL structures are effective in companies with large-scale, standardized production. However, these structural relationships are statistically robust, regardless of company size, which validates the universal application of the proposed model.

These results allow us to conclude that organizational size does not compromise the validity of the structural model presented, indicating that MIZ-PUL-PIT relationships are scalable and that small and medium-sized companies can implement MIZ, expecting to obtain effectiveness rates comparable to those of large corporations, which democratizes the benefits obtained from lean manufacturing.

4.8.5 Department

In this grouping, no significant differences were identified between personnel belonging to the production department ($n = 496$) and others ($n = 277$), as the β values were similar for all relationships: MIZ→PUL ($\Delta\beta = 0.015$, $p = 0.826$), PUL→PIT ($\Delta\beta = 0.084$, $p = 0.236$), and MIZ→PIT ($\Delta\beta = 0.068$, $p = 0.334$). However, it is important to note that the production staff had a greater effect on the MIZ→PIT relationship ($\beta = 0.476$ vs. $\beta = 0.408$), which was not statistically significant. This invariance suggests that the benefits of MIZ today transcend functional boundaries, impacting the perception and need for synchronization of those who work directly on the production lines as well as those who provide support and depend on the flow of materials in the automotive industry. This consistency in perception implies that improvement initiatives in the MIZ and PUL can involve multi-departmental teams, as the benefits are known across the board, facilitating successful interdepartmental collaboration.

4.9 Recommendations connected to business outcomes

The managerial implications for each hypothesis converge on a set of actions whose value can be expressed in measurable business terms. As suggested above, the formalization of internal supply through fixed and scheduled routes is linked to production continuity and fewer line stoppages due to component shortages, whereas controlled replenishment without surplus contributes to lower inventories and more reliable delivery performance. The diminishing marginal returns of the three relationships provide a criterion to use the lean implementation budget more effectively by focusing early investment to stabilize supply and changing it to PUL-system development, Heijunka, and bottleneck management as soon as MIT reaches operational maturity. Finally, the structural invariance across position, seniority, company size, and department allows lean training to be delivered as a single unified program, containing training costs, while the synchronization achieved through these actions sustains higher productivity across the production line. The only caveat is the sectoral conditions, as the electronics and electrical sector gain more from strengthening the PUL system than direct supply.

5 Conclusions

This study developed and validated a partial least squares structural equation model (PLS-SEM) to examine the hypothesized influence relationships between MIZ, PUL, and PIT in the context of LM. Based on 773 valid responses obtained from the Mexican maquiladora industry, the results confirm the three proposed hypotheses with statistical significance ($p < 0.001$), showing that MIZ is a critical antecedent for both the operationalization of PUL ($\beta = 0.683$, $ES = 0.467$) and the maintenance of production PIT. The dual structure of the effects identified in the MIZ→PIT relationship reveals that 63.6% of the total effect ($\beta = 0.712$) is direct, while the remaining 36.4% flows through the

PUL system as a mediator, underscoring the importance of both influence pathways for production synchronization. The overall model explains 58.5% of the variance in PIT, far exceeding the recommended minimum thresholds and demonstrating robust predictive power, as validated by the Tenenhaus index (GoF = 0.619).

In addition, the multigroup analysis using the Satterthwaite method indicated that the proposed model is robust and invariant in four of the five demographic categories analyzed: job position, seniority, organization size, and department of affiliation of the respondent. A significant difference was found in the electrical electronics sector (β = 0.318) for the MIZ→PIT relationship compared to other sectors (β = 0.523, $p = 0.028$), indicating that the supply to maintain production rates varies according to sector characteristics.

From a theoretical perspective, this study contributes to the literature on LM by providing quantitative empirical evidence on relationships that had previously been established mainly conceptually or through isolated case studies. The findings support and extend the theoretical frameworks of the Toyota Production System and Theory of Constraints, suggesting that the systemic integration of lean tools is associated with measurable synergies beyond their individual effects. From the perspective of invariance, this study indicates that the hypothesized influence relationships between MIZ, PUL, and PIT are generalizable regardless of employees' hierarchical level, work experience, company size, and functional area of assignment. This result externally validates the model and suggests that the principles of lean manufacturing tools operate interchangeably across various industries. However, the moderation of the industrial sector in the MIZ→PIT relationship indicates that there are conditions that alter the magnitude of the effects, which enriches the understanding of the nature of the relationships between lean manufacturing tools that have been reported by Gayer et al. [7].

