The Impact of Internet of Things for Real – Time Data in Warehouse Operations

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Abstract: *This study examines the impact of Internet of Things (IoT) technologies on real-time data utilization and warehouse operational performance in Sri Lanka. Using a quantitative approach, data were collected from warehouse professionals across multiple industries. The study evaluates four key IoT dimensions: sensor and device utilization, real-time data collection, predictive capabilities, and data-driven decision-making. Findings reveal that IoT integration significantly enhances warehouse performance, explaining a high proportion of variance in operational outcomes. Among the dimensions, data-driven decision-making emerges as the strongest predictor, highlighting the importance of effectively using IoT-generated data rather than merely adopting technology. Although other factors show strong positive correlations, their individual effects are limited due to multicollinearity. The study contributes to the Resource-Based View by positioning IoT capabilities as strategic assets. It also provides practical insights for managers to prioritize analytics-driven decision-making to achieve greater efficiency, responsiveness, and competitiveness in warehouse operations.*

Keywords: internet of things (IOT), real-time data, warehouse operations, data-driven decision-making, operational performance, supply chain management

INTRODUCTION

A warehouse management system aims to control the movement and storage of materials within a warehouse and process the associated transactions, including shipping, receiving, put-away and picking (A, N. Subramanya and M. Rangaswamy, 2012). The major roles include: buffering the material flow along the supply chain to accommodate variability (Hamdy, Al-Awamry and Mostafa, 2022).The number of warehouses has grown globally in the last two decades (Modica, Perotti and Melacini, 2021), Faced with relentless competitive pressures in an increasingly global marketplace, firms have responded with a variety of business strategies aimed at enhancing customer value (Kembro and Norrman, 2025). (Karunarathna, Wickramarachchi and Vidanagamachchi, 2019) status that with the competitive market conditions and the dynamic customer demands, it has been difficult to meet the requirements with the traditional warehouse management approaches, due to their complexity and low efficiency. Without real-time data in the warehouse, businesses may rely on outdated information, leading to delayed or less effective decision-making. This can result in missed opportunities, reduced competitiveness, and a slower response to market changes, further businesses may struggle to address customer needs promptly, leading to delays and poor service. "As an emerging technology, Internet of things (IoT) can offer promising solutions to transform the operation of many existing manufacturing system into a smart level. Sensory, communication, networking, and information processing technologies provide the foundations for IoT. RFID (Radio Frequency Identification) is one of the most important in these foundational technologies" (Liu, Zhang and Zhong, 2018). This study addresses this research gap by quantitatively examining how IoT technologies impact real-time data utilization and operational performance in Sri Lankan warehouse facilities.

Research Questions

RQ 1. What is the current level of IoT adoption in Sri Lankan warehouses?

RQ 2. How does the use of real-time data through IoT affect operational performance?

RQ 3. Which IoT features are most influential in enhancing warehouse productivity?

Organization

The rest of the paper is organized as follows: Section 2 provides the literature review. Section 3 provides the research design. Section 4 presents the data analysis and results. Section 5 describes the discussion. Section 6 presents practical Implementation. Finally, conclude the study in Section 7.

LITERATURE REVIEW

In today's data-rich environment, real time data-driven decision-making is vital for large companies' success (Ghadimi, Baghayi and Shateri, 2024). IoT accommodates the digital connectivity of the physical and digital components to present real-time data storage and sharing, positively impacting the customer's satisfaction level (Garay-Rondero *et al.*, 2019) Real-time data storage and sharing provide a massive amount of data and location of goods as continuous moving information (Vicuna et al., 2019). Thus, the virtue it gives to the product enhances the movement accuracy and greater visibility of products (Mahroof, 2019).

Theoretical Underpinning: Resource-Based View

In the context of warehouse and supply chain operations, Internet of Things (IoT) technologies can be interpreted as **strategic organizational resources** that enhance decision-making, visibility, automation and coordination. As highlighted by Ben-Daya et al. (2019), IoT provides real-time connectivity and intelligence that strengthens operational processes across logistics networks.

From an RBV perspective, IoT-enabled practices represent **unique digital capabilities**, including:

- **Sensor and device utilisation**, which improves accuracy, reduces human error and enhances data quality — forming a valuable and difficult-to-copy operational asset.
- **Real-time data collection**, which enables immediate responses to operational changes and contributes to rare and agile supply chain competencies (Addo-Tenkorang and Helo, 2016).

