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The effect of Kanban on just-in-time, one-piece flow and economic sustainability in Mexican maquiladoras

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Abstract

This study examines the interrelationships between Kanban (KAN), One-Piece Flow (OPF), Just-In-Time (JIT), and economic sustainability (ENS) in the Maquiladora industry of Ciudad Juarez, Mexico. The research analyzes data from 511 industry professionals to assess the efficacy of these lean manufacturing tools in enhancing operational and economic performance. The variables are related using five hypotheses validated using a structural equation model. The results reveal that Kanban significantly boosts JIT and OPF efficiencies, with respective variances explained as 16.6% and 35.6%. Additionally, the findings demonstrate that OPF substantially contributes to JIT efficiency, underlining the critical role of seamless production flow in optimizing JIT systems. Both JIT and OPF positively impact ENS, highlighting the potential of lean practices to promote cost reduction and profit enhancement. The study underscores the importance of integrating lean methodologies to drive sustainable economic benefits in manufacturing. Future research should explore the longitudinal effects of these practices and their applicability across diverse industrial contexts, considering the integration of technological advancements to streamline operations further.

Keywords: Kanban, one-piece flow, economic performance, structural equation model.

1. Introduction

Just-in-Time (JIT) aims to eliminate all sources of production waste by ensuring the precise delivery of the necessary quantity of product at the right location and time. Central to the JIT system is the Kanban (KAN) methodology, which plays a crucial role in guiding the operations of manufacturing organizations (Yurdakul et al. 2020). KAN is indispensable for managing the production process and facilitating communication across production units (Kojima et al. 1998). Defined variably by scholars as methods, methodologies, subsystems, mechanisms, scheduling systems, and tools, KAN is a pull method that regulates production rates and inventory levels according to customer demand forecasts, functioning through a signal that prompts suppliers to produce and deliver a new batch as existing materials are utilized (Cheng et al. 2015).

KAN is recognized as one of the simplest yet most effective and economical methods for managing production and inventory (Mukhopadhyay and Shanker, 2005). It is also a component of the Toyota Production System (TPS), which is occasionally devised to manage inventory levels, production, and the supply of components, including raw materials (Lage Junior and Godinho Filho 2010). Essentially, KAN serves as a Material Flow Control mechanism, regulating the quantity and timing of production to meet specific requirements (Graves et al. 1995).

KAN effectively enhances team productivity by minimizing downtime, thereby optimizing logistics from a production standpoint and facilitating JIT implementation (Wakode et al. 2015; Ohno 2019). The system is characterized by its principles of work visualization, limiting work-in-process (WIP), focusing on workflow, and fostering continuous improvement. It incorporates cards and containers; cards indicate when materials need to be moved within a facility or from an external supplier to the production site, thereby hastening product replenishment, while containers with removable cards containing product details are exchanged in a cycle that involves warehouses and suppliers to maintain material flow (Wakode et al. 2015).

Thus, KAN is recognized as a versatile visual management methodology applicable across various contexts and organizations. This approach, predicated on visualizing and controlling workflows, offers numerous benefits, including reduced inventories, minimized stock-outs, reduced reliance on computers, lowered overhead costs, and enhancements in empowerment, service, and quality (Monden 2011). It also boosts productivity by enhancing visibility, collaboration, and delivery times (Senapathi and Drury-Grogan 2021), while curtailing email usage, improving deadline management, and overcoming challenges associated with managing electronic resources (McLean and Canham 2018). Particularly in software companies, KAN is instrumental in increasing work visibility, reducing errors, streamlining development processes, and enhancing team coordination (Ahmad et al. 2016).

From an economic standpoint, KAN generates significant benefits by optimizing inventory control, enhancing flexibility, and reducing operational costs (Mojarro-Magaña et al. 2018). Electronic KAN systems enhance stock management, reduce warehouse operator hours, and improve inventory level management (Phumchusri and Panyavai 2015).

