Article | Received 30 May 2026; Revised 23 June 2026; Accepted 2 July 2026; Published 9 July 2026
https://doi.org/10.55092/am20260008

Jidoka 4.0 as a data-driven lean capability: a structural model linking smart automation to sustainability outcomes in manufacturing

Jorge Luis García Alcaraz[1,]*, Jorge Limón Romero[2], Yashar Aryanfar[3,4], Jorge Manuel Cueva Estrada[5] and Omar Celis Gracia[1]

[1] Department of Industrial Engineering and Manufacturing, Universidad Autónoma de Ciudad Juárez, Ciudad Juárez, Mexico
[2] Faculty of Engineering, Architecture and Design, Universidad Autónoma de Baja California, Ensenada, Mexico
[3] Department of Chemical Engineering, National Cheng Kung University, Tainan, China
[4] Thermo-Fluids Research Group, Department of Mechanical Engineering, Khazar University, Baku, Azerbaijan
[5] School of Economics and Business Administration, Universidad Politécnica Salesiana, Guayaquil, Ecuador

* Correspondence author; E-mail: jorge.garcia@uacj.mx.

Highlights:

- Jidoka 4.0 functions as a data-driven capability for predicting digital sustainability (β = 0.588).
- Digital sustainability mediates nearly half of the environmental impact of Jidoka.
- The DISU→ENSU relationship was linear, suggesting continuous environmental returns.
- High digital sustainability increases the probability of environmental sustainability to 64.8%.
- Nonlinear effects reveal diminishing environmental returns as Jidoka matures.

Abstract: Lean manufacturing is now called Industry 4.0, in which traditional production tools are data-driven and have implications for corporate sustainability. Jidoka (JIDO) has been transformed into JIDO 4.0, which employs Internet of Things (IoT) systems and sensors to gather data from the production process for real-time monitoring and decision making. Based on three hypotheses, this study proposes a structural equation model (SEM) to examine the relationships between JIDO 4.0, digital sustainability (DISU), and environmental sustainability (ENSU) in manufacturing companies. The SEM was tested with data from 834 responses to a questionnaire for managers, engineers, and supervisors, validated using Lawshe's content validity ratio and Aiken's V. The Warp3 algorithm in WarpPLS 8.0 was used to detect nonlinear relationships between constructs. The results indicate that the three proposed hypotheses are supported, showing that JIDO has the greatest direct effect on DISU (β = 0.588), and DISU is the most influential predictor of ENSU (β = 0.553). The indirect effect of JIDO on ENSU, mediated by DISU (β = 0.325), was nearly equal to the direct effect (β = 0.342), indicating that DISU acts as a bridge between intelligent autonomy and environmental benefits. A sensitivity analysis based on conditional probabilities indicated that when DISU was high, the probability of achieving a high ENSU was 64.8%. These results indicate that JIDO is a data-driven organizational capability with direct and indirect effects on ENSU, and that it provides managers with empirical evidence to prioritize their investments in smart and lean technology.

Keywords: Jidoka 4.0; data-driven manufacturing; smart autonomation; digital sustainability; environmental sustainability; lean Industry 4.0; PLS-SEM

1. Introduction

For years, the manufacturing industry has sought to integrate operational efficiency and increasingly demanding environmental commitments into production processes. To address this challenge, lean manufacturing (LM) has been employed, given its focus on eliminating waste and pursuing continuous improvement, and has proven effective in various contexts [1]. However, Industry 4.0 has transformed and extended traditional LM through process digitization. Now, Internet of Things (IoT) sensors, cyber-physical systems, machine learning algorithms, and business intelligence platforms have transformed traditional LM mechanisms into data-generating and data-processing systems that directly influence organizational sustainability [2]. This transformation has resulted in lean and data-driven manufacturing capabilities.

One such tool is Jidoka (JIDO), a pillar of the Toyota Production System (TPS). JIDO is also known as autonomation and seeks to equip machines with the ability to detect anomalies and halt operations so that defects do not spread, thereby ensuring quality from the beginning of the process [3]. This traditional JIDO has evolved into JIDO 4.0, which integrates advanced sensors, computer vision, and cyber-physical systems that enable the detection of anomalies on production lines, such as the classification of defects or deviations from a process parameter. The collected data are used to feed real-time monitoring dashboards, predictive quality models, and algorithms to optimize the process [2,4]. Thus, JIDO 4.0 is data-driven, and its operational logic is based on the capture, transmission, and data analysis. Therefore, JIDO has evolved from a quality control tool into a data-driven organizational capability with implications for digital sustainability (DISU) and environmental sustainability (ENSU).

The relationship between LM tools and ENSU has been previously studied. For example, García Alcaraz *et al.* [5] demonstrated, using a structural equation model (SEM) applied to the manufacturing industry, that JIDO—when integrated with Total Productive Maintenance (TPM) and Overall Equipment Effectiveness (OEE)—has positive effects on ENSU, economic sustainability (ECSU), and social sustainability (SOSU), owing to their ability to reduce waste and setbacks caused by unidentified defects. Through a systematic review of the literature, Ferrazzi *et al.* [1] indicate that companies that have adopted LM report a positive impact on ENSU, although the mechanisms through which this occurs have not been clearly established.

However, DISU, understood as the ability of digital technologies and practices to generate value without compromising the integrity of information systems, emerges in this context as a construct that mediates the relationship between automation levels and ENSU [6,7]. Studies analyzing the convergence of digitalization and ENSU vary. For example, Feroz *et al.* [8] identified four domains in which digital transformation generates environmental improvements: pollution control, waste management, sustainable production and urban sustainability. Chen *et al.* [9] indicated that digitalization in the manufacturing industry reduces carbon emissions through technological innovation and compliance with government and social regulations. Finally, Sarfraz *et al.* [10] indicate that ENSU is mediated by organizational capabilities to adopt innovative processes and new tech systems.

Despite the many advances in studies integrating digital transformation and ENSU, gaps remain that must be analyzed, as no studies have been identified that analyze JIDO 4.0 as a data-driven LM capability in Industry 4.0 and investigate its effects on ENSU and DISU through an integrated model, nor has it been evaluated whether DISU can mediate that relationship. The analysis of this relationship has practical implications for the manufacturing industry, as it seeks to align its investments in technological and intelligent LM tools that enable it to achieve its corporate sustainability goals, and for the research agenda in data-driven and artificial intelligence-oriented manufacturing that aims to connect the digital transformation of production lines with sustainability.

This study aims to address this gap by proposing and testing a SEM that integrates three hypotheses linking JIDO, DISU, and ENSU, which are grounded in the socio-technical systems (STS) theory and dynamic capabilities framework. The SEM proposed that JIDO 4.0 has a direct effect on DISU (H_1) and ENSU (H_2) and that DISU influences ENSU. The model was validated using data from managers, engineers, and supervisors on production lines in the manufacturing industry.

The remainder of this paper is organized into six sections. Following this introduction, Section 2 presents the theoretical framework and justifies the hypotheses; Section 3 describes the methodology used; Section 4 reports the results and calculations performed; Section 5 discusses and interprets this; and Section 6 summarizes the conclusions, limitations, and future research directions.

