Golden Sun-Rise
International Journal of Multidisciplinary on Science and Management
ISSN: 3048-5037/ Volume 3 Issue 2 Apr-Jun 2026 / Page No: 179-192
Paper Id: IJMSM-V3I2P121 / Doi:10.71141/30485037/V3I2P121

Research Article

The Moderating Role of Technology Acceptance on the Relationship Between Smart TPS Pillars and Logistics Performance: A Case Study of Uratex Cebu

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Received: 21 May 2026 Revised: 23 May 2026 Accepted: 25 May 2026 Published: 28 May 2026

***Abstract** - This study explores how Uratex Cebu has adapted to five years of Internet of Things (IoT) integration within the Toyota Production System (TPS). As organizations mature, they often face a "performance plateau," where technical gains stabilize, and further improvements become harder to achieve. To understand this challenge, the research examines how the TPS pillars of Smart Just-in-Time (JIT) and Smart Jidoka relate to employees' perceptions of logistics performance. A cross-sectional design was used, drawing on multiple sources of data and responses from 134 employees with at least five years of tenure ensuring that insights reflect stabilized, long-term experiences rather than short-term novelty. Findings suggest that while IoT infrastructure sets the foundation for efficiency, employee acceptance of technology measured through Perceived Usefulness (PU) and Perceived Ease of Use (PEOU) plays a decisive role in sustaining progress.In particular, human alignment with digital tools helps prevent "Digital Muda," or inefficiencies that arise when systems are bypassed. The study closes by proposing a diagnostic framework for re-synchronizing people and technology, offering practical guidance for organizations moving toward the human-centered vision of Industry 5.0.*

***Keywords** - Digital Lean, Industry 5.0, Internet of Things, Logistics Performance,Technology Acceptance Model, Toyota Production System.*

I. INTRODUCTION

The global logistics industry has been going through a major transformation that is sometimes referred to as Logistics 4.0, and in which traditional logistic systems are being complemented more and more by cyber physical systems [8]. Logistics is still the lifeline of trade in today's economy, but the human interaction with these processes is being replaced by very integrated and technology-driven operations [5]. Within this shift, the Toyota Production System (TPS) has been transformed to a "Digital Lean" system by incorporating Internet of Things (IoT) technologies [13]. This change is not merely a technological one, but a sociotechnical one in which operational practices like Smart Just-in-Time (JIT) and Smart Jidoka meet with the employees' acceptance of technology [4]. Smart JIT uses real time data to minimize waste, and Smart Jidoka serves as a digital safety guard for automated quality assurance. Yet, the success of these pillars depends heavily on human alignment, underscoring that technical systems alone cannot sustain progress [8].

A recurring challenge in mature industrial settings is the so-called "Productivity Paradox" or "Performance Plateau" [15]. This is a stage that is generally reached after approximately five years of system institutionalization and corresponds to the stage in which the achievements of technology leveling off, making further technology gains difficult to attain [9]. The idea of such plateaus frequently is attributed to a "sociotechnical mismatch", where technology advances faster than social subsystem behavior adjustment [6].

After the early “novelty effect” of the IoT integration wears off, staff may see digital interfaces as tedious, even using manual workarounds in some cases [12].

These practices give rise to “Digital Muda,” a condition where data-driven protocols lose connection with operational reality, ultimately undermining efficiency and quality outcomes [7]. This study focuses on an important question about how these underutilized efficiencies could be “unblocked.” Previous studies have investigated the variables in the Technology Acceptance Model (TAM) and the Smart TPS pillars individually, there has been little empirical study that investigates the role of TAM as a moderator in the context of a mature environment [2]. This research takes a look at Uratex Cebu, a facility that reached its 5-year mark, and evaluates if there is a means to support technical advances through user acceptance. The study's analysis is conducted by applying TAM and Sociotechnical Systems (STS) theory to support the transition to a more human-centric approach in Industry 5.0 [10].

II. MATERIALS AND METHODS

This section outlines the procedures used to examine how technology acceptance moderates the impact of IoT-enabled TPS pillars. Guided by Sociotechnical Systems (STS) Theory, the methodology treats organizational performance as the product of both technical subsystems (Smart TPS practices) and social subsystems (Technology Acceptance). Because the researcher holds a professional role at the Cagayan de Oro branch, safeguards were introduced such as limiting the study to the Cebu branch to ensure objectivity, reduce bias, and protect data integrity.

A. Conceptual Framework

The framework, shown in Figure 1, applies a socio-technical lens to evaluate Uratex Cebu’s operations after five years of IoT integration. Instead of assuming a simple cause-and-effect relationship, it presents a relational model where the effectiveness of Smart JIT and Smart Jidoka depends on human behavioral factors. This moderation design is especially relevant for overcoming the “performance plateau” that occurs when performance is reaching a maximum point, and further increases depend on the way employees are using and adjusting to digital systems. That is, the framework emphasizes that successful improvement requires both technical design and quality of the human-technology interface.

