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# AI-Integrated Supply Chain Management and Operational Efficiency in Urban Logistics: Structural Evidence from Bengaluru

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**Abstract:** Artificial intelligence (AI) is increasingly used to coordinate demand planning, routing, warehousing, service interactions, risk control, and environmental performance in logistics. This study examines how six AI-integrated supply chain practices influence perceived supply chain efficiency in three major courier organizations operating in Bengaluru. A cross-sectional survey of 400 operational and managerial employees was analysed through descriptive statistics, confirmatory factor analysis, and structural equation modelling. The seven-factor measurement model showed good fit, chi-square (160) = 320.40, chi-square/df = 2.00, CFI = .965, TLI = .958, RMSEA = .045, and SRMR = .035. Reliability, convergent validity, and Fornell-Larcker evidence were satisfactory. The structural model also fitted the data well and explained 65% of the variance in efficiency. Route optimization had the strongest effect (beta = .32), followed by demand forecasting (beta = .28), warehouse and inventory management (beta = .21), customer experience and service quality (beta = .19), risk and fraud detection (beta = .12), and sustainable logistics (beta = .10); all six paths were significant. The findings show that operationally embedded AI produces the greatest gains when forecasting and routing capabilities are integrated with customer, risk, and sustainability systems. The article offers a multi-dimensional capability model and a staged implementation agenda for logistics organizations.

**Keywords:** Artificial intelligence, supply chain management, logistics, structural equation modelling, route optimization, demand forecasting, Bengaluru

## 1. Introduction

Logistics performance depends on the synchronized movement of goods, information, capacity, and decisions. E-commerce growth, urban congestion, volatile demand, shorter delivery expectations, and sustainability pressure have made this synchronization more difficult. Conventional planning systems can struggle when conditions change faster than schedules and manually configured rules. AI offers a different operating logic: it can learn from historical and real-time data, detect patterns, update forecasts, recommend routes, identify exceptions, and support high-volume service interactions.

The strategic issue is not whether an organization possesses isolated AI tools, but whether those tools are integrated into the supply chain processes that determine delivery speed, resource utilization, reliability, and customer outcomes. Prior work frames AI-enabled supply chain solutions as coordinated operational capabilities rather than stand-alone automation *(Nagaraju et al., 2024).* Cloud and serverless architectures can further support scalable data processing and modular deployment, although technical architecture creates value only when linked to stable workflows and governance *(Vanisree et al., 2025).*

Empirical evidence remains uneven in emerging urban logistics settings. Much of the literature describes applications or technical possibilities, whereas fewer studies test a multi-dimensional model across forecasting, routing, warehousing, customer service, risk management, sustainability, and overall efficiency. Bengaluru is a useful setting because its dense delivery networks, technology workforce, traffic variability, and concentration of national and international logistics providers expose both the potential and the operational limits of AI.

This study examines employees from DHL, Blue Dart, and

Delhivery in Bengaluru. It asks: (1) how strongly are AI-integrated practices embedded across six supply chain domains; (2) does the proposed seven-construct measurement model demonstrate adequate reliability and validity; and (3) which AI-enabled practices most strongly predict supply chain efficiency? The contribution is an empirically tested capability architecture that connects operational and supporting AI practices to a common efficiency outcome.

# 2. Literature Review and Hypothesis Development

## 2.1. AI as an integrated supply chain capability

AI applications in supply chains include machine-learning forecasts, dynamic routing, computer-vision and robotic warehouse systems, conversational service, anomaly detection, and emissions optimization. Their performance effects are interdependent. A forecast has limited value when replenishment rules cannot respond; a route recommendation adds little when dispatch and driver systems are disconnected; and a customer chatbot can increase friction when it lacks reliable shipment data. This interdependence supports a capability view in which data, models, process integration, employee competence, and governance jointly produce operational outcomes.

Research on enterprise systems similarly indicates that implementation quality, user satisfaction, and organizational performance are linked *(Kishore et al., 2025)*. Predictive resource-allocation studies also show the broader relevance of graph-based learning for complex urban systems, where network relationships and changing constraints determine allocation quality *(Gera et al., 2026)*. Applied to logistics, these insights imply that AI should be evaluated through measurable workflow outcomes rather than adoption labels.

## 2.2. Demand forecasting and planning

AI-based forecasting can combine sales history, seasonality, promotions, local events, weather, and real-time demand signals. Better forecasts can reduce stock-outs, excess inventory, emergency movements, and capacity mismatch. When planning decisions are updated through predictive information, logistics resources can be positioned before demand materializes. Accordingly, H1 proposes that AI-enabled demand forecasting and planning positively affects supply chain efficiency.