2. Theoretical framework and hypothesis development

2.1. Theoretical perspective

SEM is grounded in two theories that provide complementary explanations that neither can offer independently, as one operates at the internal level and the other at the strategic level. STS theory indicates that optimal organizational performance is the result of the integration between technical and social systems within the company. In smart manufacturing, JIDO 4.0 can be analyzed as a socio-technical interface that connects automatic anomaly detection (via IoT sensors and algorithms) with human responses, digital information flows, and protocols that ensure continuous improvement. When JIDO undergoes a digitization process, it does not entirely replace the operator but rather enhances their ability to act on real-time data. When an event occurs and data are detected, this triggers a decision requiring the operator to act in accordance with established standards. The result of this automated system is improved performance and reduced waste, which STS predicts when technical and social components are genuinely integrated into the system. For example, Ma *et al.* [2] reported a study in which intelligent autonomy supported by cyber-physical technologies achieved peak performance by integrating as a technical capability through sensors and human responsiveness. Without such integration, significant technological investments in data collection lose their advantages without human response.

The dynamic capabilities view (DCV) in this study explains how organizations generate competitive advantages by sensing opportunities, capturing value, and reconfiguring assets in changing environments [11]. In the SEM reported here, JIDO 4.0 is not analyzed as a static operational tool but rather as a dynamic capability that allows for real-time monitoring of the production process through data, which generates knowledge and enables the reconfiguration of processes for environmental improvement. Applications of this theory can be found in Bag, Gupta *et al.* [12], who argue that Industry 4.0 technologies generate capabilities that positively affect sustainable development. Meanwhile, García-Alcaraz *et al.* [13] indicated that JIDO, as a machinery and control tool, is a predictor of sustainability in the manufacturing context.

The combined approach of STS and DCV articulates all the relationships within the proposed SEM without overlaps or contradictions and places JIDO 4.0 within the broader agenda of data-driven and artificial intelligence-oriented manufacturing, a field where digital technologies are measured not only by their computational sophistication but also by the organizational capabilities they generate.

2.2. Hypothesis development

With the new Industry 4.0 approach, JIDO 4.0 has become a data generation system. When a sensor detects an anomaly and triggers a machine shutdown, it generates a data event, such as a timestamp, deviation value, parameter reading, or machine identifier. As these events are repeated across several production cycles, a dataset is generated that feeds into dashboards for real-time monitoring, models for predict quality, and algorithms to optimize processes [2,4]. The ability to produce, manage, and utilize data from the production process is known as DISU. Alatrista-Corrales, *et al.* [14] indicated that human-in-the-loop automation systems generate digital indicators related to OEE and specific energy consumption, which leads to sustainable manufacturing on the shop floor. Azli *et al.* [15] reported that Industry 4.0 sensors enable the establishment of real-time monitoring systems that facilitate decision-making. Therefore, the DCV establishes that JIDO 4.0 is an organizational sensing capability that identifies and transforms signals from the production process into digital assets, leading to the following hypothesis:

H_1: Jidoka/Autonomation has a positive and direct effect on DISU.

JIDO 4.0 has an environmental logic that operates through data obtained from the process, making it more precise than its analog version. When a sensor detects a defect and production is halted before more nonconforming products move further down the value chain, two things occur: no further defects are produced and the data are recorded. This record allows for the adjustment of process parameters, identification of a component supplier, or retraining of the operator. Over time, this data-driven approach to quality eliminates rework, material consumption, energy use and labor time [5]. Fewer reworks imply less waste, lower energy consumption, and reduced emissions resulting from them.

The literature includes several studies that analyze the relationship between JIDO and ENSU. For example, García-Alcaraz *et al.* [13] reported that JIDO directly affects ENSU by reducing waste and emissions into the environment. Additionally, Ferrazzi *et al.* [1] identified in a systematic review that LM principles enabling early anomaly detection have the greatest positive environmental impact, as they address the root cause rather than the consequences. Thus, in this study, from the DCV perspective, JIDO 4.0 is configured as a capability of the production process, where anomaly detection is a data-driven signal that facilitates the reduction of the environmental footprint owing to improved production efficiency. This allows us to propose the following hypothesis:

H_2: Jidoka/Autonomation has a positive effect on ENSU.

The literature includes cases establishing that companies with well-established digital capabilities have more tools at their disposal to minimize their environmental impacts. For example, Feroz *et al.* [8]

indicated that digital transformation facilitates pollution control and waste management and promotes sustainable production. Chen *et al.* [9] confirm that digitization in the manufacturing sector reduces carbon emissions through technological innovation and compliance with social responsibility. From an administrative perspective, Sarfraz *et al.* [10] indicate that digital transformation strategies affect ENSU, which is often mediated by the innovation capacity installed.

Zhang *et al.* [7] report evidence from the Chinese manufacturing sector and notated that DISU promotes environmentally responsible practices and aligns digitalization objectives with environmental goals. Zhou *et al.* [16] reported that digital transformation minimizes carbon emissions in the manufacturing industry through a mechanism called servitization, which demonstrates that digital maturity is an enabler of ENSU regardless of the sectoral context. Thus, from the DCV perspective, DISU adds value and positions companies with a competitive advantage by improving their ENSU and responding to government and social regulations. Therefore, the following hypothesis is proposed:

H_3: DISU has a positive and direct effect on ENSU.

Figure 1 summarizes the research model and the three hypotheses tested in this study. The model positions JIDO 4.0 as the exogenous construct, ENSU as the final endogenous construct, and DISU as an intervening construct. Two sequential paths are proposed, from JIDO to DISU (H_1) and from DISU to ENSU (H_3), together with a direct path from JIDO to ENSU (H_2). This configuration allows JIDO to influence ENSU both directly and indirectly through DISU, so that the mediating role of DISU can be evaluated alongside the direct environmental effect of intelligent autonomy.

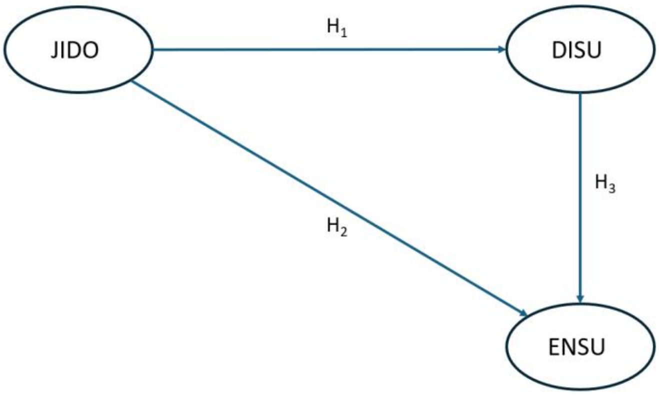

Figure 1. Proposed hypotheses.

3. Methods

3.1. Instrument design and content validation

The data were collected through a structured Likert-scale questionnaire, based on instruments previously validated in the literature of LM and sustainability. Each item was formulated to reflect perceptions about the three latent constructs of the model (JIDO, DISU and ENSU).

The content validity was assessed using two complementary methods. The first was Lawshe's method, which yields a Content Validity Ratio (CVR) for each item based on the judgment of a panel of experts [17]; the second was Aiken's V, which captures the level of agreement among judges regarding the relevance, clarity, and coherence of each item [18]. The panel comprised eleven experts: four academics with research experience in LM and sustainability, and seven managers from the manufacturing industry. Following Lawshe's criterion for a panel of this size, items were retained when their CVR was at least 0.59 and their Aiken's V reached 0.70 or higher. Only items that satisfied both thresholds were kept in the final version of the scale.