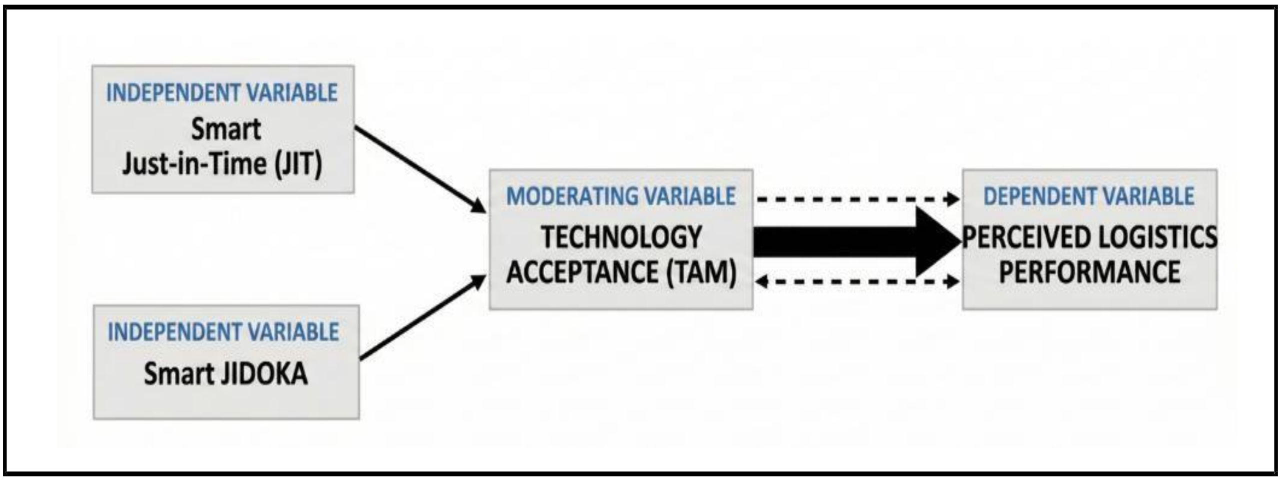

Figure 1. Schematic Diagram of the Conceptual Framework

Note. The framework illustrates the predictive relationship between Industry 4.0 Lean practices (Smart JIT and Smart JIDOKA) and Perceived Logistics Performance, with Technology Acceptance (TAM) serving as a moderating variable.

a. The Independent Variables (IV): Smart TPS Pillars

The study focuses on two core pillars of the Toyota Production System, enhanced through digital technologies to create a “Digital Lean” environment.

- **Smart Just-in-Time (JIT)**: This reflects the technical subsystem’s capacity to support rapid replenishment and continuous, real-time data flow, enabled by Internet of Things (IoT) sensors.

- **Smart Jidoka**: This represents the automated quality assurance subsystem, where cyber-physical systems detect abnormalities and halt processes to minimize human error.

b. The Moderating Variable (MV): Technology Acceptance (TAM)

Technology Acceptance serves as the "Behavioral Anchor" in this framework. Based on Davis (1989), it is measured using Perceived Usefulness (PU) and Perceived Ease of Use (PEOU) that influence a person's tendency to use and trust digital signals. In this model, TAM acts as a psychological barrier, which can either enhance or diminish the effects of the Smart TPS practices on logistics performance. This is an important moderating effect to recognize, particularly in more mature environments where "performance plateau" may happen when the acceptance of the new decreases.Such declines often lead to manual workarounds that bypass digital protocols, undermining efficiency. In systems that have reached the five-year mark, technical gains from IoT integration tend to stabilize, shifting the responsibility for further improvement from the technical subsystem to the social subsystem's alignment with technology [6, 12].

c. The Dependent Variable (DV): Perceived Logistics Performance

The dependent variable in this study is Perceived Logistics Performance, which captures employees' subjective assessments of operational outcomes rather than relying solely on departmental-level KPIs. This construct reflects the broader "socio-technical alignment" required to sustain excellence as the industry moves toward a human-centric Industry 5.0 paradigm. It is examined across two key dimensions:

1. **Efficiency**: Employees' perceptions of speed, flow, and the elimination of waste (muda), with particular attention to transport, motion, and excess inventory.
2. **Quality Accuracy**: The perceived reliability of data and the effectiveness of built-in quality behaviors supported by Smart tools.

Together, these dimensions provide a holistic view of how workers experience logistics performance in a digitally integrated environment, highlighting the interplay between technical systems and human engagement. The following hypotheses were developed to be tested through quantitative analysis. They are concerned with the relationship between the technical aspects of the Toyota Production System and the social aspect of technology acceptance. This study aims to identify the influence of human behavioral factors on the effectiveness of a mature IoT-integrated environment by focusing on the perceived logistics performance.

- H1: Smart JIT
  Smart Just-in-Time (JIT) is expected to show a significant correlation with perceived logistics performance, particularly in terms of operational efficiency.
- H2: Smart Jidoka
  Smart Jidoka is hypothesized to be significantly correlated with perceived logistics performance, especially in relation to quality and accuracy behaviors.
- H3: Technology Acceptance
  Technology Acceptance (measured through PU and PEOU) is proposed to significantly moderate the relationship between the Smart TPS pillars (JIT and Jidoka) and perceived logistics performance.