In manufacturing, KAN ensures uniform workflow and adapts seamlessly to fluctuating capacity needs, thereby improving inventory management, production, and component supply. Adopting KAN is a strategic approach to achieving business efficiency, quality, and satisfaction in product and service development and maintenance. Moreover, KAN synergizes with other lean manufacturing tools, facilitating material flow along assembly lines and endorsing the production of only necessary quantities, positioning it as a precursor to the JIT and one-piece flow (OPF) methodologies. Studies highlight KAN's critical role in enhancing JIT performance alongside other practices such as team readiness, pull system support, and supplier quality (Sakakibara et al. 1993; Li and Barnes 2000). Using signaling systems to facilitate material flow through OPF translates into tangible economic advantages (Wänström and Medbo 2009). However, it has been noted that KAN initiatives are often discontinued early in the implementation phase due to challenges in measuring the accrued benefits (Jagan Mohan Reddy et al. 2021).

This article aims to quantify the interrelations between KAN, JIT, and OPF and how these relationships yield economic sustainability (ENS) for companies. To this end, a structural equation model is utilized, gathering data from the industry to statistically validate these relationships and provide empirical insights into their economic impacts.

Quantifying the relationship between the variables analyzed in this study will allow industry managers to prioritize resource allocation and better assign resources to different programs, ensuring sound financial performance.

Following this introduction, the subsequent sections propose hypotheses, outline the methodology, present findings, and discuss these in detail, offering conclusions and recommendations.

2. Hypotheses and literature review

2.1. Relationship between KAN and JIT

JIT originated as a strategic approach to management, primarily focused on tailoring supply and production rates to match consumer demand directly (Javadian Kootanaee et al. 2013). JIT is characterized by producing a product unit that seamlessly integrates into a downstream process at precisely the right time (Ebrahtmpour and Schonberger 1984), ensuring that the necessary components are available on the production line exactly when needed, and only in the required quantities (Friedman, 2017).

In JIT systems, both sellers and buyers engage in a collaborative, long-term partnership aimed at creating a cost-efficient inventory system within the supply chain (Perez and Torres 2019). This efficiency is often achieved through the adoption of smaller lot sizes and increased frequency of deliveries, embodying the JIT delivery principle (Matsui 2007).

Central to the functioning of JIT is the use of various tools, among which KAN is pivotal. KAN enhances communication and information flow and reduces the costs related to inventories and work-in-process, all while maintaining superior customer service. By authorizing production and purchase orders, KAN facilitates the effective implementation of JIT.

The interdependence of KAN and JIT has been the subject of numerous studies. Sakakibara et al. (1993) observed that KAN not only supports JIT performance but also enhances overall firm performance by fostering improved customer relationships (Li and

Barnes 2000). Similarly, Takahashi et al. (1997) noted that KAN systems are integral to JIT production planning and inventory control across multistage production processes. The integration of KAN within JIT systems is essential for lean production, leading to reduced inventory levels, better production synchronization, and enhanced operational efficiency (Amer et al. 2016). Based on these insights, we propose the following hypothesis:

H1: KAN has a direct and positive effect on JIT.

2.2. Relationship between KAN and OPF

OPF is a manufacturing technique deployed within cellular environments to produce a single part correctly at a time. This approach reduces unplanned stoppages and shortens lead times (Bagshaw 2020). By allowing for a more organized and sequential manufacturing process, OPF helps mitigate issues associated with long queues and batch production and eliminates non-value-added movements (Tang et al. 2016). OPF focuses primarily on the immediate processes essential to product or transactional activities rather than on waiting, storage, or transportation (Bagshaw 2020).

OPF is particularly advantageous when handling hazardous materials and enhancing containment and safety protocols (Movsisyan et al. 2016). In this context, KAN functions as a signaling system that regulates the flow of materials and information, ensuring a streamlined and efficient production process (Pradeep and Balaji 2022). Specifically, KAN aids in controlling intermediate stock levels within production lines by regulating production quantities.