3.2. Sample and data collection

The questionnaire was posted through Google forms between 20th January and 20th April 2026. A link to the questionnaire was emailed to potential respondents together with an explanation of the purpose of the survey and how the information would be used. If no response was received after two weeks, up to two reminders were sent and if no response was received after that period, the case was discarded.

The target population was made up of managers, engineers, and supervisors of the manufacturing industry in Ciudad Juárez (Chihuahua, Mexico), one of the regions with the highest concentration of maquiladora and export-oriented manufacturing companies in North America. The sampling was by convenience with two inclusion criteria; having at least two years of experience in the position and at least two finished projects regarding JIDO implementation, to ensure that the respondents knew the effects of JIDO on the DISU and ENSU in their organizations [5]. While these criteria ensured that respondents had direct knowledge of JIDO and its effects, the use of a non-probability convenience sample favors respondent expertise over statistical representativeness. The email list was provided by a regional organization of export-oriented maquiladora companies.

3.3. Database cleaning

The downloaded database was cleaned in a two-stage process prior to the analysis. In the first stage, the cases that did not accept the privacy statement were excluded, in accordance with the ethical principles approved by the Institutional Committee. In the second stage outliers were identified by standardizing each item and deleting observations with standardized values beyond the conventional cutoff point of ± 3.29 standard deviations. Additionally, *careless* responding was assessed by standardizing the responses for each case; those with variances close to zero or systematic inconsistencies were excluded from the final dataset [19].

Furthermore, the median was reported as a measure of central tendency and the interquartile range (IQR) as a measure of data dispersion, given that the data were on an ordinal scale and were robust to asymmetric distributions, which are common when collecting perception data in industrial contexts.

3.4. Model estimation with PLS-SEM

The SEM was evaluated using WarpPLS v.8 software via the partial least squares approach (PLS-SEM), which is recommended for models with reflective constructs, as it has demonstrated robustness in the absence of normality in the data or when analyzing small samples, and has been applied in studies of the industrial sector [13].

Construct validation was performed using the indices from Kock [20], including composite reliability (CR > 0.70), Cronbach's alpha (α > 0.70), average variance extracted (AVE > 0.50), R^2 and adjusted R^2 (> 0.20) as indicators of the model's parametric explanatory power, and the Q^2 statistic (> 0) as its nonparametric equivalent. Discriminant validity was confirmed using the Fornell *et al.* [21] criterion, which verified that the square root of the AVE for each construct was greater than its correlations with the others, and using HTMT ratios with their 95% confidence intervals [22]. The presence of multicollinearity was examined using VIFs for full multicollinearity, with an acceptability criterion of ≤ 5 and an ideal criterion of ≤ 3.3 [20]. Additionally, Jarque-Bera normality tests are reported to justify the use of PLS-SEM instead of a variance-based approach (CB-SEM) and the skewness indices for each construct.

The Warp3 algorithm (Stable version) was used to evaluate the relationships between constructs, as it allows for the identification of nonlinear relationships, which is one of the main contributions of this study. While the implementation of a tool such as JIDO 4.0 often yields greater initial benefits, these benefits diminish as the tool becomes more established or mature [20]. To evaluate the fit and quality indices of the overall model, the average path coefficients (APC), average R^2 (ARS), average adjusted R^2, average block variance inflation factor (AVIF), average full collinearity variance inflation factor (AFVIF), and Tenenhaus index were used to measure the fit of the data to the model.

To measure common method bias, Harman's one-factor test [23] was conducted, verifying that a single unrotated factor did not explain more than 50% of the total variability of all items analyzed. However, the variance inflation indices proposed by Kock *et al.* [24] are also used, which must be less than 3.3. To determine the appropriate sample size, the inverse square root and exponential gamma methods were used, with a 95% confidence level, 80% statistical power, and the minimum β estimated in the model.

3.5. Data-driven operationalization of the JIDO construct

In this study, the JIDO construct was operationalized as a data-oriented LM capability. The five items that comprise it aim to integrate behavior in operational terms based on the data generated by machines. The list of constructs with their items is provided as Supplementary Material, where aspects are analyzed regarding whether machines stop automatically upon detecting defects, whether the production line can be stopped immediately when a problem is identified, whether the machine I operate visually notifies me when something is malfunctioning, whether the operator has the authority to stop production if quality is at risk, and whether the machine is capable of automatically separating good parts from defective ones. These functions undoubtedly indicate the implementation of JIDO 4.0, since, according to Ma *et al.* [2] and Rohit *et al.* [4], performing the activities of these five items requires machine vision or algorithms based on sensors installed on machines.

Thus, in this study, JIDO is analyzed as a distributed system that enables the collection of and response to data within the production process; that is, sensors generate data, and systems transmit and classify it, allowing operators to act upon it. This operationalization of the items is consistent with the data-driven manufacturing paradigm [4] and the conceptualization of JIDO 4.0 as a driver of autonomy in a smart LM environment enabled by cyber-physical systems [2].

3.6. Analysis of effects, nonlinearity, and fit indices

To quantify the relationship between the two constructs or hypotheses, the standardized β coefficient and its associated p-value were calculated to measure statistical significance at a 95% confidence level. For each β parameter, the confidence interval and t-value are also reported. The variance explained in DISU and ENSU as endogenous variables was determined using the R^2 coefficient, and to measure the contribution of each exogenous construct to an endogenous one, the effect size (f^2) is reported, following the Cohen [25] thresholds: small ($f^2 \geq 0.02$), medium ($f^2 \geq 0.15$), and large ($f^2 \geq 0.35$).

In the PLS-SEM, three types of effects were estimated: direct effects, which allow for testing or verifying the hypotheses proposed in Figure 1; indirect effects, to measure the mediating role of JIDO in ENSU through DISU; and total effects, which represent the sum of the direct and indirect effects.

For each of the direct effects proposed in Figure 1, graphs showing the best fit and unstandardized values are reported; these were generated by the Warp3 algorithm, which allows for the analysis of the behavior of the relationship at different levels of construct implementation [20]. These graphs allow us to see for the linearity or non-linearity between the constructs, as *the β* coefficients are reported to determine whether the relationship is constant in certain segments, intensifies, or experiences diminishing returns. This is one of the main contributions of this study, as traditionally, the analysis between variables is conducted assuming linearity; however, in manufacturing and sustainability contexts, the returns on capabilities are inherently bounded [26].

Finally, this study reports a sensitivity analysis based on the probabilities of occurrence for the constructs at their low and high levels of implementation, calculated using the WarpPLS 8.0 software [20]. A standardized *z-score* of less than −1 for a construct is considered to indicate a low level of implementation, but when it is greater than 1, it is assumed to have a consolidated or mature level of implementation. Three probabilities are reported: marginal probabilities when the construct occurs in isolation and independently, joint occurrence probabilities, and conditional probabilities. The latter two can occur in a combination of states, providing managers and decision-makers with a diagnostic tool that allows them to identify the potential risks.

4. Results

4.1. Sample characterization and descriptive statistics

At the end of the data collection period, 852 responses were received from the 2835 emails sent, for a response rate of 30.05%. After data cleaning, 834 valid cases for analysis were obtained; these included 4 cases rejected for not accepting the privacy statement and 14 cases rejected for non-committed responses, all of them from the manufacturing industry in Ciudad Juárez, Mexico. The raw data appear as Supplementary Material in Supplementary Table S1.