- **Predictive analytics**, which uses IoT data to anticipate demand and disruptions, forming an advanced analytical capability.
- **Data-driven decision-making**, which embeds analytical thinking into organisational routines and creates a non-substitutable managerial capability (Gunasekaran et al., 2017).

These IoT-enabled capabilities align closely with RBV's VRIN criteria, as they improve coordination, reduce inefficiencies, and provide operational visibility that competitors may find difficult to imitate (Ivanov et al., 2019; Queiroz et al., 2020). Therefore, RBV offers a strong theoretical foundation for explaining why IoT integration enhances warehouse operational performance.

The empirical results of this study — particularly the strong and significant influence of **data-driven decision-making** — reinforce RBV's central argument: organizations that utilize their digital resources effectively gain superior operational performance. IoT technologies become valuable not simply by their presence, but by how they are integrated into decision-making processes and operational routines

Internet of things and integration

IoT has become one of the most popular topics in recent years. IoT can be defined as the infrastructure of physical "things" embedded with electronics, software (service), sensor, mobile, intelligent, and network technology. The connectivity enables it to achieve greater value, including real-time data exchange(Shammar and Zahary, 2020) monitoring, and control. IoT aims to promote a broad range of people's lives (Atzori, Iera and Morabito, 2010). Many devices are connected to IoT, data is generated, and great business opportunities around IoT. The industry predicts that at the beginning of 2020, there will be around 50 billion physical devices(*Dave: How the next evolution of the internet is changing... - Google Scholar*, no date)

Radio-frequency identification technology RFID

Radio-frequency identification technology RFID is a supporting technology that is considered a promising solution to address inventory inaccuracy (*Warehouse efficiency improvement using RFID in a humanitarian supply chain: Implications for Indian food security system - ScienceDirect*, no date). The use of RFID technology positively detects numerous objects simultaneously at different distance levels in an instant way of communicating (Hinkka and and Främling, 2012). This advanced technological tool capable of enhancing information accuracy and visibility through seamless monitoring. The usage of RFID in the warehouse management system is commonly to track and trace goods exclusively for the inconsistency of information due to changes and updates of the warehouse activities (Lee *et al.*, 2018). Data retrieval using RFID technology also supports automatic identification and automated product identity extraction. Therefore, human participation in the warehouse systems is slightly altered from an actively involve worker to a human operator (Buntak et al.,2019). The utilization of RFID technology in a warehouse is renowned for eliminating inefficiency and ineffectiveness (Chen *et al.*, 2013). RFID technology's advantages simplify warehouse management to provide better-quality control enablement, product visibility and delivery reliability improvement(*RFID enhanced MAS for warehouse management: International Journal of Logistics Research and Applications: Vol 10 , No 2 - Get Access*, no date). The integration of RFID technology with other intelligence tolls such as sensors enables monitoring of goods in the warehouse, making operation more flexible (Abad et al.,2007). RFID could also be used for improving storage efficiency and process refinement by combining the technology with warehouse management tools, resulting in a labor waste reduction (Xiao et al.,2017). Besides its tracking performance, RFID is used to enhance information systems by coordinating warehouse operations such as planning, execution

Real-time data systems

A real-time system is perceived as a reaction to external events that a computer system encounters within some stipulated deadline (Tongren, 1998). Real-time systems' primary requirements include a stringent and low delay pattern and continuity of variation in time relation between the data entities. (*A review on big data real-time stream processing and its scheduling techniques: International Journal of Parallel, Emergent and Distributed Systems: Vol 35 , No 5 - Get Access*, no date) defined the real-time system as an operation that behaves within the "real-world" time limit. The use of real-time data positively contributes to the quality of decision-making. The result of performance measurement based on its real-time value is required for allowing data visibility in operations (Erkayaoglu and and Dessureault, 2019) .A real-time thing such as real-time location or real-time data can provide the exact positioning of an object when combines with other supporting technology (Halawa *et al.*, 2020).