When a buffer reaches its preset maximum capacity, the preceding machine receives a signal to halt the production of that specific part. KAN signals are crucial in maintaining an inventory of frequently used items within a facility, facilitating a continuous, piece-by-piece flow (Balram 2003). Using KAN cards to indicate the need for more parts when necessary, helps prevent overproduction and supports a more balanced production system. This alignment with the principles of OPF leads us to propose the following hypothesis:

H2: KAN exerts a direct and positive influence on OPF efficiency.

2.3. Relationship between OPF and JIT

OPF is a Lean Manufacturing (LM) tool known for its benefits, which include shortened production times, reduced in-process inventory, minimized production footprints, and the facilitated detection of operational inefficiencies. OPF enhances production efficiency, enables accurate lead time estimation, and minimizes waste (Hu et al. 2013). It seeks to lessen the production cycle duration and heighten the proportion of value-adding time within that cycle, thereby augmenting productivity. Implementing OPF not only streamlines production methods but also optimizes supply chain management for manufacturing entities (Wang and Li 2013).

JIT comprises a set of principles, tools, and techniques designed to enable a firm to produce and deliver products in minimal quantities and with shortened lead times explicitly tailored to meet exact customer requirements. In essence, JIT ensures the delivery of the right items at the right time and in the correct quantity, allowing for agile responses to daily fluctuations in customer demand (Liker 2004). Nevertheless, the effectiveness of JIT is significantly enhanced by a precise OPF system that supports inventory management (Liker 2004).

Characterized by the processing of individual items sequentially without delays, OPF embodies the JIT philosophy of manufacturing only what is necessary at the moment it is needed (Ward and Zhou 2006). Based on this alignment, the following hypothesis is proposed:

H3: OPF exerts a direct and positive impact on JIT performance.

2.4. Relationship between OPF and ENS

ENS involves developing superior methods for evaluating essential aspects, setting resource allocation priorities, and maximizing productive systems' efficiency (Borgonovi and Compagni 2013). It strives to achieve a delicate equilibrium between maintaining short-term effectiveness and securing long-term viability (Rezaee 2018).

Practices aimed at ENS are known to promote the efficient utilization of resources, such as water and energy, and to minimize waste generation, which translates directly to financial savings (Mani et al. 2014). Sustainable production represents a vital strategy for enhancing financial outcomes while concurrently achieving social and environmental objectives (Sharma 2021). From an environmental and economic standpoint, sustainable manufacturing practices are imperative for long-term operational sustainability (Akbar and Irohara 2018). Manufacturers are increasingly adopting production methods that safeguard economic benefits while minimizing environmental and social impacts (Zhou et al. 2016).

The comprehensive adoption of lean practices, including KAN and OPF, has significantly enhanced asset performance (Fullerton et al. 2014). OPF, which involves processing each item individually without delays, is a fundamental aspect of lean manufacturing designed to streamline production, reduce waste, and increase efficiency, thereby facilitating significant cost reductions (Borazon et al. 2022). Moreover, integrating capabilities related to green supply chain management—which positively correlates with both environmental and economic outcomes—has demonstrated the potential to boost economic performance in sectors like electronics, mainly when OPF is employed (Rajić et al. 2020). In light of the preceding discussion, we propose the following hypothesis:

H4: OPF positively influences the ENS of companies.

2.5. Relationship between JIT and ENS

While the JIT approach initially centered on inventory management, its broader financial implications were soon recognized by organizations such as Toyota. Specifically, JIT, in conjunction with production flow techniques, has been shown to positively affect sales and customer order fulfillment metrics, thereby generating substantial economic benefits (Dieste et al. 2021).

Extensive research has corroborated this relationship. Mackelprang and Nair (2010) noted that JIT practices could significantly enhance performance metrics within an organization, suggesting a direct impact on individual performance levels. Similarly, Rahman et al. (2010) discussed how JIT facilitates faster delivery compared to competitors, reduces unit costs, boosts overall productivity, and enhances customer satisfaction—all of which can lead to economic advantages for a company. Additionally, Alcaraz et al. (2016) and Alcaraz et al. (2014) identified the economic performance of firms as one of the notable benefits associated with JIT reported in the literature. Given these findings, the following hypothesis is proposed:

H5: JIT exerts a direct and positive impact on the ENS of a company.