Regarding profiles, 35.4% were supervisors (n = 295), 34.4% were engineers (n = 287) and 30.2% were managers (n = 252). 42.9% of the respondents had 2 to 5 years of experience in the position (n = 358), 28.2% had 5 to 10 years of experience (n = 235) and 28.9% had more than 10 years of experience (n = 241). For industry sector, 26.6% were in the automotive sector (*n* = 222), 23.3% in the medical sector (*n* = 194), 21.9% in communications (*n* = 183), 21.1% in electronics/electrical (*n* = 176), and 7.1% in plastics (*n* = 59). By company size, 71.3% worked in large companies (*n* = 595), 18.9% in medium-sized companies (*n* = 158), and 9.7% in small companies (*n* = 81). By department, the majority belonged to production (64.6%, *n* = 539), followed by maintenance (13.3%, *n* = 111), quality (12.8%, *n* = 107), and supply chain (9.2%, *n* = 77).

The Supplementary Material Supplementary Table S2 displays the descriptive statistics of the items in a table. The medians for all items ranged from 3.535 to 4.279 indicating an overall positive perception of the practices assessed within the three constructs. The lowest median was found in JIDO5 (My machine automatically separates good parts from bad parts, Mdn = 3.535, IQR = 2.791) and JIDO1 (My machine stops automatically when it detects a defect, Mdn = 3.616, IQR = 2.455), both of which also had the highest dispersion within the construct, indicating heterogeneity in the degree of automated detection technology deployed across participating companies. For the ENSU construct, the highest medians were ENSU3 (I immediately report any leaks, spills, or situations that may contaminate the environment, Mdn = 4.279, IQR = 1.754) and ENSU5 (I know and follow the environmental procedures established for my job, Mdn = 4.241, IQR = 1.795) with low dispersion, which indicates consistent practice of reactive environmental compliance behaviors. In contrast, ENSU1 (I regularly monitor and record water and energy consumption, Mdn = 3.669, IQR = 2.640) exhibited the highest degree of variation within the construct, suggesting differences in the formalization of environmental monitoring practices across organizations. Medians were relatively homogenous (range: 3.722–4.072) for the DISU construct, with the greatest dispersion for DISU1 (I use digital tools to monitor and optimize energy consumption, Mdn = 3.722, IQR = 2.395), in line with the uneven adoption of energy-oriented digital monitoring systems in the JIDO construct.

The minimum sample size was calculated using the inverse square root method and the gamma-exponential method, considering a minimum absolute path coefficient of 0.342 (the lowest significant β in the model), significance of 0.05, and statistical power of 0.80 [24]. The minimum number of cases was 53 using the inverse square root method and 40 using the gamma-exponential method (see Supplementary Figure S1 in the Supplementary Material). The final sample of 834 valid cases is well above both thresholds providing adequate statistical power to detect the effects estimated in the model.

4.2. Overall model fit

The overall model fit indices exceeded the criteria established by Kock [20], as shown in Table 1. The average path coefficient (APC = 0.494, $p < 0.001$) and average R^2 (ARS = 0.495, $p < 0.001$) were statistically significant. The multicollinearity indices remained well below the acceptable thresholds (AVIF = 1.525; AFVIF = 2.346, both ≤ 3.3), ruling out multicollinearity issues. Common method bias was assessed using Harman’s one-factor test [23], which confirmed that a single unrotated factor explained 42.36% of the total variance, which was below the 50% threshold. The Tenenhaus goodness-of-fit index (GoF = 0.605) was greater than the threshold of 0.36, indicating an adequate fit. This allows us to conclude that the model can be interpreted as follows.

Table 1. Overall model fit indices.

Index	Value	Criterion
APC	0.494***	p < 0.001
ARS	0.495***	p < 0.001
AVIF	1.525	≤ 3.3 (ideal)
AFVIF	2.346	≤ 3.3 (ideal)
GoF	0.605	≥ 0.36 (large)

**p < 0.001

4.3. Construct validation

Table 2 presents the validity and reliability indices for the constructs in the model. It can be seen that the composite reliability is greater than the 0.90 threshold in all cases (JIDO = 0.916; DISU = 0.952; ENSU = 0.949), and that the Cronbach’s alpha coefficients are satisfactory and range from 0.885 to 0.937, exceeding the cutoff value of 0.7. The average variance extracted for each construct was greater than the minimum cutoff value of 0.5 for the three constructs analyzed and ranged from 0.687 to 0.800, confirming convergent validity. This is further confirmed by the factor loadings, which are statistically significant ($p < 0.001$) and range from 0.776 to 0.916, exceeding the recommended threshold of 0.70 and are available in Supplementary Table S3 of the Supplementary Material. The VIFs ranged from 1.844 to 2.812, which were below the cutoff value of 3.3. Similarly, the Q^2 values are similar to those of R^2 for all endogenous constructs (DISU: $Q^2 = 0.346$; ENSU: $Q^2 = 0.645$), confirming the model's non-parametric power.

Table 2. Construct validation indicators.

Construct	CR	α	AVE	VIF	R²	Q²
JIDO	0.916	0.885	0.687	1.844	—	—
DISU	0.952	0.937	0.8	2.382	0.346	0.346
ENSU	0.949	0.937	0.728	2.812	0.645	0.645

Note: CR = Composite reliability (threshold ≥ 0.70); α = Cronbach's alpha (threshold ≥ 0.70); AVE = Average variance extracted (threshold ≥ 0.50); VIF = Variance Inflation Factor for full collinearity (threshold ≤ 3.3); R^2 = Coefficient of Determination (threshold ≥ 0.20); Q^2 = Nonparametric Coefficient of Predictive Relevance (threshold > 0). — = Exogenous construct. Source: Kock [20].

Table 3 reports the Fornell-Larcker criterion for assessing discriminant validity, where the square roots of the AVE appear on the diagonal and exceed all relationships between constructs, confirming that each construct captures a domain that is distinct from the others. Finally, to confirm discriminant validity, the HTMT ratios are reported with 95% confidence intervals in Supplementary Table S4 of the Supplementary Material, and none exceed 0.85.

Table 3. Fornell-larker criterion.

	JIDO	DISU	ENSU
JIDO	**0.829**	0.584	0.665
DISU	0.584	**0.894**	0.754
ENSU	0.665	0.754	**0.853**

Note: Square roots of the AVE on the diagonal (bold).

4.4. Direct effects and nonlinearity analysis

The standardized path coefficients, t-values, 95% confidence intervals, and effect sizes (f^2) for each hypothesis are shown in Table 4 for each relationship between the constructs. It can be seen that all of them are statistically significant ($p < 0.001$), indicating that the three hypotheses in the model are supported.

Table 4. Direct effects, t-statistics, and confidence intervals.

Hypothesis	Relationship	*β*	*t*	95% CI	*f* ²	Result
H_1	JIDO → DISU	0.588	17.818	[0.522, 0.654]	0.346	Supported
H_2	JIDO → ENSU	0.342	10.059	[0.275, 0.408]	0.228	Supported
H_3	DISU → ENSU	0.553	16.758	[0.488, 0.618]	0.417	Supported

Note: β = Standardized trajectory coefficient; t = Student's t-statistic (two-tailed critical value ≥ 1.960; 95% CI = 95% confidence interval; f^2 = Effect size (small ≥ 0.02; medium ≥ 0.15; large ≥ 0.35). *** p < 0.001. Source: Cohen [25].