The IoT could be built on the pervasive deployment of a variety of things, such as RFID tags, sensors, actuators, mobile phones that are able to interact with each other and cooperate with other services to reach common goals6. In fact, the integration of data generated by this myriad of sensors with other data, such as location, environmental context and social media data allows the development of context-aware applications that could help citizens taking more informed decisions regarding their day's activities. For instance, it is now possible to develop services for better traffic routing throughout the city, detect and immediately act to environmental pollution peaks or automatically optimize the logistics chain by allowing instantaneous reactions to external triggers and contextual changes (Malek *et al.*, 2017)

METHODOLOGY

This research paper is based on positivist approach. A quantitative study makes it possible to verify the hypotheses developed. The time horizon of this study is cross-sectional. Data were collected within the month of March to April in 2025. The target population for this study comprises warehouse professionals from medium to large-scale organizations in Sri Lanka that have implemented or are in the process of adopting Internet of Things (IoT) technologies. These include warehouse managers, IT officers, and supply chain professionals responsible for inventory, operations, and technology integration."

A total of 200 warehouse professionals were selected from Apparel and textile n = 75, FMCG (Fast-Moving Consumer Goods) n= 60, Pharmaceutical distribution n= 30, Third-party logistics (3PL) companies n =35.

All the warehouse professionals were within the age range of 28-45 as they were the senior professionals within the organization. The sampling method used in this study is convenience sampling. Although the sampling method should be a probability sampling technique for a quantitative study to satisfy generalizability, with the existing time constraint, the researchers have chosen non-probability sampling (convenient sampling) method, which is a limitation of this study. All participants verbally agreed to participate voluntarily in the research work prior to being administered the questionnaire based survey. The questionnaire consisted of four parts and 41 items were included.

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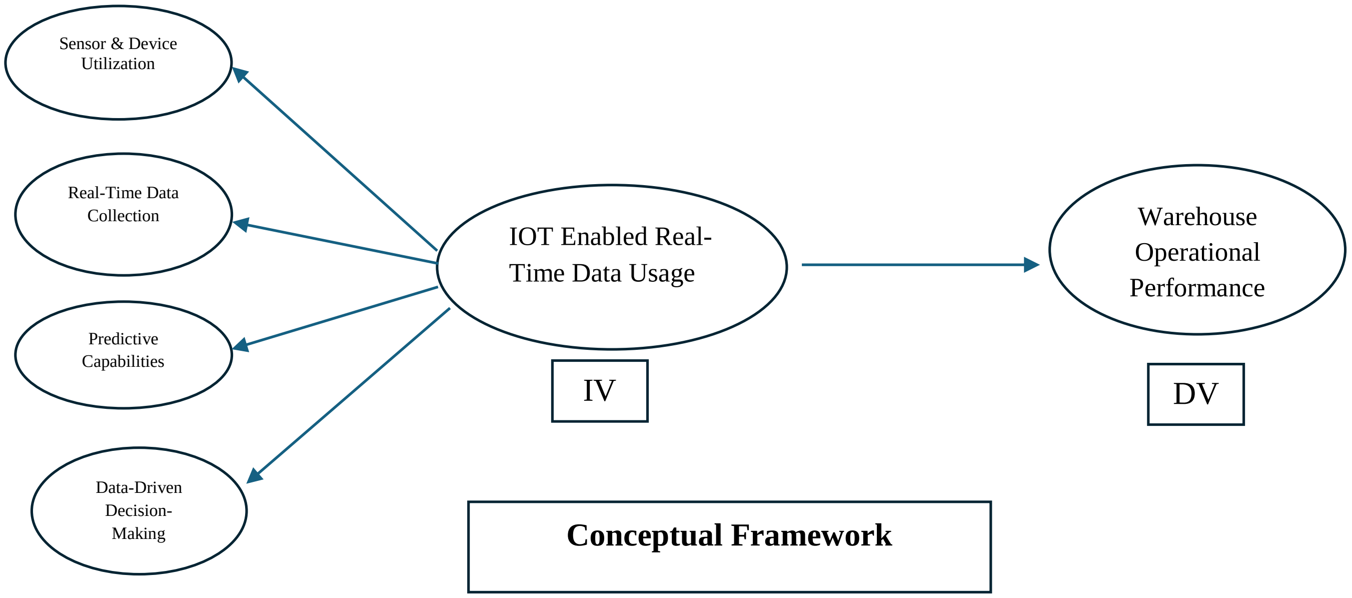