B.Research Design

This study employs a multi-source, cross-sectional, and correlational design. To minimize the risk of social desirability bias linked to the researcher's insider role, the investigation was limited to the Uratex Cebu branch. This geographic separation gave the researcher objective distance from his/her participants. Data were triangulated using two sources: primary behavioral surveys and secondary audited KPI records, which together helped validate the "performance plateau" narrative.

C.Ethical Considerations and Insider Status

Because the researcher also serves as a Plant Manager within the organization, safeguards were established to protect the integrity of the social subsystem data. The study followed the standards of the MSU-IIT University

Ethics Review Board (UERB), with formal clearance secured under Certificate No. UERB-2025-00504 prior to data collection.

A Management Non-Interference Memo was issued to ensure a neutral environment during survey administration. Participation was voluntary, and responses were anonymized using alphanumeric codes to encourage honest feedback free from managerial influence. In addition, the Cebu branch was chosen as the study site to maintain clear separation from the researcher's home branch in Cagayan de Oro City, reinforcing objectivity and academic validity.

D. Population and Sampling

The target population consists of 200 operational employees at Uratex Cebu involved in the IoT-enabled Toyota Production System (TPS). Using Slovin's formula with 95% confidence level, the required sample size was determined to be 134 respondents.

Proportional stratification was applied across three functional areas:

- Warehouse and Inventory: 45% (n = 60)
- Production and Jidoka: 40% (n = 54)
- Logistics and Dispatch: 15% (n = 20)

E. Inclusions and Selection Criteria

To ensure the study captures a mature system interaction, a purposive sampling strategy was used with the following criteria:

- **Tenure**: Participants must have a minimum of five years of experience to ensure "novelty effect" of IoT has dissipated.
- **Operational Interaction**: Respondents must use digital infrastructure (ERP tablets, IoT scanner, etc.) as a mandatory part of daily routines.

F. Research Instrumentation

The primary tool for data collection in this study was a structured survey questionnaire designed to capture both behavioral and operational perceptions. This was complemented by a secondary data sheet that recorded objective organizational metrics. Together, these instruments provided a multi-source approach consistent with the sociotechnical framework, ensuring that both social and technical subsystems were measured.

a. Primary Instrument: Sociotechnical and TAM Survey

The survey employed a 5-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree), allowing qualitative perceptions to be converted into interval data suitable for Hierarchical Moderated Regression Analysis (MRA). The instrument was organized into four sections:

- **Part I**: Demographic and Professional Profile – Collected information on department, years of experience, and IoT usage frequency. A filter ensured that only respondents with at least five years of tenure were included, establishing a baseline for mature system interaction.
- **Part II**: Smart TPS Pillars (IV) – Six items adapted from Buer et al. (2018) measured the perceived maturity of Smart JIT and Smart Jidoka practices.
- **Part III**: Technology Acceptance (MV) – Six items adapted from Davis (1989) assessed Perceived Usefulness (PU) and Perceived Ease of Use (PEOU).
- **Part IV**: Perceived Logistics Performance (DV) – A 14-item composite scale adapted from Monden (2012) evaluated operational efficiency and quality/accuracy.

The distribution of items and their supporting references is summarized in Table 1.

Table 1. Summary of Research Instrumentand Distribution of Items

Variable	No. of Items	Scale Type	Supporting Reference
Smart TPS (IV)	6	5-point Likert	Buer et al. (2018)

Technology Acceptance (MV)	6	5-point Likert	Davis (1989); Vilaça (2025)
Perceived Performance (DV)	14	5-point Likert	Monden (2012); Culler (2021)
Logistics Performance (Context)	3	Operational Logs	Uratex Official Record

b. Secondary Instrument: Official Branch Logistics KPI Reports

To anchor the study in objective reality, audited Logistics KPI Reports from Uratex Cebu management were used. These records span a five-year period (2021–2025), capturing the maturity phase of the digital-lean implementation. The reports track three key metrics that directly align with the Smart TPS pillars:

- **Lead Time Records**: Average order fulfillment cycle times, serving as an indicator of Smart JIT performance.
- **Dispatch Logs**: On-time delivery percentages, providing a benchmark for distribution reliability.
- **Audit Logs**: Inventory accuracy percentages, used to evaluate the effectiveness of Smart Jidoka and automated monitoring tools.

Together, these longitudinal KPI measures complement the survey data, ensuring that the analysis reflects both employee perceptions and verifiable operational outcomes.

G. Data Analysis Procedure

Data analysis was carried out using SPSS Statistics, following a structured sequence of steps:

1. **Preliminary Screening**: Internal consistency of the survey instrument was verified using Cronbach's Alpha (α) to ensure reliability across constructs.
2. **Mean Centering**: Independent and moderating variables were mean-centered to reduce multicollinearity and prepare for interaction term creation.
3. **Hierarchical Moderated Regression Analysis (MRA)**: A five-step regression procedure was applied. Control variables (tenure, department) were entered first, followed by the main effects, the moderator, and finally the interaction terms. This progression allowed the incremental variance explained by each block to be assessed, with particular attention to the contribution of the moderation effect.