From a practical standpoint, this study offers managers an evidence-based criterion for prioritizing lean investment: systematizing internal supply through MIZ emerges as a precondition for the PUL system and stable production PIT rather than a secondary logistics concern. The presence of diminishing marginal returns further suggests that early investment in supply stabilization yields the highest returns, while structural invariance across position, seniority, company size, and department supports a unified approach to lean training and extends the model's applicability to small- and medium-sized firms. Detailed managerial actions and their connection to business outcomes are presented in Sect. 4.9.

5.1 Limitations, benefits and future research

These results should be interpreted considering the following limitations. Data were collected from the maquiladora industry in Ciudad Juarez, Mexico, which may restrict the transferability of the results to other geographical or industrial contexts with different operational characteristics. Another limitation is the cross-sectional design: the model is based on established theory, and the relationships estimated are consistent with previous evidence; however, the data reflect associations and theory-consistent directional relations at one point in time and do not confirm temporal causality among the constructs. Finally, the use of self-reported perceptions could lead to social desirability bias, but the full collinearity VIF values make a serious common method bias problem unlikely.

Despite these limitations, the research has benefits at two levels. In theory, it provides quantitative empirical support for a MIZ-PUL-PIT chain that had previously been supported only by conceptual arguments or by a few case studies, and it specifies how the effect on PIT is distributed between the direct and indirect pathways. In practice, the model provides managers with an evidence-based basis for sequencing lean investment and for anticipating the operational and financial results outlined in Sect. 4.9, including more continuous production, lower inventory, fewer line stoppages, more reliable deliveries, more efficient use of the lean budget, contained training costs, and higher productivity through synchronization.

Given these limitations, future research should explore several directions. For example, testing the model in other geographical and industrial contexts outside the maquiladora industry will help determine whether its invariance extends across different cultural and economic environments. Given that no significant differences were found regarding company size, seniority, or position, future studies could examine whether other variables, such as lean maturity, the degree of digitalization of production processes, or organizational culture, have a moderating effect. Sectoral contrasts seem to be a particularly promising avenue, given the lower dependence on MIT in the electronics industry. Finally, longitudinal designs would allow for tracking the temporal dynamics of these relationships and testing the invariance of the model across successive stages of lean implementation maturity.

Supplementary Information The online version contains supplementary material available at https://doi.org/10.1007/s00170-026-18620-6.

Acknowledgements Jorge Luis García Alcaraz is grateful for the scholarship granted by the Secretariat of Science, Humanities, Technology and Innovation (SECIHTI) of Mexico for a sabbatical stay at the Autonomous University of Baja California – Ensenada Campus.

The authors would also like to express their sincere gratitude to the managers, engineers, and supervisors from the Mexican maquiladora industry, who generously participated in this study. We recognize that your professional responsibilities demand significant amounts of time and effort; as such, we deeply appreciate your willingness to contribute to this research despite your busy schedule. Their valuable information and practical experience were essential for the successful conclusion of this study, and we hope that the results will be useful to them.

Funding This research received no specific grants from any funding agency in the public, commercial, or not-for-profit sectors.

Data availability The datasets generated and analyzed during the present study are available as supplementary material and from the corresponding author upon reasonable request.

Code availability Not applicable.

Declarations

Ethical approval This study was conducted in accordance with the ethical standards of the Institutional Research Committee and the 1964 Helsinki Declaration and its later amendments. The final version of the questionnaire was evaluated and approved by the Institutional Research Ethics Committee (approval number CEI-2022-1-613).

Informed consent Informed consent was obtained from all the participants included in the study.

Conflict of interest The authors declare no conflicts of interest.

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