Conceptual Framework

Hypothesis

H1: IoT integration for real-time data has a significant positive impact on warehouse operational performance

H1a: Sensor & device utilization has a significant positive impact on warehouse operational performance

H1b: Real-time data collection has a significant positive impact on warehouse operational performance

H1c: Predictive capabilities have a significant positive impact on warehouse operational performance

H1d: Data – driven decision - making has a significant positive impact on warehouse operational performance

IoT Integration for Real-Time Data (Independent Variable)

IoT integration for real-time data refers to the application of Internet of Things (IoT) technologies in warehouse operations to enable continuous, automatic, and real-time data collection, monitoring, and communication. This integration is considered a strategic enabler of operational visibility, efficiency, and responsiveness in supply chain and warehouse environments (Rosati and Lynn, 2020; Gubbi *et al.*, 2013). In the context of this study, IoT integration is conceptualized as a multidimensional construct that captures the extent to which key IoT-enabled capabilities are deployed and utilized in warehouse management practices.

The level of IoT integration is measured using a 20-item scale developed based on relevant literature and expert validation. The construct consists of four sub-dimensions: Sensor & Device Utilization, Real-Time Data Collection, Predictive Capabilities, and Data-Driven Decision-Making. Each sub-dimension includes five items, capturing the specific technological applications and data functionalities that represent the broader concept of IoT integration. Participants are required to respond to each item using a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree), indicating the degree to which the listed IoT practices are applied within their warehouse operations. A higher composite score indicates a higher level of IoT integration for real-time data usage.

Warehouse Operational Performance (Dependent Variable)

Warehouse operational performance refers to the efficiency, accuracy, and responsiveness of warehouse functions that support the broader supply chain. It encompasses the ability of a warehouse to manage inventory effectively, fulfill orders on time, minimize operational costs, and respond quickly to changes in demand or disruptions (Gunasekaran, Patel and McGaughey, 2004; Gunasekaran et al., 2004; Ali et al., 2021). In the context of this study, warehouse operational performance is conceptualized as a multidimensional construct that reflects key performance indicators (KPIs) relevant to warehouse efficiency and service quality.

The construct is assessed using a 20-item scale, adapted from existing performance measurement literature. Respondents are asked to indicate their level of agreement on a 5-point Likert scale, ranging from 1 (strongly disagree) to 5 (strongly agree). Higher scores indicate stronger performance in warehouse operations.

RESULTS/ FINDINGS

A structured questionnaire-based survey used to gather primary data for the study. The questionnaire was distributed among 30 warehouse professionals.

Market competition requires continuous improvement in the design and operation of production-distribution networks, which in turn requires higher performance from warehouses. The adoption of new management philosophies such as Just-In-Time (JIT) or lean production also brings new challenges for warehouse systems, including tighter inventory control, shorter response time, and a greater product variety. On the other hand, the widespread implementation of new information technologies (IT), such as bar coding, radio frequency communications (RF), and warehouse management systems (WMS), provides new opportunities to improve warehouse operations.

The results of the quantitative analysis

conducted to test the relationships between IoT dimensions and warehouse operational performance. All analyses were performed in SPSS. Procedures included data screening, reliability analysis (Cronbach's alpha), descriptive statistics, normality checks (Explore / Shapiro–Wilk), Pearson correlations, and multiple linear regression. The sample comprised **27** respondents.

Data screening and missing data

Case processing showed **27 valid cases** and no missing values for the study items (Q4–Q25) or demographic variables. Frequency tables confirm all items used the intended 1–5 Likert scale and there were no empty rows in the active dataset.

Reliability (internal consistency)

Cronbach's alpha was computed for each construct (items listed in parentheses).

Construct	Items	Cronbach's α	Interpretation
Sensor & Device Utilization	Q4–Q6	**.984**	Excellent
Real-Time Data Collection	Q7–Q9	**1.000**	Perfect (note: extremely high, suggests redundancy)
Predictive Capabilities	Q10–Q12	**.749**	Acceptable
Data-Driven Decision-Making	Q13–Q17	**.789**	Acceptable
Warehouse Operational Performance	Q18–Q25	**.930**	Excellent

Interpretation. All constructs show acceptable to excellent internal consistency. The extremely high alpha for Real-Time Data Collection (1.000) and very high for Sensor & Device Utilization (.984) suggest items are highly similar (possible redundancy). Predictive Capabilities (.749) and Data-Driven Decision-Making (.789) are acceptable (> .70). Performance (DV) is highly reliable (.930).