III. RESULTS AND DISCUSSION

A. Preliminary Screening and Reliability

The reliability analysis of the 26-item instrument produced a Cronbach's Alpha of 0.897, as shown in Table 2. This result exceeds the conventional 0.70 threshold for acceptable internal consistency, demonstrating that the measurement scale exhibits reliable inter-item covariance across the intended constructs: Smart JIT, Smart Jidoka, Technology acceptance (PU and PEOU), and perceived Logistics Performance. This statistical baseline justifies the aggregation of individual items into composite variables for subsequent parametric testing.

Table 2. Reliability Statistics of the Full Survey Instrument

Cronbach's Alpha (α)	N **of Items**
0.897	26

To ensure the suitability of the constructs for subsequent regression analysis wherein they function as independent, moderating, and dependent variables internal reliability was evaluated at the construct level, as summarized in Table 3.

Table 3. Reliability Statistics by Research Construct

Construct	**Cronbach's Alpha** (α)	N **of Items**
IoT-enabled TPS Pillars	0.736	6
Technology Acceptance (TAM)	0.852	6
Perceived Logistics Performance	0.825	14

Note: N = 134. Internal consistency metrics for each individual research dimension safely exceed the universally accepted baseline threshold of 0.70.

- **IoT-enabled TPS Pillars (Smart JIT and Smart Jidoka)**: Produced an α coefficient of 0.736 across 6 items, validating its deployment as an independent predictor block.
- **Technology Acceptance Model (TAM)**: Generated an α coefficient of 0.852 across 6 items, confirming
- its suitability as a moderating construct.
- **Perceived Logistics Performance**: Produced an α coefficient of 0.825 across 14 items, confirming high measurement stability for the dependent variable.

B. Descriptive Statistics

This section qualitatively explains the demographic profile of the 134 valid cases to ensure the research theory is grounded in a representative sample.

a. Frequency and Percentage Distribution for the demographic profile (Department, Tenure, and Iot Usage)

The frequency and percentage distribution of the demographic profile covering department, tenure, and IoT usage provides important context for interpreting the study's findings. Table 4 indicates that the highest percentage of respondents were from the Warehouse (44.80%) and Production (39.60%) positions, with Logistics/Delivery making up 15.70%. The distribution indicates that the majority is clustered in operational areas directly related to inventory handling and production, meaning that it correlates well with the focus of this study on the IoT pillars.

The relatively balanced representation between Warehouse and Production ensures that both material flow and manufacturing perspectives are well captured. The smaller but significant Logistics/Delivery group provides information on downstream distribution processes. Overall, the spread of demographics further indicates that the sample represents the main operational departments that are most largely impacted by the integration of IoT, which enhances the reliability of the subsequent analysis.

Table 4. Frequency and Percentage Distribution by Department

Department	**Frequency** (*n*)	**Percentage** (%)
Logistics/Delivery	21	15.70
Production	53	39.60
Warehouse	60	44.80
Total	**134**	**100.00**

Note: N = 134. Participants are concentrated across core supply chain units directly integrated with the facility's digital lean manufacturing practices.

b. Years of Experience

The frequency distribution for years of experience, presented in Table 5, it is seen that the respondents are distributed across three experience groups, 5 years (39.60%), 6 years (29.10%) and 7 years and above (31.30%). The spread shows that majority of the respondents are experienced staff who have been working in the organization long enough to be familiar with the TPS practices through IoT. The distribution in the tenure groups ensures, which helps to get the view of the more experienced workers as well as the medium-level workers. This experience diversity boosts the credibility of the conclusions drawn regarding the influence of the acceptance of technology on logistics performance, since they are a reflection of experiences that have been gained through the sustained contact with digital lean systems.

Table 5. Distribution of Respondents by Years of Experience

Years of Experience	**Frequency** (*n*)	**Percentage** (%)
5	53	39.60
6	39	29.10

7	42	31.30
Total	**134**	**100.0**

Note: N = 134. All participants meet a strict five-year minimum tenure baseline criteria.

c. Usage of IoT

The frequency distribution for IoT usage, presented in Table 6, shows that the vast majority of respondents (83.60%) interact with IoT tools on a daily basis. A smaller proportion (13.40%) said that they used it frequently, and 3.00% said they used it occasionally. This pattern shows how well the company has integrated IoT technologies into its routine, causing them to face the same digital-lean routines every day, including Smart JIT and Smart Jidoka. The substance of the study results is reinforced by the fact that the opinions expressed are based on the daily use of the IoT systems, and not on occasional or limited use. The level of interaction suggests that the sample is representative of employees who are more deeply involved in the digital workflow, and therefore more helpful in giving insight into the moderating effect of technology acceptance.