## 2.3. Route optimization and last-mile execution

Urban route performance is shaped by traffic, weather, vehicle capacity, delivery windows, driver availability, and failed-delivery risk. AI-enabled routing can update sequence and allocation decisions as these conditions change. This can reduce travel time, fuel use, and turnaround while improving delivery reliability. H2 therefore proposes that AI-enabled route optimization positively affects supply chain efficiency.

## 2.4. Warehouse, service, risk, and sustainability capabilities

Warehouse AI can support inventory visibility, replenishment, sorting, picking, packing, and exception handling. These applications can reduce error and dwell time while improving resource utilization; H3 predicts a positive effect on efficiency. Customer-facing AI can improve tracking, notification, complaint handling, and personalization. Because service information can prevent avoidable contacts and failed deliveries, H4 predicts a positive efficiency effect.

Anomaly detection and predictive risk models can identify suspicious transactions, delivery requests, or operational disruptions. Although their direct throughput effect may be smaller, preventing fraud and interruption protects reliability; H5 predicts a positive effect. AI can also support fuel optimization, emissions reduction, eco-packaging decisions, and reverse-flow planning. Market-based resilience research emphasizes that operational stability increasingly depends on coordinated economic and sustainability decisions *(Ghouse et al., 2025)*. H6 therefore predicts that AI-enabled sustainable logistics positively affects efficiency.

**Table 1:** Constructs and hypotheses

| Code | AI-integrated practice | Expected relationship |
|---|---|---|
| H1 | Demand forecasting and planning (DFP) | DFP → EFF (+) |
| H2 | Route optimization and efficiency (ROE) | ROE → EFF (+) |
| H3 | Warehouse and inventory management (WIM) | WIM → EFF (+) |
| H4 | Customer experience and service quality (CESQ) | CESQ → EFF (+) |
| H5 | Risk and fraud detection (RFD) | RFD → EFF (+) |
| H6 | Sustainability and green logistics (SGL) | SGL → EFF (+) |

# 3. Materials and Methods

## 3.1. Design, setting, and sample

A descriptive and exploratory cross-sectional design was used. The target population comprised employees with operational or managerial exposure to supply chain activities in DHL, Blue Dart, and Delhivery facilities in Bengaluru. Purposive sampling was used to reach respondents familiar with logistics operations and AI-supported processes. The final analytical sample contained 400 usable responses. The source profile indicates substantial representation from DHL (42%) and Blue Dart (34%), with associates (45%) and operational managers (32%) forming the largest role categories.

### 3.2. Instrument and measures

A structured questionnaire measured six AI-integrated practices and one efficiency outcome on five-point agreement scales. DFP, ROE, WIM, CESQ, RFD, and EFF each contained three observed indicators; SGL contained two. Items addressed forecast accuracy and stock balance, route and last-mile improvement, warehouse automation, tracking and service, security and predictive risk, fuel and packaging sustainability, and overall efficiency, turnaround, and resource utilization.

### 3.3. Analysis strategy

The analysis proceeded in three stages. First, means and standard deviations described the perception profile. Second, confirmatory factor analysis tested the seven-factor measurement model. Internal consistency was assessed with Cronbach's alpha and composite reliability (CR), convergent validity with average variance extracted (AVE), and discriminant validity with the Fornell-Larcker criterion. Third, structural equation modelling estimated the six direct paths to EFF. Model adequacy was evaluated using chi-square/df, CFI, TLI, RMSEA with its confidence interval, and SRMR. Statistical decisions used the reported p values.

The study is perception-based and cross-sectional; consequently, significant structural paths are interpreted as predictive associations within the proposed model, not as definitive causal effects.