Figure 2 illustrates the model estimated using standardized values, p-values for each variable, and R^2 values for the endogenous constructs. The relationship between JIDO and DISU in H_1 was the strongest, with β = 0.588, and a medium-to-large effect size (f^2 = 0.346). These values confirm that intelligent autonomy is a predictor and facilitator of DISU in the manufacturing industry. For the relationship in H_2 (JIDO → ENSU, β = 0.342), a moderate direct effect is observed (f^2 = 0.228); however, the total effect of JIDO on ENSU is greater when considering the indirect effect that occurs through DISU as a mediating construct. For the relationship in H_3 (DISU → ENSU, β = 0.553), the second-largest direct effect was observed with f^2 = 0.417, positioning DISU as the most important predictor of improving ENSU in the model.

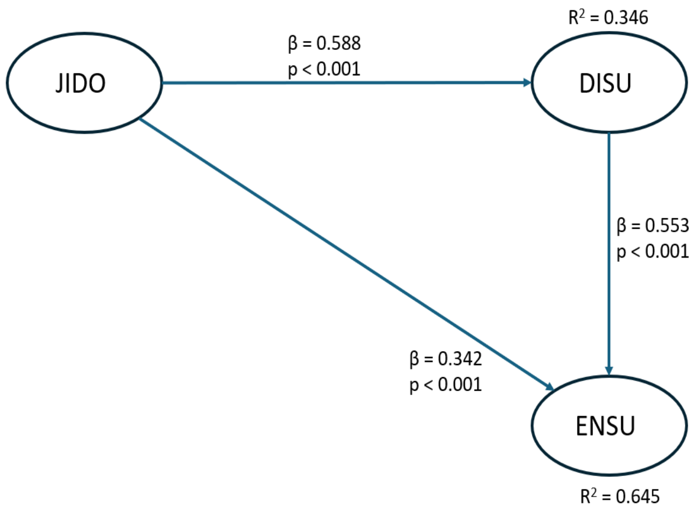

Figure 2. The model was evaluated using β, p and R^2 values.

Figures 3 through 5 present the graphs showing the relationships for each of the hypotheses or direct variables generated using the Warp3 algorithm. For H_1 (JIDO → DISU), a U-shaped nonlinear pattern is observed, where the β coefficients are larger at low levels of JIDO implementation (β = 0.94) and at high levels (β = 1.03), with a reduction in the intermediate range (β = 0.49). This indicates that the benefits generated in DISU by JIDO are greater in the initial and advanced stages of implementation.

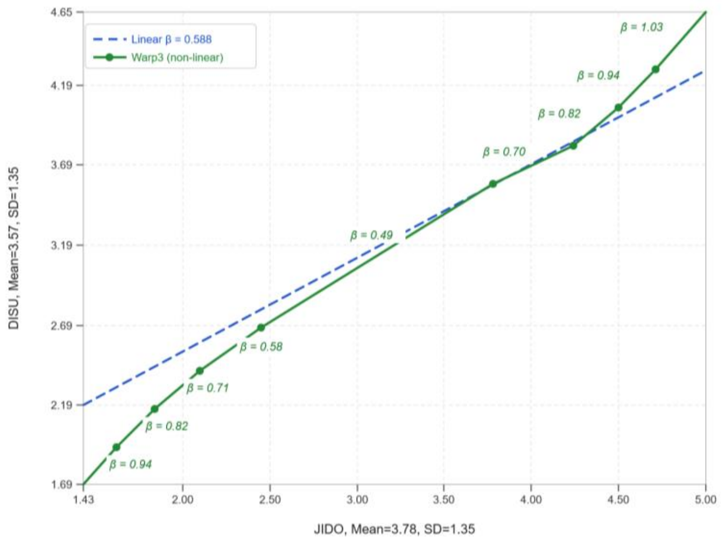

Figure 3. JIDO and DISU relationship.

For the JIDO → ENSU relationship in H_2, diminishing marginal returns are observed, as the value of β progressively decreases from 0.48 at low implementation levels to 0.31 at high implementation levels of JIDO. These values indicate that the environmental benefits derived from the implementation of JIDO diminish as the tool reaches maturity. Finally, for the DISU → ENSU relationship in H_3, this relationship is linear with $\beta = 0.51$, remaining constant across the entire evaluated range, indicating that the environmental benefits generated by DISU accumulate uniformly and without an observable saturation limit.

4.5. Indirect and total effects

Table 5 summarizes the direct, indirect, and total effects of the model. In this case, there was only one indirect effect of JIDO on ENSU via DISU ($\beta = 0.325$, $p < 0.001$, $f^2 = 0.217$), which was nearly equal to the direct effect ($\beta = 0.342$), indicating that approximately half of JIDO's impact on ENSU occurred through the path mediated by DISU. Therefore, the total effect of JIDO on ENSU was 0.667 ($p < 0.001$, $f^2 = 0.444$), indicating that this was the predictor with the greatest influence on environmental benefits when both direct and indirect pathways were considered.

Table 5. Indirect and total effects.

Relationship	**Direct**	**Indirect**			**Total**		
	β	β	**95% CI**	f^2_{ind}	β	**95% CI**	f^2
JIDO → DISU	0.588*	—			0.588*	[0.522, 0.654]	0.346
JIDO → ENSU	0.342*	0.325*	[0.261, 0.389]	0.217	0.667*	[0.601, 0.733]	0.444
DISU → ENSU	0.553*	—			0.553*	[0.488, 0.618]	0.417

**p* < 0.001*

4.6 Sensitivity analysis

Table 6 illustrates the probability-based sensitivity analysis, showing the probabilities of isolated, joint, and conditional occurrences, which complements the diagnostic perspective of the structural model and the standardized values analyzed previously. In this case, high levels of implementation for each construct are represented by (+) and low levels by (−).

Table 6. Sensitivity analysis: conditional probabilities.

			JIDO		**DISU**	
			+	−	+	−
			0.200	0.188	0.211	0.199
DISU	+	0.211	& = 0.115 IF = 0.575	& = 0.011 IF = 0.057		
	−	0.199	& = 0.005 IF = 0.024	& = 0.188 IF = 0.561		
ENSU	+	0.191	& = 0.119 IF = 0.593	& = 0.007 IF = 0.038	& = 0.191 IF = 0.648	& = 0.002 IF = 0.012
	−	0.187	& = 0.000 IF = 0.000	& = 0.116 IF = 0.618	& = 0.004 IF = 0.017	& = 0.132 IF = 0.663

Note: & = joint probability; IF = conditional probability.

The probabilities obtained from the sensitivity analysis reinforce the proposed hypotheses and have useful diagnostic implications. For example, when JIDO is at a high implementation level (JIDO+), the probability of obtaining a high DISU (DISU+) is 57.5%, compared to 5.7% when JIDO is low (almost 10 times lower). The relationship between JIDO and ENSU is even more striking, as the probability of ENSU+ when JIDO+ is 59.3%, whereas the probability of ENSU− when JIDO+ is zero, confirming that JIDO is a vital driver of ENSU.

Finally, when DISU+ occurs, the probability of obtaining ENSU+ is 64.8%, the highest value in the model, indicating that it is the most effective construct for maximizing the environmental benefits. However, when DISU− occurs, the probability of obtaining ENSU− is 66.3%, which represents a risk. These values indicate that if companies do not invest in DISU, manufacturing firms will be vulnerable and at risk of receiving administrative sanctions for non-compliance with government regulations.