Table 6. Frequency of IoT Usage Among Respondents

Usage of IoT	**Frequency** (n)	**Percentage** (%)
Daily	112	83.60
Frequently	18	13.40
Occasionally	4	3.00
Total	**134**	**100.00**

C. Hierarchical Moderated Regression

The results that come out of the hierarchical moderated regression analysis are presented in four blocks for testing the effect of Smart JIT, Smart Jidoka, and the moderating effect of Technology Acceptance (TAM) on Logistics Performance.

a. Model Progression and Variance Explained

As shown in Table 7, the analysis progresses through four distinct blocks:

Table 7. Hierarchical Moderated Regression Results for Logistics Performance

Predictor	**Model 1** (β)	**Model 2** (β)	**Model 3** (β)	**Model 4** (β)
Step 1: Controls				
(Constant)	3.780	3.729	4.008	3.946
Department	-0.079	0.052	0.043	0.046
IoT Usage	-0.022	0.019	-0.034	-0.025
Years of Experience	0.078	0.027	-0.006	0.005
Step 2: Main Effects				
Smart JIT		0.314**	0.204**	0.169**
Smart Jidoka		0.128*	0.055	0.055
Step 3: Moderator				
TAM			0.356**	0.336**
Step 4: Interactions				
$JIT \times TAM$				-0.113*
$Jidoka \times TAM$				0.034
Model Summary				
R^2	0.030	0.320	0.461	0.480

Adjusted R^2	0.008	0.293	0.435	0.446
ΔR^2	0.030	0.290	0.141	0.019
F Change	1.355	27.244	33.148	2.276
Sig. F Change	.260	<.001	<.001	.107

Note: N=134. Standardized coefficient (β) are reported * p <.05, ** p <.01, *** p <.001

a) **Model 1 (Control Variables)**: The control variables (Years of experience, department, and IoT usage) explain only 3.0% of the variance (R^2 = 0.030), and the change is not significant (p = .260) , indicating minimal influence from demographic characteristics.
b) **Model 2 (Main Independent Variables)**: The addition of the IoT-enabled TPS pillars (Smart JIT and Smart Jidoka) resulted in a substantial, statistically significant increase in explained variance, bringing the total model capacity to 32.0% (R^2 = 0.320, ΔR^2 = 0.290, p <.001).
c) **Model 3 (Moderator)**: The introduction of TAM significantly strengthened the model (R^2 = 0.461), explaining an additional 14.1% of the operational variance (ΔR^2 = 0.141, p <.001). This confirms that technology acceptance has a strong direct effect on logistics performance outcomes.
d) Model 4 (Interaction Terms): The final step incorporated the interaction terms (JIT × TAM and Jidoka × TAM) to evaluate the moderating effects of Technology Acceptance. While the overall model remains highly significant (F = 14.399, p<.001), the addition of these interaction products yielded a modest 1.90% increase in variance. At the individual parameter level, the interaction term for Smart JIT is statistically significant (β = -0.113, p <.05), confirming that TAM actively moderates the relationship between Smart JIT and logistics performance. Conversely, the interaction effect for Smart Jidoka did not achieve statistical significance (p=.591), indicating that the moderating influence of user acceptance is restricted to specific operational pillars.

b. Econometric Diagnostic Testing

To ensure the statistical validity of the ordinary least square (OLS) estimations, diagnostic testing was conducted to verify compliance with the classical linear regression assumptions:

- **Independence Residuals**: The model yielded a Durbin-Watson statistic of 1.828. Because this value falls within the optimal academic range of 1.5 to 2.5, it confirms the absence of first order auto correlation in the error terms.
- **Multicollinearity Diagnostics**: Independent and moderating constructs were mean-centered prior to generating product terms. Post-centering analysis revealed that all Variance Inflation Factors (VIF) remained strictly below 2.0 (maximum VIF < 2.0) and all Tolerance values exceeded .60. Furthermore, the maximum Condition Index in the final model was 22.187, staying safely beneath the conservative structural threshold of 30.0. This proves that multi-variable overlap does not distort or destabilize the regression coefficients.
- **Normality and Homoscedasticity**: Standardized residuals plotted against predicted values revealed a balance distribution ranging from -2.68 to +2.74. This tight cluster stays safely within the standard threshold of ± 3.0, demonstrating zero-mean homoscedastic variance and confirming the absence of extreme multivariate outliers that could skew the final model.

c. Coefficient and Moderation Analysis

The individual predictors demonstrated varying levels of influence across the four models, as detailed in Table 8. In the final model (Model 4), Smart JIT remained a highly significant predictor of logistics performance (B = 0.169, β 0.255, p = .003). Conversely, Smart Jidoka did not retain its statistical significance in the later stages of the analysis (B = 0.055, t = 1.070, p = .287), indicating that its initial impact in Model 2 was likely absorbed by the inclusion of technology acceptance factors. Technology Acceptance (TAM) emerged as the most powerful direct predictor in the study (B = 0.336, β = 0.425, p < .001), confirming that employee perceptions of usefulness and ease of use are critical drivers of operational outcomes. Regarding the moderation hypotheses, the interaction term JIT × TAM was statistically significant (B = - 0.113, β = -0.176, p = .043). This confirms that technology acceptance moderates the relationship between Smart JIT and logistics performance; specifically, the negative beta coefficient suggests a diminishing returns effect where the marginal gains from JIT practices may decrease at exceptionally high levels of technology acceptance. However, Jidoka × TAM interaction was not significant (B = 0.034, β = 0.045, p = .591) , implying that the operational benefits of Smart Jidoka are direct and stable, regardless of varying levels of user acceptance.