Normality and distribution

Explore (histograms, boxplots, Q–Q plots) and Shapiro–Wilk tests were computed for individual items and later for computed construct means.

Item-level Shapiro–Wilk (summary): Most individual items returned **p < .05** on the Shapiro–Wilk test (e.g., Q5, Q6, Q7, Q8, …), indicating rejection of strict normality for many single items. A few items had p > .05 (e.g., Q4: p = .029 shows Q4 slightly non-normal as well; overall most are non-normal).

Note on means: Because subsequent analyses use construct mean scores (SensorM, RealTimeMean, PredictiveMean, DataDrivenMean, PerformanceMean), the distribution of these means is more important than individual-item normality. With N = 27, the central limit theorem is only partially reassuring; however, inspection of descriptive statistics (skewness/kurtosis values reported in the output) indicates construct means are reasonably symmetric:

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Construct mean	**Mean**	**Std. Dev.**	**Skewness / Kurtosis (from Descriptives)**
SensorM	3.5062	1.1634	(see output — small skew)
RealTimeMean	3.5926	1.1851	(small skew)
PredictiveMean	3.6543	1.0232	(small skew)
DataDrivenMean	3.6296	0.7975	(near symmetric)
PerformanceMean	3.5278	0.8480	(near symmetric)

Interpretation. Individual items are often non-normal. Construct means appear reasonably distributed; given sample size N = 27, proceed with parametric tests but interpret cautiously and report limitations (see Section 4.9).

Descriptive statistics

Descriptive statistics for the five construct means:

Construct	**Mean**	**Std. Deviation**	**Minimum**	**Maximum**
SensorM	**3.5062**	1.16344	1.00	5.00
RealTimeMean	**3.5926**	1.18514	1.00	5.00
PredictiveMean	**3.6543**	1.02316	2.00	5.00
DataDrivenMean	**3.6296**	0.79750	2.80	5.00
PerformanceMean	**3.5278**	0.84803	2.75	5.00

Interpretation. On average, respondents tend to agree (scores ~3.5–3.7 on a 1–5 scale) that IoT dimensions and data-driven practices positively affect warehouse performance.

Correlation analysis

Pearson correlations were computed among constructs (pairwise). Below are the key extracted correlations (all reported as significant at $p < .001$ in the SPSS output):

Pair	**Pearson r**
SensorM – RealTimeMean	**.992** (very strong)
SensorM – PerformanceMean	**.791**
RealTimeMean – PerformanceMean	**.724**
PredictiveMean – PerformanceMean	**.724*** (output shows strong positive association)
DataDrivenMean – PerformanceMean	(DataDriven correlated strongly; regression indicates strong relation)
SensorM – PredictiveMean	**.713**
SensorM – DataDrivenMean	**.718**
RealTimeMean – PredictiveMean	**.683**
RealTimeMean – DataDrivenMean	**.648**
PredictiveMean – DataDrivenMean	reported as moderate–strong

Note: SPSS output indicates all listed correlation coefficients were statistically significant ($p < .001$).

Interpretation. All IoT dimensions are positively and strongly correlated with warehouse operational performance. Sensor usage and real-time data collection are very highly correlated with each other ($r = .992$), indicating these constructs overlap substantially in this sample.

Multiple regression analysis (Hypothesis testing)

A multiple linear regression tested the simultaneous effect of the four IoT constructs on warehouse operational performance:

Model: PerformanceMean = β0 + β1(SensorM) + β2(RealTimeMean) + β3(PredictiveMean) + β4(DataDrivenMean) + ε

Model summary:

- R = **.987**
- R^2 = **.974**
- Adjusted R^2 = **.969**
- F(4, 22) = **207.422**, $p < .001$
- Durbin–Watson = **1.533** (no substantial autocorrelation)

Interpretation: The model explains **97.4%** of the variance in warehouse operational performance; the overall model is highly significant.