Figure 1 illustrates the hypothesized relationships among the variables.

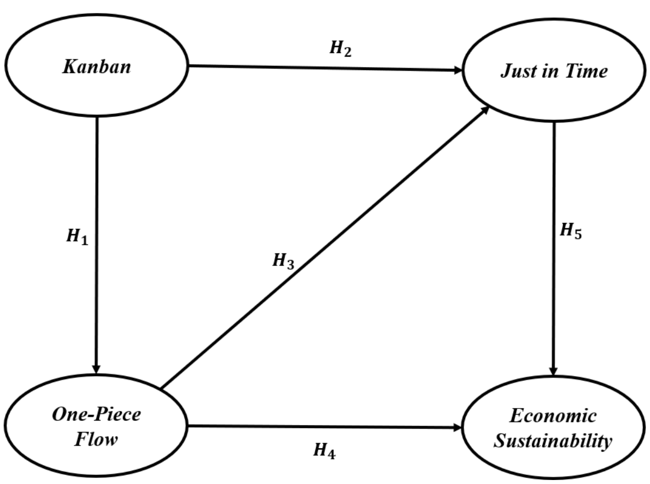

Figure 1. Proposed model

3. Methodology

Data from the industry were required to statistically validate the relationships among the variables depicted in Figure 1. Consequently, the Maquiladora sector in Ciudad Juarez, Mexico, was chosen as the focus of this study. The process of validating the hypotheses involved several steps, as outlined below:

3.1. Creation of a questionnaire

A comprehensive review of the literature was undertaken to identify prior studies that had assessed the levels of implementation of KAN, JIT, OPF, and CSA in companies. This review was a rational validation, building upon previously identified research items (García-Alcaraz et al. 2014).

To adapt these items to the local region's specific industrial context and ensure their comprehensibility to respondents, five experts—comprising two academics and three industry managers from the region—reviewed the literature-derived items. These experts evaluated the items based on several criteria, including relevance and representativeness, clarity and precision of wording, adequacy of instructions, structural and organizational aspects of the questionnaire, overall length, suitability of response options, neutrality of the items, and the internal consistency of the questionnaire (MacIel-Monteon et al. 2020).

The questionnaire was structured into three sections: the first section collected demographic information from the respondents, the second section focused on the three lean manufacturing tools being analyzed (KAN, JIT, OPF), and the third section gauged the economic benefits that companies derived from implementing these tools. Responses for sections two and three were captured using a 5-point Likert scale, where a rating of 1 indicated that the related activity was never performed, and a rating of 5 indicated that it was always performed. Intermediate values of 2, 3, and 4 were used to represent varying degrees of implementation frequency.

3.2. Application of the questionnaire

The questionnaire was distributed to engineers working in the maquiladora industry of Ciudad Juarez using an online platform, Google Forms. All potential participants were identified and contacted via email, including a questionnaire link. The invitation encouraged them to contribute to the research by completing the questionnaire. This phase of data collection was conducted from September 1 to December 1, 2023.

3.3. Data capture and analysis

Upon completing the data collection period, the responses were extracted from Google Forms on December 2, 2023, and downloaded as an XLS file, subsequently opened in Microsoft Office Excel. The data was then imported into SPSS software (version 25) for comprehensive analysis. The analysis focused on descriptive statistics, explicitly calculating the median for each item to establish a measure of central tendency and the interquartile range to determine the dispersion of responses.

3.4. Model validation

Given the nature of the variables under study, which are latent and include observed variables referred to as items, a structural equation modeling (SEM) approach using partial least squares (PLS) was selected for hypothesis validation (García et al. 2014). This method is particularly suitable for data measured on an ordinal scale, as in this study.