Table 8. Coefficient and Moderation Analysis for Logistics Performance

Predictor	**Unstandardized** (B)	**Std. Error**	**Standardized** (β)	t	**Sig.** (p)
Constant	3.946	0.278		14.204	<.001***
Step 1: Controls					
Department	0.046	0.049	0.066	0.943	.348
IoT Usage	-0.025	0.074	-0.023	-0.343	.732
Years of Experience	0.005	0.041	0.008	0.119	.906
Step 2: Main Effects					
Smart JIT	0.169	0.056	0.255	3.026	.003**
Smart Jidoka	0.055	0.051	0.081	1.07	.287
Step 3: Moderator					
TAM	0.336	0.062	0.425	5.413	<.001***
Step 4: Interactions					
JIT × TAM	-0.113	0.056	-0.176	-2.043	.043*
Jidoka × TAM	0.034	0.062	0.045	0.538	.591

Note: N = 134. Indented variables indicate step placement within the hierarchical regression sequence. * p <.05,** p <.01,*** p <.001

D. Contextual Triangulation and Trend Analysis

The contextual triangulation of secondary KPI data (2021-2025) substantiates the regression findings by demonstrating a distinct plateau in logistics performance. While the early years of the observation period reflect strong efficiency and accuracy gains, subsequent years reveal stabilization followed by an eventual decline.

a. Secondary KPI Operational Trends

Average performance across the secondary KPIs is high, with low to moderate variability supporting the performance plateau hypothesis. As detailed in Table 9, On-time delivery has a high mean of 94.57% (SD=12.64%), while Inventory Accuracy averaged 97.40% (SD=7.22%). Order fulfillment Cycle time was on average 6.83 days, indicating that speed increased at the beginning and then levelled off. The low standard deviation for these KPIs reinforces the finding that the organization's TPS implementation with IoT is approaching maturity.

Table 9. Descriptive Statistics for Secondary KPI data (2021-2025)

Variables	**Mean**	**Std. Deviation**	**Minimum**	**Maximum**
On-time Delivery (%)	94.57%	12.64%	30.00%	100.00%
Inventory Accuracy (%)	97.40%	7.22%	70.00%	100.00%
Order Fulfillment (Days)	6.83	6.09	5	45

b. Performance Maturity and Diminishing Returns

The integrated interpretation of the KPI trends from Figure 2 shows a long period of stability and high efficiency followed by a sudden drop towards the end of the observation window around periods 55-60. As summarized in Table 10, the logistics system transitioned from a highly optimized state to one of systemic strain. This trend reflects that the organization had high level of control for a substantial period, suggesting a performance plateau, before experiencing sudden disturbances in 2025.

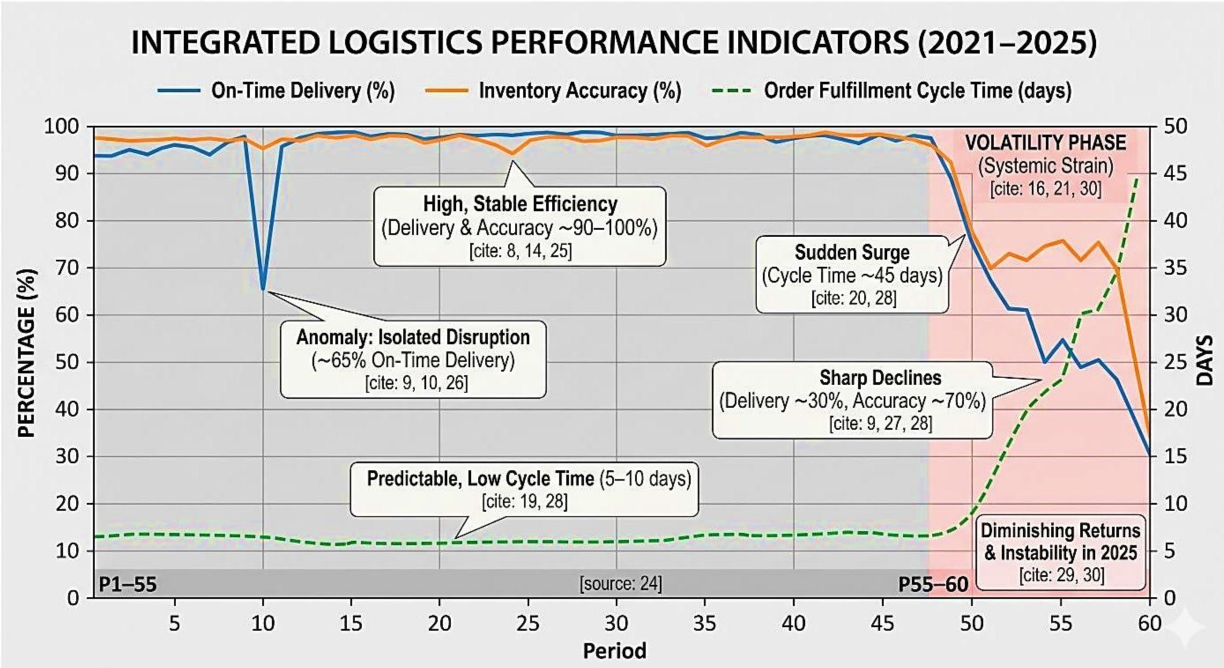

Figure 2. Integrated Trend Analysis of Logistics KPIs (2021-2025)