Coefficients (from SPSS output):

Predictor	**B (unstd.)**	**SE B**	**Beta (std.)**	**t**	**p**
Constant	-0.114	0.216	—	-0.526	.604
SensorM	0.460	0.392	0.632	1.176	**.252**
RealTimeMean	-0.274	0.358	-0.383	-0.766	**.452**
PredictiveMean	-0.118	0.073	-0.142	-1.620	**.119**
DataDrivenMean	**0.948**	0.134	**0.892**	**7.055**	**< .001**

Interpretation of coefficients:

- **Data-Driven Decision-Making (DataDrivenMean)** is the only statistically significant predictor in the model (B = 0.948, $\beta = .892$, $p < .001$). This indicates that, holding other predictors constant, a one-unit increase in DataDrivenMean is associated with an average increase of **0.948** units in PerformanceMean.
- Other predictors (SensorM, RealTimeMean, PredictiveMean) are **not significant** when entered simultaneously ($p > .05$).

Multicollinearity diagnostics:

- The correlation matrix and collinearity diagnostics indicate **very high intercorrelations**, especially between SensorM and RealTimeMean ($r = .992$). Condition Index values reported up to **157.69**, which is a strong signal of multicollinearity.
- Variance proportions (SPSS output) show large proportions loading on the final dimension for multiple predictors — consistent with multicollinearity.

Implication: Multicollinearity likely inflates standard errors and obscures some predictors that would otherwise appear significant in isolation. The very high intercorrelation between SensorM and RealTimeMean suggests these two constructs overlap strongly in the respondents' perceptions; they may represent a single factor in practice.

Hypotheses summary

H1 (overall): IoT integration (Sensor utilization, Real-time data collection, Predictive capabilities, Data-driven decision-making) positively influences warehouse operational performance.

- **Result: Supported.** The full regression model is significant and explains 97.4% of variance ($R^2 = .974$, $F(4,22) = 207.422$, $p < .001$).

H1a — Sensor & Device Utilization → Performance

- **Result: Not supported** as an independent predictor in the full model ($\beta = .632$, $p = .252$). Note: bivariate correlations show SensorM strongly correlated with performance; lack of significance in the model is likely due to multicollinearity.

H1b — Real-Time Data Collection → Performance

- **Result: Not supported** in the full model ($\beta = -.383$, $p = .452$). Again, bivariate relationship is positive, but multicollinearity suppresses unique contribution.

H1c — Predictive Capabilities → Performance

- **Result: Not supported** in the full model at $\alpha = .05$ ($\beta = -.142$, $p = .119$).

H1d — Data-Driven Decision-Making → Performance

- **Result: Supported.** DataDrivenMean is the only predictor significant when all IVs are entered ($\beta = .892$, $p < .001$).

Overall interpretation: While all IoT constructs correlate positively with operational performance, **Data-Driven Decision-Making** shows an independent and strong predictive effect in the multivariate context. Other constructs' unique effects are masked by severe multicollinearity (particularly between Sensor usage and Real-time data).

Robustness, assumptions, and limitations

1. **Sample size:** N = 27 is small for multiple regression with four predictors. Results are sensitive; effect sizes may be unstable. Interpret R^2 and coefficients cautiously.
2. **Normality:** Many individual items violated Shapiro–Wilk normality ($p < .05$). Construct means are more symmetric but with N = 27, parametric assumptions are borderline. Consider nonparametric checks or bootstrapped confidence intervals as robustness checks.
3. **Multicollinearity:** Extremely high correlations among IVs (SensorM ↔ RealTimeMean $r = .992$) and large condition index (> 30 and up to 157 in output) indicate problematic multicollinearity. This inflates SEs and may hide true effects of some predictors. Remedies include:
    - Combine highly overlapping predictors (e.g., SensorM + RealTimeMean into a single factor).
    - Use Principal Component Analysis (PCA) or exploratory factor analysis to extract orthogonal factors.
    - Use ridge regression or drop one of the highly collinear variables.
    - Report results from separate regressions (each predictor entered singly) to show bivariate contributions.
4. **Item redundancy:** Very high Cronbach's α values (≈ 1.00) for some constructs suggest redundancy—consider revising or reducing items in future questionnaires.
5. **Generalisability:** Small sample and convenience sampling limit generalization.