3.4.1. Validation of variables

Prior to their analysis or integration into the structural model, the variables were subjected to rigorous statistical validation. Internal validation was conducted using Cronbach's alpha and composite validity indices to assess reliability and overall consistency. Convergent validity was determined through the average variance extracted (AVE), ensuring that their latent variable accounts for a significant portion of the variance in the observed variables. The coefficients R2 and adjusted R2 were utilized to assess parametric predictive validity, providing insights into the model's explanatory power. Additionally, the variance inflation index was employed to evaluate the presence of collinearity among the variables, adhering to the maximum or minimum threshold values recommended for each index (Kock 2019).

3.4.2. Structural equation model

Upon the statistical validation of the variables, they were incorporated into the structural equation model. The model's robustness and appropriateness were subsequently confirmed based on a series of indices recommended by Kock (2021). These include the average path coefficient (APC), average R^2 (ARS), average adjusted R^2 (AARS), average variance inflation index (AVIF), and the Tanenhous index. Together, these metrics facilitated a comprehensive assessment of the model's predictive validity, the degree of collinearity among variables, and the overall fit of the data to the proposed model.

3.4.3. Validation of hypotheses

The structural equation modeling (SEM) analysis was conducted using WarpPLS v. 8 software, with data managed in an Excel database. All statistical calculations, including parameter estimation and the assessment of efficiency indices, were performed with a 95% confidence level. Three effects or relationships among the analyzed variables were estimated in the PLS-SEM framework. Direct effects were primarily used to validate the hypotheses illustrated in Figure 1. For this purpose, a standardized coefficient β was computed, representing the change in standard deviations of the dependent variable for a one-unit change in the independent variable (Ned 2010). A statistical hypothesis test was carried out to assess the significance of this relationship, contrasting the null hypothesis H0: $\beta=0$ against the alternative hypothesis H1: $\beta\neq0$.

A statistically significant non-zero value of β ($\beta\neq0$) indicates a substantive relationship between the variables, suggesting that changes in the independent variable significantly impact the dependent variable. Conversely, a β value of zero ($\beta=0$) implies no relationship between the variables under study. The effect size (ES) was also calculated to quantify the variance in the dependent variable explained by the independent variable.

Additionally, indirect effects mediated through third variables were examined. Since two variables can have multiple indirect pathways involving different mediators, this study reported the aggregated sum of these indirect effects across all identified pathways. Finally, total effects, which represent the arithmetic sum of direct and indirect effects, were detailed in the analysis.

3.4.4. Sensitivity analysis

The WarpPLS v.8 software facilitates the calculation of probabilities for variables within the model based on the likelihood of specific values occurring (Kock 2015). This analysis identifies a low-probability scenario when the standardized zeta value falls below minus one, represented as $P(Z < -1)$. Conversely, a high probability scenario is recognized when the standardized value is one or more excellent, denoted as $P(Z > 1)$. Specifically, this study reports on three types of probabilities:

- Probability of a variable independently reaching either a high or low level.
- Probability of two variables co-occurring in scenarios where their levels are a combination of high and low.
- The conditional probability of the dependent variable presenting in either a high or low scenario, contingent upon the occurrence of the independent variable in either a high or low state.

4. Results and discussion

4.1. Description of sample and items

From a total of 2,117 survey requests, 411 were completed and deemed valid, yielding a response rate of 19.41%. The demographic composition of respondents included 177 women and 234 men, predominantly employed in key industry sectors such as automotive, medical, textiles, and electronics. Large companies employed most participants: 147 respondents worked in companies with over 1,000 employees, 89 in companies with between 500 and 1,000 employees, and 54 in companies with more than 5,000 employees. Table 1 provides a detailed breakdown of the item medians and interquartile ranges according to their descriptions. Notably, very few items recorded medians below four, yet most were above three, indicating a generally high level of agreement or occurrence related to the surveyed aspects.