5. Discussion

This study evaluated whether JIDO, in terms of intelligent autonomy, has a direct effect on DISU and ENSU in manufacturing firms and whether DISU acts as a mediating construct between JIDO and ENSU. PLS-SEM provides empirical evidence supporting the three proposed hypotheses, and their theoretical and practical implications are discussed in the following sections.

5.1. H_1: Jidoka as a driver of DISU

Hypothesis H_1 proposed that JIDO has a direct effect on DISU. The most robust relationship was found to be $\beta = 0.588$ and $f^2 = 0.346$, which demonstrates the transformative nature of JIDO 4.0 in an Industry 4.0 environment. These results align with those of Rohit *et al.* [4], who indicated that JIDO, when enabled by cyber-physical technologies, is one of the LM tools that best integrates with Industry 4.0 owing to its ability to obtain real-time control and monitoring information that is superior to its analog version, allowing autonomous anomaly detection to be converted into a data asset that should be used strategically by the company.

Similarly, Anosike *et al.* [27] demonstrated that combining automation with IoT technologies improved information flows and facilitated decision-making in manufacturing environments, which form the operational core of DISU. Shriram *et al.* [28] extended this evidence to a specific process, reporting that the integration of JIDO with IoT systems in the paper industry generated benefits that exceeded those obtained by each of these technologies independently and isolated manner. Therefore, this study demonstrates that the synergy achieved between digital autonomy and connectivity drives DISU at the organizational level.

The analysis of nonlinearity in Figure 3 reveals a U-shaped pattern, indicating that the highest returns obtained from JIDO in DISU occur at the extremes of the implementation process. This is because, at the outset, when automatic detection systems are implemented, the impact on DISU is high, as any system improves data collection ability. In the intermediate range of implementation, firms are in a consolidation phase, where marginal gains temporarily decline until technological maturity is reached, as observed at high levels. From the DCV perspective, this phenomenon is consistent with the sensing-capture-reconfiguration cycles described by Teece *et al.* [11], where firms do not generate dynamic capabilities linearly, as learning thresholds require returns that change over time.

This intermediate decline is consistent with the productivity J-curve described by Brynjolfsson *et al.* [29], who show that general-purpose technologies tend to depress measured returns at first because firms must absorb complementary intangible investments, such as process redesign, employee retraining and organizational restructuring, before the gains materialize. In the case of JIDO 4.0, the early returns stem from the immediate improvement in data capture, whereas the intermediate stage reflects the cost of reorganizing routines and integrating the new detection systems into existing workflows. Once these adjustments mature, the marginal contribution of JIDO to DISU rises again, which accounts for the recovery of the coefficient at high implementation levels.

The results of this relationship allow us to propose a new research agenda in manufacturing, but one oriented toward artificial intelligence, since it is demonstrated that when JIDO 4.0 is based on information obtained by IoT sensors and intelligent platforms, it becomes an infrastructure capable of collecting real-time data from the production process. These DISU capabilities, such as production process monitoring, data management practices, and optimization of available energy, are outcomes that every manager seeks. Therefore, the PLS-SEM reported in this study provides empirical evidence demonstrating that investing in JIDO and modernizing the production system increases the capacity to obtain data that facilitates decision-making. Similarly, the transition from traditional JIDO to JIDO 4.0 results in leaner and more standardized production processes.

5.2. H_2: Jidoka and the direct environmental impact

The relationship between JIDO and ENSU (β = 0.342, f^2 = 0.228) demonstrates that intelligent automation has a direct effect on ENSU in the manufacturing industry, without considering the indirect effect mediated by DISU. This finding aligns with that of García-Alcaraz *et al.* [13], who demonstrated that JIDO impacts ENSU due to a reduction in rework resulting from defect minimization. This finding also coincides with that of Ferrazzi *et al.* [1], who state that LM principles focused on the early identification of anomalies have the greatest positive environmental impact, as they act at the source of the process rather than on its consequences.

Figure 4 shows the diminishing marginal returns relationship between these two constructs. In the context of high levels of JIDO, the environmental benefits decrease indicating that benefits are gained in the initial stages of the implementation process. This behavior has practical implications for small companies or those with limited financial resources. This is consistent with the findings of Zheng *et al.* [30], who found an inverted U-shaped relationship between the level of digitalization and carbon emissions generated during the production process. This indicates that digital strengths and capabilities have diminishing returns in terms of environmental performance. From the perspective of STS, the explanatory mechanism might be the integration between technical defect detection and human response, as when such integration reaches high levels of maturity, the benefits to the environment decrease as the main sources of waste have been identified and eliminated.

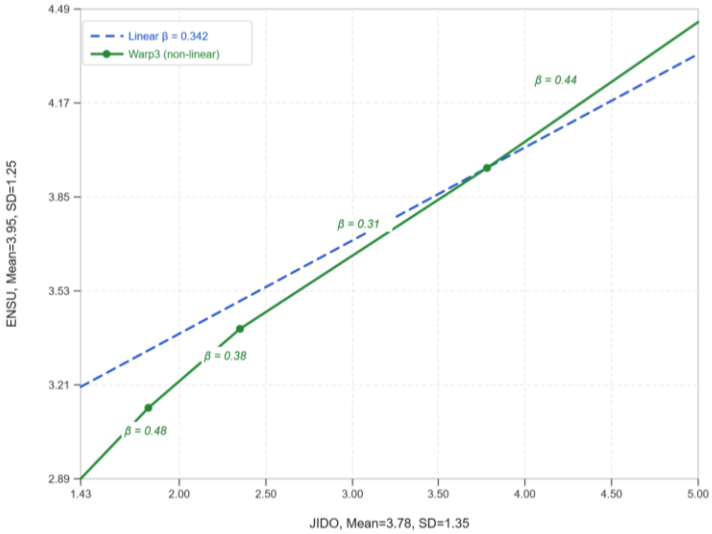

Figure 4. JIDO-ENSU relationship.

5.3. H_3: DISU as an environmental lever

Hypothesis H_3 (DISU → ENSU, $\beta = 0.553$, $f^2 = 0.417$) shows the largest effect size in the model, demonstrating that DISU is the variable that most influences environmental benefits in the maquiladora industry. This result empirically corroborates the results of previous studies; for instance, Feroz *et al.* [8] found similar results, showing that digital transformation enhances pollution control and waste management improvements. The results of Chen *et al.* [9] prove that the manufacturing industry reduces carbon emissions through technological innovation processes through digitization. Furthermore, Sarfraz *et al.* [10] argued that environmental performance is influenced by digital strategies, and the effect is mediated by innovation capabilities.

Figure 5 illustrates the linear relationship of these two constructs with a constant β of 0.51, signifying the environmental benefits of DISU are accrued uniformly and without any indication of saturation, in contrast to the non-linear patterns of H_1 and H_2. The maturity of JIDO means its capabilities decline over time. DISU capabilities do not decline. In this respect, DCV would entail that DISU is a value-capturing capability, through which companies that responsibly manage their digital resources continuously expand their opportunities for environmental improvement without depleting or reducing them.