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Practical summary and recommendations

- The IoT constructs collectively explain a large share of variation in perceived warehouse performance ($R^2 = .974$).
- **Data-driven decision-making** stands out as the strongest unique predictor — organizations that prioritize using IoT data for decisions report higher operational performance.
- Sensor deployment and real-time data collection are strongly associated with performance at the bivariate level; however, they overlap so closely in respondents' minds that their unique contributions cannot be separated in the current regression model.

Reliability coefficients (Cronbach's α)

Construct	**Items**	**Cronbach's α**
Sensor & Device Utilization	Q4–Q6	.984
Real-Time Data Collection	Q7–Q9	1.000
Predictive Capabilities	Q10–Q12	.749
Data-Driven Decision-Making	Q13–Q17	.789
Warehouse Operational Performance	Q18–Q25	.930

Descriptive statistics (construct means)

Construct	**M**	**SD**
SensorM	3.5062	1.1634
RealTimeMean	3.5926	1.1851
PredictiveMean	3.6543	1.0232
DataDrivenMean	3.6296	0.7975
PerformanceMean	3.5278	0.8480

Key Pearson correlations (two-tailed)

Variables	1	2	3	4	5
1. SensorM	—	.992**	.713**	.718**	.791**
2. RealTimeMean	.992**	—	.683**	.648**	.724**
3. PredictiveMean	.713**	.683**	—	(see output)	.724**
4. DataDrivenMean	.718**	.648**	(see output)	—	(see output)
5. PerformanceMean	.791**	.724**	.724**	(see output)	—

Note: All reported correlations were significant at $p < .001$.

Multiple regression predicting PerformanceMean

Predictor	B	SE B	Beta	t	p
(Constant)	-0.114	0.216	—	-0.526	.604
SensorM	0.460	0.392	.632	1.176	.252
RealTimeMean	-0.274	0.358	-.383	-0.766	.452
PredictiveMean	-0.118	0.073	-.142	-1.620	.119
DataDrivenMean	**0.948**	0.134	**.892**	**7.055**	**< .001**

Model: $R = .987$, $R^2 = .974$, Adjusted $R^2 = .969$, $F(4,22) = 207.422$, $p < .001$, Durbin–Watson = 1.533.

DISCUSSION OF KEY FINDINGS

The purpose of this study was to examine how Internet of Things (IoT) factors — specifically sensor and device utilisation, real-time data collection, predictive capabilities, and data-driven decision-making — influence warehouse operational performance in the Sri Lankan apparel and logistics sector.

The analysis reveals several important findings.

IoT Integration Strongly Predicts Warehouse Operational Performance (Supported Overall)

The regression model explained **97.4%** of the variance in warehouse operational performance ($R^2 = .974$), demonstrating that IoT practices collectively have a powerful impact on operational outcomes. This aligns with existing literature that highlights IoT's transformative role in enhancing visibility, accuracy, responsiveness, and coordination across supply chain activities.

For example, prior works (Ashton, 2010; Ben-Daya et al., 2019) emphasize that IoT-enabled visibility and automation reduce errors, reduce lead times, and increase the reliability of warehouse operations. The findings of this study support these assertions within the Sri Lankan context.

Data-Driven Decision-Making is the Strongest Predictor (Supported)

Among all predictors, **Data-Driven Decision-Making** was the only statistically significant independent predictor of warehouse operational performance ($\beta = .892$, $p < .001$).

This suggests:

- Warehouses that actively utilise IoT-generated data
- And integrate it into planning, coordination, and managerial decision-making
- Experience the highest operational improvements

This finding aligns with modern supply chain literature, which argues that analytics, automated insights, and real-time decision-making are the true sources of competitive advantage — not merely the presence of IoT devices.

Sensor Utilisation and Real-Time Data Collection Are Highly Correlated

The study found an extremely high correlation between SensorM and RealTimeMean ($r = .992$). This means respondents viewed these two constructs almost identically.

This suggests:

- In practice, organisations that adopt sensors also simultaneously adopt real-time data flows
- Employees perceive these two aspects as part of the same IoT capability
- Distinguishing them as separate constructs is statistically challenging due to multicollinearity

This aligns with research indicating that sensor usage is the technical foundation of real-time data environments (Addo-Tenkorang & Helo, 2016).