Table 1. Items central tendency and dispersion

KAN	Median	IQR
Do you always know how much to produce?	4.20	1.56
Is the product manufactured or transported with its production order?	4.11	1.63
Does its official order always accompany each request to manufacture a product?	4.22	1.53
Is the inventory of the final product handled in the company small?	3.53	2.08
Are there indicators that warn when a batch should be discontinued?	3.89	1.87
Is Kanban used to signal to the downstream operation that a task has been completed and that components or materials need to be replenished to continue work?	3.94	1.85
One-piece flow		
Is production on a particular job based on the current demand for its subsequent job?	4.12	1.47
Is a production lot manufactured only if there is a customer's purchase order?	4.27	1.50
Does the customer request only the specific quantity manufactured?	4.23	1.50
Are the workstations making good use of the pull system?	4.11	1.54
Inventory investment shows a decreasing trend over time.	3.95	1.62
Production lead times, as well as set-up times, are reduced/shortened over time.	4.07	1.55
Just in time		
The internal flow of materials is efficient and continuous between operations.	3.94	1.60
Product reprocessing is reduced to an acceptable minimum.	3.92	1.57
The implementation of improvements to reduce waste is encouraged.	4.15	1.51
Material transport is minimized.	4.04	1.62
Waste in the production process and the supply chain is identified.	4.09	1.52
ENS		
Reduction of production costs	4.15	1.48
Improved profitability	4.11	1.45
Reduced product development costs	4.17	1.43
Reduction of energy costs	4.13	1.48
Reduction of inventory costs	4.19	1.43
Reduction of rejects and rework costs	4.21	1.41

4.2. Validation of variables

Table 2 presents the validation indices for the variables used in the model, as depicted in Figure 1. The table's last row indicates each index's acceptable minimum or maximum thresholds. The data confirm that all variables meet these criteria, indicating they possess adequate predictive, internal, and convergent validity and are free from collinearity issues. Therefore, they are suitable for integration into the model.

Table 2. Validation indices

	KAN	JIT	OPF	ENS	Best if
R^2		0.453	0.356	0.455	>0.02
Adj. R^2		0.45	0.355	0.452	>0.02
CoR	0.906	0.926	0.93	0.955	>0.7
CrA	0.87	0.9	0.906	0.944	
AVE	0.659	0.716	0.727	0.781	>0.7
VIF	1.64	2.212	1.968	1.776	<3.3
Q2		0.452	0.357	0.456	>0

CoR: composite reliability; CrA: Cronbach's alpha; AVE: Average variance extracted; VIF: Variance inflation factor; VIF: Variance inflation factor.

4.3. Model validation

After incorporating the variables into the model and executing the analysis using WarpPLS v.8 software, the efficiency indices were obtained and are displayed in Table 3. This table also specifies the desirable values for each parameter. The results demonstrate that the model meets all required indices with at least 95% confidence. Consequently, the model was interpreted based on these robust findings.

Table 3. Model efficiency indices

Index	Validation	Acceptable value
Average Path Coefficient (APC)	Predictive	$P < 0.05$
Average R-Squared (ARS) and Average	Predictive	$P < 0.05$
Adjusted R-Squared (AARS)		
Average block VIF (AVIF)	Collinearity	Acceptable if ≤ 5, ideally ≤ 3.3
Average Full collinearity VIF (AFVIF)	Collinearity	Acceptable if ≤ 5, ideally ≤ 3.3
Tenenhaus GoF (GoF)	Data model fit	≥ 0.36

4.4. Structural equation model

Figure 2 displays the evaluated model. For each relationship within the model, the value of β, the associated p-value, and the effect size—which measures the variance explained—are provided. The direct effects depicted in Figure 2 substantiate the conclusions drawn regarding the proposed hypotheses, as summarized in Table 4. Given that all β coefficients are nonzero and the p-value associated is lower than 0.001, we conclude that all hypotheses are statistically significant, indicating that the independent variables directly and positively affect the dependent variable.