Table 10. Characteristics of Logistics Performance Phases

Phase	Time Period	Operational Characteristics	KPI Status
Optimization/ Plateau	2021-2024	Peak efficiency; mature IoT-enabled TPS.	High stability; near-perfect accuracy.
Saturation/Decline	2025	Diminishing returns; systemic stressors.	Sudden volatility; sharp spike in cycle time.

c. Supplemental Time-Series Regression Analysis

To evaluate the longitudinal trajectory of operations across the 60 observed periods displayed in Figure 2, formal ordinary least squares (OLS) time-series regressions were performed using time (Period) as the independent predictor against each secondary Operational KPI.

- **Inventory Accuracy Trend**: The regression model revealed a statistically significant negative temporal trend ($R^2 = 0.224$, $F(1, 58) = 16.75$, $p < .001$). The unstandardized slope coefficient ($b_{time} = -0.20$, $t = -4.09$, $p < .001$) indicates that inventory precision systematically declined at an average rate of .20 percentage points per period, providing empirical evidence of late-stage system saturation.
- **Order Fulfillment Cycle Time Trend**: The regression model demonstrated a statistically significant positive temporal trend ($R^2 = .112$, $F(1, 58) = 7.32$, $p = .009$), confirming a systematic expansion in fulfillment duration. The unstandardized slope ($b_{time} = +0.12$, $t = 2.71$, $p = .009$) quantifies an efficiency loss of 0.12 days per period, which statistically validates the transition of the logistics flow from stable plateau to an active operational strain.
- **On-time Delivery Trend**: The regression model indicated a weak negative relationship over time $R^2 = 0.049$, $F(1,58) = 2.99$, $p = .089$). Although the negative slope ($b_{time} = -0.16$, $t = -1.73$, $p = .089$) did not cross the $p < .05$ threshold for statistical significance, the marginal downward trend matches the visual pattern of a prolonged efficiency plateau punctured by high late-stage operational volatility.

A primary methodological limitation of this investigation is its reliance on a cross-sectional research design for the primary behavioral data collection. The measurements from the primary survey were successfully triangulated with 5 years (60 periods) of objective, longitudinal secondary KPI records, providing historical context; however, the individual-level employee perceptions were collected at one time. Therefore, the hierarchical moderated regression analysis results do provide statistically strong predictive associations and interaction effects among the variables but this cross sectional structure restricts direct and definite causal inferences regarding the direction of technology acceptance and perceived logistics performance.

The observed correlations could be subject to alternative structural explanations or unobserved co- founders. Future investigations should deploy true longitudinal panels or cross-lagged structural equation modeling (AS) tracking behavioral shifts across multiple operational waves to empirically map the causal mechanisms underlying the digital lean performance plateau.

IV. CONCLUSION

This study empirically validates the conceptual framework mapping the interactions between IoT-enabled TPS pillars, user technology acceptance, and logistics performance. The final structural block (Model 4) demonstrates robust explanatory capacity, accounting 48.0% of the total variance ($R^2 = 0.480$) in perceived logistics performance ($F = 14.399$, $p < .001$). The empirical evidence confirms a selective moderation mechanism: Technology Acceptance (TAM) significantly moderates the relationship between Smart JIT and logistics outcomes ($\beta = -0.176$, $p = .043$), but exerts an unmoderated, direct effect on Smart Jidoka ($\beta = 0.045$, $p = .591$). Long-term operational data verified that technical infrastructure alone encounters diminishing returns. Secondary KPI date triangulated over a 60-period time frame revealed an initial optimization plateau (2021-2024) and major system degradation in late 2025. Therefore, to maintain the operational efficiency in the mature cyber-physical systems, a dual strategy is required: continually innovate the process and maximize user behavioral alignment by TAM to avoid process saturation.

Practically, these insights fulfill the study's objective by providing a diagnostic framework for re-synchronizing human behavior and cyber-physical systems. The results change the direction of management from system stabilization to proactive next generation lean upgrades. Digital lean implementation is not a set point, but rather an indicator of digital technology acceptance through technology acceptance metrics that can be used as early warning signs of behavioral friction before KPI degradation. In conclusion, this study highlights the importance of a human-centered approach, which is not just a complement but a fundamental requirement to face the socio-technical challenges and maintain the competitive edge in Industry 5.0 environment.

Appendix 1. Survey Instrument

Research Title: The Moderating Role of Technology Acceptance on the Relationship Between Smart TPS Pillars and Logistics Performance: A Case Study of Uratex Cebu
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General Instruction: Please read each item carefully. This survey is anonymous, and your responses will be handled with strict confidentiality. For each statement, please check the box or circle the number that best reflects your honest opinion based on your experience with the company's IoT tools.

How to Choose Your Response:
Scale 1–5: Use this scale if the statement describes a process or tool that is part of your specific job duties.

- **Select "5** – Strongly Agree" if the digital tool or process is a consistent, daily reality that works perfectly to improve your performance.