Predictive Capabilities Show Positive Association but Not Independent Significance

Although PredictiveMean had a strong positive correlation with warehouse performance ($r = .724$), it did not show significance in the multivariate model.

This suggests:

- Predictive insights are beneficial
- But organisations may not yet be fully utilising predictive models or forecasting algorithms
- Predictive systems may be less mature compared to basic sensor and real-time monitoring features in Sri Lanka

This is consistent with regional studies showing that advanced predictive analytics adoption lags behind basic IoT monitoring due to limited skills and investment.

Implementations to Research Practice

Theoretical Implications

The study contributes meaningful insights to the knowledge of IoT and warehouse management:

1. Supports Resource-Based View (RBV)

Data-driven decision-making emerges as a strategic capability that enhances operational efficiency — consistent with RBV's claim that information-based capabilities generate sustainable performance advantages.

2. Indicates Overlapping IoT Constructs

The extremely high correlation between sensor utilisation and real-time data suggests these dimensions may not be independent in developing markets.

3. Highlights Importance of Human–Technology Integration

Even with IoT technologies implemented, performance improvements depend on management commitment, analytical culture, and collaborative practices — reinforcing socio-technical systems theory.

Practical Implications

1. Managers should prioritise data-driven culture

Investing in sensors alone is insufficient. Managers need to ensure:

- Staff are trained to interpret and use IoT data
- Decision-making processes incorporate real-time digital insights
- IoT dashboards and analytics tools are part of daily operations

2. Integrated IoT systems improve visibility and reduce operational issues

Strong correlations indicate that IoT adoption:

- Improves coordination
- Reduces delays
- Enhances customer satisfaction

Warehouses can expect measurable operational benefits.

3. Predictive analytics should be further developed

Companies should gradually invest in:

- Demand prediction models
- Inventory forecasting tools
- Predictive maintenance

These will amplify long-term productivity.

4. Policy and investment support are needed

Sri Lankan warehouses may require:

- Subsidies for IoT adoption
- Skill development programmes
- Industry–university partnerships

Limitations of the Study

Despite meaningful findings, the study has limitations:

1. Small Sample Size (N = 27)

Regression results may lack statistical power and generalisability.

2. Multicollinearity among IoT variables

SensorM and RealTimeMean overlap heavily, limiting the ability to isolate their independent effects.

3. Cross-sectional design

Findings capture perceptions at a single point in time; causality cannot be firmly established.

4. Self-reported data

Responses may include bias, limited by employees' knowledge of IoT systems.

Recommendations for Future Research

1. Use larger samples across more industries

This will improve generalisability and stability of regression estimates.

2. Combine overlapping variables

Sensor utilisation and real-time data may be merged into a single IoT dimension.

3. Conduct longitudinal studies

Tracking performance over time can provide stronger causal claims.

4. Apply advanced statistical techniques

- Structural Equation Modelling (SEM)
- Principal Component Analysis (PCA)
- Bootstrapped regression
  These reduce multicollinearity and improve model stability.

CONCLUSION

This study demonstrates that IoT adoption plays a significant role in improving warehouse operational performance in the Sri Lankan apparel and logistics sector. While all IoT dimensions correlate positively with performance, **data-driven decision-making** stands out as the strongest predictor. This highlights that organisational culture and analytical utilisation — not just technological investment — drive performance improvements.

The findings contribute to theory, provide practical guidance for managers, and highlight pathways for future research. Ultimately, the study reinforces that IoT-enabled warehouses can significantly enhance efficiency, responsiveness, and competitiveness when supported by strong data-driven decision processes.

Future Research

Future studies should expand this research by using larger and more diverse samples across multiple industries to improve generalizability. Longitudinal research designs are recommended to better understand causal relationships between IoT adoption and warehouse performance over time. Additionally, future researchers can address the issue of multicollinearity by combining overlapping constructs such as sensor utilization and real-time data into a unified dimension or by applying advanced techniques like Structural Equation Modelling (SEM) or Principal Component Analysis (PCA). Further investigation into the role of predictive analytics is also needed, as its impact was not significant in the current model despite showing positive associations. Moreover, qualitative studies could explore managerial perceptions and organizational readiness for IoT adoption. Finally, future research can examine external factors such as technological infrastructure, employee skills, and organizational culture to provide a more comprehensive understanding of IoT implementation success in warehouse operations

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