For instance, in the KAN→JIT relationship, an increase of one standard deviation in KAN results in a 0.293-unit increase in JIT, with a 99.9% confidence level. Additionally, JIT accounts for up to 16.6% of the variance in KAN, suggesting that KAN is a precursor to JIT and must be effectively implemented for JIT to succeed.

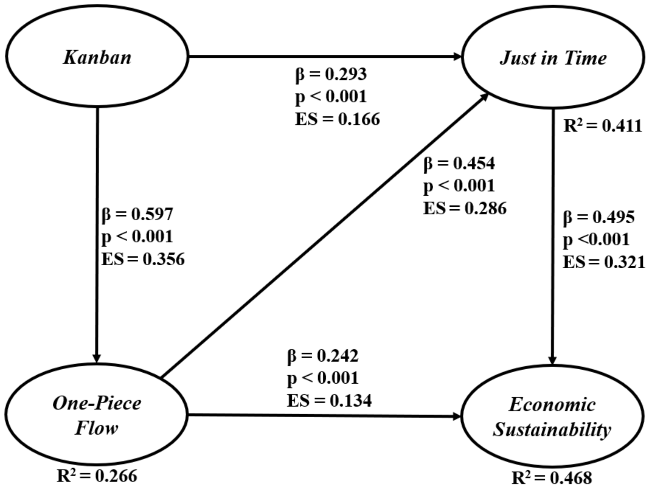

Figure 2. Model evaluated

Table 4. Hypotheses validation

Rel	β (p-value)	EN	Conclusion
KAN→JIT	0.293(< 0.001)	0.166	Accept
KAN→OPF	0.597(< 0.001)	0.356	Accept
OPF→JIT	0.454(< 0.001)	0.286	Accept
JIT→ENS	0.495(< 0.001)	0.321	Accept
OPF→ENS	0.242(< 0.001)	0.134	Accept

Notably, the most vital relationship is observed in the KAN→OPF pathway, where β equals 0.597. This correlation is logical, given that KAN labels enhance the management and administration of inventories on production lines. Other relationships within the model were interpreted similarly.

4.5. Sum of direct and total effects

Table 5 presents the sum of indirect and total effects, all statistically significant across the relationships, as indicated by the p-values associated with each estimated β coefficient. It is critical to note that indirect effects were calculated through mediator variables, as specified in the fourth column of the table. For instance, the indirect effect in the KAN→JIT relationship is mediated by OPF. This mediation suggests that an increase of one standard deviation in KAN leads to a corresponding increase of 0.271 in JIT, attributable to the influence exerted by OPF. Among the indirect effects analyzed, the KAN→ENS relationship exhibits the most vital connection due to the inclusion of both JIT and OPF as mediating variables.

Regarding total effects, which combine direct and indirect influences, the relationship between KAN and OPF displayed the highest ratio, with no indirect effects observed. However, the KAN→JIT relationship, with a total effect of 0.564, also stands out. This relationship comprises a direct effect of 0.293 and an indirect effect of 0.271, indicating that the indirect effect is nearly as substantial as the direct effect. This underscores the significant role of OPF in this dynamic.

Table 5. Direct and indirect effects

The sum of indirect effects			
Relation	β (p-value)	EN	Mediating variables
KAN→JIT	0.271 (p<0.001)	0.154	OPF
KAN→ENS	0.424 (p<0.001)	0.171	OPF, JIT
OPF→ENS	0.225 (p<0.001)	0.124	JIT
Total effects			
KAN→JIT	0.564 (p<0.001)	0.320	OPF
KAN→OPF	0.597 (p<0.001)	0.356	
KAN→ENS	0.424 (p<0.001)	0.171	OPF, JIT
JIT→ENS	0.495 (p<0.001)	0.321	
OPF→JIT	0.454 (p<0.001)	0.286	
OPF→ENS	0.467 (p<0.001)	0.258	JIT

4.6 Sensitivity analysis

Table 6 details the sensitivity analysis results conducted on the variables incorporated in the model. In the analysis, low levels are denoted by "-" and high levels by "+". For instance, KAN- signifies a low level of KAN implementation, whereas ENS+ indicates a high level of environmental sustainability.