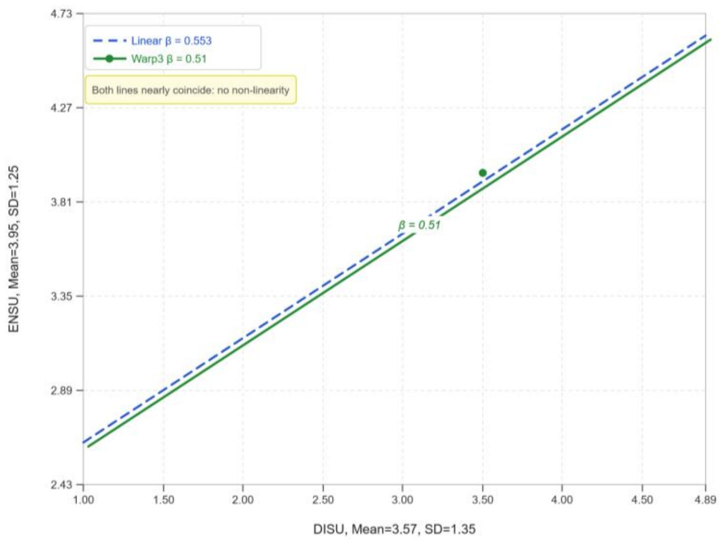

Figure 5. DISU-ENSU relationship.

5.4. Mediated effects and sensitivity analysis

One of the most important findings of this study is that it analyzes the indirect effect of JIDO on ENSU, which occurs through DISU (β = 0.325), which is nearly equal to its direct effect (β = 0.342). This indicates that nearly half of JIDO's impact on ENSU occurs through a path mediated by DISU. This result has theoretical implications, as JIDO provides environmental benefits not only through waste reduction on production lines but also through firms' digital capabilities. These two effects—direct and indirect—are consistent with STS, which explains the direct mechanism through the socio-technical integration of the production process, whereas DCV explains the mechanism mediated by DISU and dynamic capabilities.

A probability-based sensitivity analysis reinforces these conclusions. For example, the probability of achieving ENSU+ when DISU+ occurs is 64.8%, which is the largest conditional value in the model, indicating that DISU is the most effective lever for managers in the manufacturing industry seeking to improve their environmental performance. Similarly, when DISU− occurs, the probability of achieving ENSU− is 66.3%, representing the greatest risk identified in the model. These results, when combined with the effects of JIDO on DISU, point to a clear organizational course of action in which investing in smart automation is not only a decision to promote production efficiency but also a strategic decision that supports ENSU.

6. Conclusions, limitations, and future research directions

6.1. Conclusions

In this study, a SEM was proposed and tested to examine the relationships between JIDO, DISU, and ENSU, which was validated using data from manufacturing companies in Ciudad Juárez, Mexico. The model was validated using data from a sample of 834 responses, and the three hypotheses were tested using the PLS approach in WarpPLS software and were found to be statistically supported.

The results indicate that JIDO, in its dimension of intelligent autonomy within Industry 4.0, is a predictor that supports DISU (H_1, β = 0.588), suggesting that the ability to automatically detect anomalies and deviations and generate real-time operational data streams serves as an effective platform for developing sustainable digital practices. It has been observed that JIDO also has a direct effect on ENSU (H_2, β = 0.342), indicating that by eliminating defects at the source of the production process, it minimizes material consumption, energy use, and waste generated by the rework. The third finding, with the largest effect size in the model, is the relationship between DISU and ENSU (H_3, β = 0.553, f^2 = 0.417), demonstrating that DISU supports ENSU with a linear relationship, indicating an absence of saturation at the observed levels of implementation.

This study makes three contributions to the literature. First, it integrates sociotechnical systems theory and the dynamic capabilities perspective into a framework that explains the internal mechanism of JIDO's technical-social integration and the strategic mechanism through which JIDO can generate greater sustainable capabilities in the manufacturing industry. Second, it proposes DISU as a mediating construct between JIDO and ENSU, a relationship that is logical but has not been empirically demonstrated. The third and most important contribution is that nonlinear relationships are reported, in which the relationship between JIDO and DISU is U-shaped, while its impact on ENSU shows diminishing returns, challenging the assumptions of linearity reported in the literature.

From a practical perspective, sensitivity analysis offers managers a diagnostic tool for identifying risks. For example, when JIDO+ occurs, the probability of obtaining ENSU− is zero, and when DISU+ is present, the probability of obtaining ENSU+ is 64.8%. With these probabilities, managers can prioritize investments and empirically diagnose risks.

From the perspective of data-driven manufacturing and artificial intelligence, this study provides evidence that smart LMTs are not peripheral to the digital transformation of production systems but rather constitutive of it. Jidoka 4.0 generates operational data that fuel manufacturing intelligence through sensors, detection algorithms, and real-time notification systems, constituting a data infrastructure from which DISU and, ultimately, environmental performance as ENSU emerge. Organizations seeking to advance their data-driven manufacturing capabilities would benefit from recognizing Jidoka 4.0 not as a lean tool adapted to Industry 4.0 but as a data-driven capability that connects production line intelligence with organizational sustainability outcomes.

6.2. Limitations and future research directions

This study has three limitations that should be considered. Its cross-sectional design prevents us from inferring causality in a strict sense or documenting how the constructs evolve over time; therefore, future research should adopt longitudinal designs that track how the gradual implementation of JIDO transforms the capabilities of DISU and ENSU, allowing us to identify the turning points in the U-shaped pattern reported here. Additionally, the analysis was conducted using data from a sample of the manufacturing industry in Ciudad Juárez, Mexico, which has unique structural characteristics, such as its export orientation and high level of automation, which may limit generalizability to other contexts. Future research should replicate the model in regions with different levels of maturity in LMTs and digitalization and incorporate moderating constructs such as digital organizational culture, transformational leadership, or regional environmental regulations to examine the conditions under which the effect of JIDO on DISU and ENSU is intensified or dampened. Third, the data were gathered through a non-probability convenience sample; although the inclusion criteria ensured that respondents were knowledgeable about JIDO implementation, this approach may introduce self-selection bias and constrain the extent to which the findings can be generalized to the broader population of manufacturing firms. Future studies could rely on probability-based sampling frames to corroborate the relationships reported here.

Supplementary data

The supplementary material is available at https://doi.org/10.17632/syst7rz6bt.1. It is provided as an Excel file containing five clearly labeled sheets:

Supplementary Table S1. Raw data. It contains a table with the data used in the model.

Supplementary Table S2. Median and IQR. It contains a table with the median and IQR of the items analyzed in the model.

Supplementary Figure S1. Sample size. It contains the figure used to determine the minimum sample size.

Supplementary Table S3. Factor loadings. It contains the factor loadings used to assess convergent validity.

Supplementary Table S4. HTMT. It contains the HTMT ratios used for discriminant validity analysis.

Data availability statement

The data supporting the findings of this study are openly available in Mendeley Data at https://doi.org/10.17632/syst7rz6bt.1. The dataset includes the anonymized raw survey responses for all 834 valid cases, item-level descriptive statistics (median and IQR), minimum sample size calculations, standardized factor loadings, and HTMT discriminant validity ratios used in the SEM estimation.

Declaration of generative AI and AI-assisted technologies

During the preparation of this manuscript, the authors used Grammarly and Paperpal for language polishing and readability improvement purposes only. These tools were not used for idea generation, data analysis, interpretation of results, or the drawing of scientific conclusions. The authors take full responsibility for the integrity, originality, and accuracy of the content of this manuscript.