N/A – Not Applicable: Select this option if the statement refers to a specific technology, machine, or task that is not used in your department.

- **Example**: If you work in Logistics/Dispatch and a question asks about Production machine sensors, select N/A.

PART 1: DEMOGRAPHIC PROFILE

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Please check [✓] the appropriate box.

1. Department: [ ] Warehouse [ ] Production [ ] Logistics / Delivery
2. Years of Experience at Uratex: [ ] 5 years [ ] 6 years [ ] 7 years or more
3. Usage of IoT Tools (Scanners, Tablets, Dashboards): [ ] Daily

[ ] Frequently (2-3 times a week) [ ] Occasionally (Once a week or less)

Please rate your level of agreement with the following statements using the scale: 1 – Strongly Disagree | 2 – Disagree | 3 – Neutral | 4 – Agree | 5 – Strongly Agree/NA-not applicable

	PART II: IoT-ENABLED TPS PILLARS	**1**	**2**	**3**	**4**	**5**
	Adapted from Buer et al.					
	A. Smart Just-In-Time (JIT)					
1	IoT tools provide real-time accuracy of our stock levels in my area.	[ ]	[ ]	[ ]	[ ]	[ ]
2	The e-kanban system triggers replenishment without manual delays.	[ ]	[ ]	[ ]	[ ]	[ ]
3	Digital tracking has reduced our material waiting times in my process.	[ ]	[ ]	[ ]	[ ]	[ ]
	B. Smart Jidoka (Autonomation)					
4	The system alerts me immediately if a quality detect or anomaly is detected.	[ ]	[ ]	[ ]	[ ]	[ ]
5	IoT sensors provide accurate data on machine or process performance.	[ ]	[ ]	[ ]	[ ]	[ ]
6	Automated quality checks/digital logs have replaced manual inspections	[ ]	[ ]	[ ]	[ ]	[ ]
	PART III: TECHNOLOGY ACCEPTANCE (MV)	**1**	**2**	**3**	**4**	**5**
	Adapted from Davis (1989)					
	C. Perceived Usefulness (PU)					
7	Using the IoT tools helps me finish my tasks more quickly.	[ ]	[ ]	[ ]	[ ]	[ ]
8	The digital dashboards make my work more effective.	[ ]	[ ]	[ ]	[ ]	[ ]
9	Overall, the IoT system is very useful for my daily job.	[ ]	[ ]	[ ]	[ ]	[ ]
	D. Perceived Ease of Use (PEOU)					
10	I find the IoT devices (tablets/scanners) easy to operate.	[ ]	[ ]	[ ]	[ ]	[ ]

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11	The interface of the software we use is clear and simple.	[ ]	[ ]	[ ]	[ ]	[ ]
12	It was easy for me to become skillful at using these tools.	[ ]	[ ]	[ ]	[ ]	[ ]

PART IV: PERCEIVED LOGISTICS PERFORMANCE (Dependent Variable)		**1**	**2**	**3**	**4**	**5**
Adapted from Davis (1989)						
E. Logistics Efficiency (Speed, Flow, and Waste Reduction)						
13	The total time from order placement to dispatch has significantly decreased.	[ ]	[ ]	[ ]	[ ]	[ ]
14	IoT-enabled processes have made our order picking faster.	[ ]	[ ]	[ ]	[ ]	[ ]
15	The digital system ensures a continuous flow of materials without bottlenecks.	[ ]	[ ]	[ ]	[ ]	[ ]
16	The use of real-time data has eliminated unnecessary waiting times between processes.	[ ]	[ ]	[ ]	[ ]	[ ]
17	I spend less time on manual coordination because of the automated digital flow.	[ ]	[ ]	[ ]	[ ]	[ ]
18	The system helps me avoid rework by providing correct instructions the first time.	[ ]	[ ]	[ ]	[ ]	[ ]
19	Overall, the logistics cycle is more efficient due to the IoT-integrated TPS.	[ ]	[ ]	[ ]	[ ]	[ ]
F. Logistics Quality and Accuracy (Reliability and Data Integrity)						
20	There is a high level of agreement between our physical stock and system records.	[ ]	[ ]	[ ]	[ ]	[ ]
21	IoT tools have minimized discrepancies and “missing items” in the warehouse.	[ ]	[ ]	[ ]	[ ]	[ ]
22	We are meeting our delivery schedules more consistently than before.	[ ]	[ ]	[ ]	[ ]	[ ]
23	Real-time tracking has reduced the number of delayed or incorrect shipments.	[ ]	[ ]	[ ]	[ ]	[ ]
24	The data captured by our scanners is highly reliable and free from errors.	[ ]	[ ]	[ ]	[ ]	[ ]
25	I can perform digital transactions (receiving/dispatch) accurately without manual workarounds.	[ ]	[ ]	[ ]	[ ]	[ ]

26	The automated Jidoka alerts effectively prevent defects from reaching the next stage.	[ ]	[ ]	[ ]	[ ]	[ ]

Conflicts of Interest

The author declares that there is no conflict of interest concerning the publication of this paper.

Funding Statement

This research was self-funded as part of a student thesis at Mindanao State University-Iligan Institute of Technology.

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