The sensitivity analysis reveals, for example, that KAN can independently occur at its high level with a probability of 0.202, compared to a probability of 0.173 for occurring at a low level. This suggests that it is more likely to observe a high level of KAN implementation (KAN+) than a low level (KAN-) in the maquiladora industry. Specifically, in the KAN→JIT relationship, the probability of both KAN and JIT concurrently occurring at high levels is 0.117. However, the conditional probability of observing JIT at a high level (JIT+), given that KAN is also at a high level (KAN+), is 0.578. This indicates that for JIT to be successfully implemented, KAN must be effectively operational. Conversely, the conditional probability that JIT will be at a low level (JIT-) given that KAN is poorly implemented (KAN-) is 0.451, highlighting that inadequate KAN practices can adversely affect JIT performance on production lines.

5. Conclusions and limitations

This study aimed to elucidate the interrelationships between KAN), OPF, JIT, and ENS within the context of the Maquiladora industry in Ciudad Juarez, Mexico. Utilizing structural equation modeling, responses from 511 participants were analyzed to validate hypotheses concerning these lean manufacturing tools and their impact on economic performance. The findings underscore the pivotal role of KAN in enhancing operational efficiencies through its significant positive effects on both JIT and OPF systems. Specifically, an increase in KAN implementation is statistically linked to improvements in JIT performance (β = 0.297, explaining 16.6% of variance) and OPF efficiency (β = 0.597, explaining 35.6% of variance). These results affirm that effective KAN practices are essential for optimizing the flow of production and inventory management, which are critical components of JIT and OPF methodologies. Moreover, the analysis confirmed that OPF contributes significantly to JIT efficiency (β = 0.454, explaining 28.6% of variance), demonstrating that the meticulous management of production flow directly enhances the JIT system's responsiveness and efficiency. This finding highlights the importance of fully integrating OPF into the production processes to leverage its benefits. In terms of ENS, JIT and OPF showed substantial positive impacts, with JIT contributing to a 32.1% variance in ENS (β = 0.495) and OPF explaining 13.4% (β = 0.242). These relationships suggest that lean manufacturing tools optimize production processes and promote ENS by reducing costs and enhancing profitability. The study's implications are profound, offering practical insights for industry practitioners aiming to enhance productivity and sustainability through lean manufacturing principles. Future research should consider exploring the potential long-term effects of these practices on ENS and extend the analysis to other industries to validate the generalizability of these findings. Additionally, examining the role of technological advancements, such as digital KAN and automated OPF systems, could provide deeper insights into the evolving landscape of lean manufacturing.

This study has several limitations. For example, only three LM tools are analyzed, even though up to 25 are reported in the literature. Therefore, future research will study the relationship that other tools have on economic sustainability and add environmental and social aspects.

Table 6. Sensitivity analysis

			KAN		OPF		JIT	
			+	-	+	-	+	-
			0.202	0.173	0.148	0.168	0.212	
JIT	+	0.212	&=0.117	&=0.005	&=0.100	&=0.010		
			IF=0.578	IF=0.028	IF=0.672	IF=0.058		
	-	0.2	&=0.010	&=0.078	&=0.010	&=0.112		
			IF=0.048	IF=0.451	IF=0.058	IF=0.667		
OPF	+	0.148	&=0.085	&=0.007				
			IF=0.422	IF=0.042				
	-	0.168	&=0.010	&=0.085				
			IF=0.048	IF=0.493				
ENS	+	0.18	&=0.092	&=0.010	&=0.075	&=0.010	&=0.092	&=0.005
			IF=0.458	IF=0.056	IF=0.508	IF=0.058	IF=0.437	IF=0.024
	-	0.163	&=0.010	&=0.054	&=0.007	&=0.092	&=0.002	&=0.119
			IF=0.048	IF=0.310	IF=0.049	IF=0.551	IF=0.011	IF=0.598

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