Acknowledgments

Jorge Luis García Alcaraz gratefully acknowledges the support of the Secretariat of Science, Humanities, Technology, and Innovation (SECIHTI) of Mexico for funding his sabbatical research stay at the Autonomous University of Baja California, Ensenada Campus, under project No. 210995.

Authors' contribution

Jorge Luis García Alcaraz: conceptualization, methodology, software, formal analysis, investigation, resources, data curation, writing—original draft preparation, visualization, project administration, funding acquisition; Jorge Limón Romero: conceptualization, validation, supervision, writing—review and editing; Yashar Aryanfar: methodology, formal analysis, visualization, writing—review and editing; Jorge Manuel Cueva Estrada: validation, investigation, writing—review and editing. All authors reviewed and approved the final version of the manuscript.

Conflicts of interest

The authors declare no conflicts of interest. The funders had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript; or in the decision to publish the results.

References

[1] Ferrazzi M, Frecassetti S, Bilancia A, Portioli-Staudacher A. Investigating the influence of lean manufacturing approach on environmental performance: a systematic literature review. *Int. J. Adv. Manuf. Technol.* 2025, 136(9):4025–4044.

[2] Ma J, Wang Q, Zhao Z. SLAE–CPS: smart lean automation engine enabled by cyber-physical systems technologies. *Sensors* 2017, 17(7):1500.

[3] Koteswarapavan C, Pattanaik LN. A novel tool-input-process-output (TIPO) framework for upgrading to lean 4.0. *Int. J. Prod. Manag. Eng.* 2024, 12(1):65–77.

[4] Rohit, Vinodh S, Vigneshvaran R. Benchmarking analysis of cyber-physical system-based lean tools using grey approaches. *Benchmarking: Int. J.* 2025, 33(3):987–1016.

[5] García Alcaraz JL, Morales García AS, Díaz Reza JR, Blanco Fernández J, Jiménez Macías E, *et al.* Machinery lean manufacturing tools for improved sustainability: the Mexican maquiladora industry experience. *Mathematics* 2022, 10(9):1468.

[6] Vergallo R, D'Alò T, Mainetti L, Paiano R, Matino S. Evaluating sustainable digitalization: a carbon-aware framework for enhancing eco-friendly business process reengineering. *Sustainability* 2024, 16(17):7789.

[7] Zhang J, Liu M. How to leverage digital sustainability orientation to promote environmentally sustainable practices of manufacturing enterprises in china. *Sustainability* 2024, 16(12):5112.

[8] Feroz AK, Zo H, Chiravuri A. Digital transformation and environmental sustainability: a review and research agenda. *Sustainability* 2021, 13(3):1530.

[9] Chen J, Guo Z, Lei Z. Research on the mechanisms of the digital transformation of manufacturing enterprises for carbon emissions reduction. *J. Clean. Prod.* 2024, 449:141817.

[10] Sarfraz M, Ye Z, Dragan F, Ivascu L, Artene A. Digital transformation strategy and environmental performance: a case study. *Int. J. Comput. Commun. Control* 2022, 17(6).

[11] Teece DJ, Pisano G, Shuen A. Dynamic capabilities and strategic management. *Strateg. Manag. J.* 1997, 18(7):509–533.

[12] Bag S, Gupta S, Kumar S. Industry 4.0 adoption and 10R advance manufacturing capabilities for sustainable development. *Int. J. Prod. Econ.* 2021, 231:107844.

[13] García-Alcaraz JL, Morales García AS, Díaz-Reza JR, Jiménez Macías E, Javierre Lardies C, *et al.* Effect of lean manufacturing tools on sustainability: the case of Mexican maquiladoras. *Environ. Sci. Pollut. Res.* 2022, 29(26):39622–39637.

[14] Alatrista-Corrales A, Moreno-Arévalo M, Zevallos-Pacheco C, Rueda-Enríquez M. Managing manufacturing efficiency using the concept of automation with human touch. *Int. J. Bus. Intell. Data Min.* 2021, 19(1):33–51.

[15] Azli AD, Abu F, Rusli MHM, Goh J, Kah GW, *et al.* Design and development of industry 4.0 smart lean kaizen manufacturing: a case study on extrusion line of vacuum hose. *Int. J. Integr. Eng.* 2024, 16(8):39–53.

[16] Zhou D, Shao Z. Digital transformation, manufacturing servitization and enterprises' carbon emissions. *J. Clean. Prod.* 2025, 520:146026.

[17] Ayre C, Scally AJ. Critical values for lawshe's content validity ratio: revisiting the original methods of calculation. *Methods Plainly Speak.* 2014, 47(1):79–86.

[18] Penfield RD, Giacobbi JPR. Applying a score confidence interval to aiken's item content-relevance index. *Meas. Phys. Educ. Exerc. Sci.* 2004, 8(4):213–225.

[19] García-Alcaraz JL, Prieto-Luevano DJ, Maldonado-Macías AA, Blanco-Fernández J, Jiménez-Macías E, *et al.* Structural equation modeling to identify the human resource value in the JIT implementation: case maquiladora sector. *Int. J. Adv. Manuf Technol.* 2015, 77(5):1483–1497.

[20] Kock N. *WarpPLS user manual: version 8.0*. 2025. Available: https://www.scriptwarp.com/warppls/UserManual_v_8_0.pdf (accessed on 05 April 2026).

[21] Fornell C, Larcker DF. Evaluating structural equation models with unobservable variables and measurement error. *J. Mark. Res.* 1981, 18(1):39–50.

[22] Henseler J, Ringle CM, Sarstedt M. A new criterion for assessing discriminant validity in variance-based structural equation modeling. *J. Acad. Mark. Sci.* 2015, 43(1):115–135.

[23] Podsakoff PM, MacKenzie SB, Lee JY, Podsakoff NP. Common method biases in behavioral research: a critical review of the literature and recommended remedies. *J. Appl. Psychol.* 2003, 88(5):879.

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

[25] Cohen J. *Statistical Power Analysis for the Behavioral Sciences*, 2nd ed. Mahwah: Lawrence Erlbaum Associates, 1988. pp. 20–26.

[26] Sordan JE, Oprime PC, Pimenta ML, Lombardi F, Chiabert P. Symbiotic relationship between robotics and Lean manufacturing: a case study involving line balancing. *TQM J.* 2022, 34(5):1076–1095.

[27] Anosike A, Alafropatis K, Garza-Reyes JA, Kumar A, Luthra S, *et al.* Lean manufacturing and internet of things – a synergetic or antagonist relationship? *Comput. Ind.* 2021, 129:103464.

[28] Shriram KR, Karthiban SK, Kumar AC, Mathiarasu SK, Saleeshya PG. Productivity improvement in a paper manufacturing company through lean and IoT-a case study. *Int. J. Bus. Syst. Res.* 2023, 17(1):97–119.

[29] Brynjolfsson E, Rock D, Syverson C. The productivity j-curve: how intangibles complement general purpose technologies. *Am. Econ. J.: Macroecon.* 2021, 13(1):333–372.

[30] Zheng L, Chotia V, Alshaghdali NO, Broccardo L, Wang L. Navigating multilevel environmental pressures and harnessing digital transparency as a catalyst for sustainable innovation: pathways to enhanced environmental performance. *Bus. Strategy Environ.* 2025, 34(6):7736–7751.