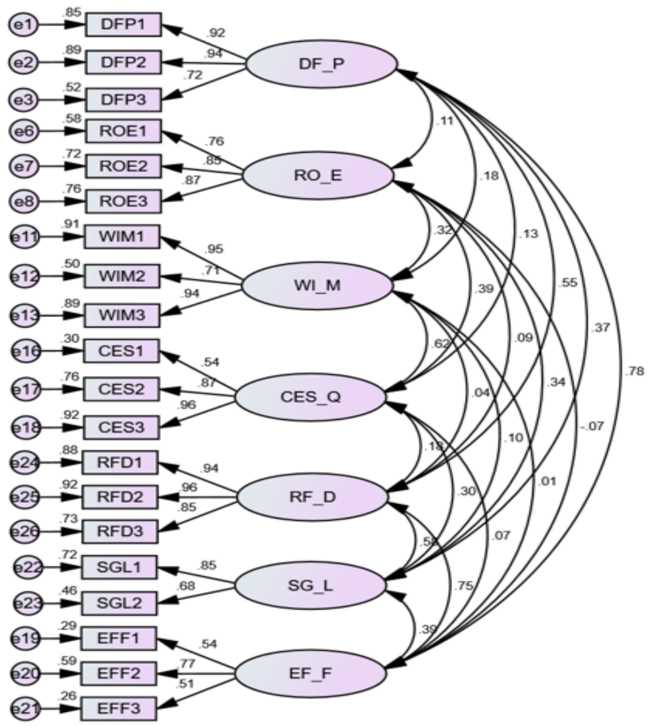
## 4. Results

### 4.1. Descriptive profile

All seven constructs were rated above the midpoint. Supply chain efficiency received the highest dimension mean (M = 4.05), followed by customer experience and service quality (M = 3.99) and route optimization (M = 3.95). Warehouse and inventory management averaged 3.84; demand forecasting and sustainable logistics each averaged 3.82; risk and fraud detection averaged 3.80. The pattern suggests broad adoption with the most visible benefits occurring in delivery execution and customer-facing processes.

**Table 2:** Descriptive statistics by construct

| Construct | Items | Dimension mean | Average SD | Interpretation |
|---|---|---|---|---|
| DFP | 3 | 3.82 | 0.91 | Positive |
| ROE | 3 | 3.95 | 0.89 | Strong positive |
| WIM | 3 | 3.84 | 0.91 | Positive |
| CESQ | 3 | 3.99 | 0.88 | Strong positive |
| RFD | 3 | 3.80 | 0.92 | Positive |
| SGL | 2 | 3.82 | 0.91 | Positive |
| EFF | 3 | 4.05 | 0.87 | Strong positive |




Note. DFP = demand forecasting and planning; ROE = route optimization and efficiency; WIM = warehouse and inventory management; CESQ = customer experience and service quality; RFD = risk and fraud detection; SGL = sustainability and green logistics; EFF = supply chain efficiency.

**Figure 1:** AMOS confirmatory factor analysis measurement model

Overall fit was good: chi-square (160) = 320.40, chi-square/df = 2.00, CFI = .965, TLI = .958, RMSEA = .045 (90% CI [.038, .052]), and SRMR = .035. The combination of incremental and residual fit indices supports the proposed measurement structure.

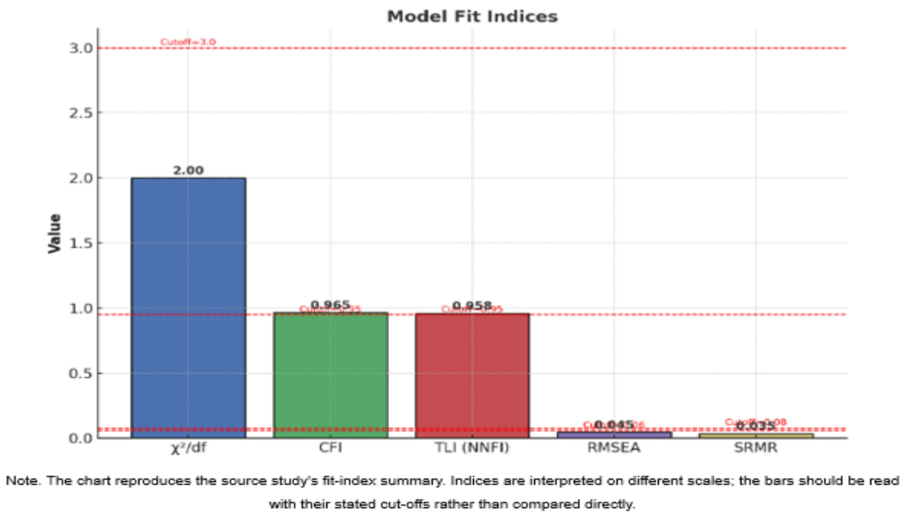



**Figure 2:** AMOS measurement-model fit profile

## 4.2. Reliability and convergent validity

Cronbach's alpha ranged from .76 to .90 and CR from .80 to .92. Every construct exceeded .50 AVE, supporting convergent validity. EFF had the strongest reliability and variance capture, while RFD and SGL were closer to minimum acceptable levels and merit continued scale refinement.

**Table 3:** Construct reliability and convergent validity

| Construct | Items | Cronbach's alpha | CR | AVE |
|---|---|---|---|---|
| DFP | 3 | .78 | .82 | .55 |
| ROE | 3 | .85 | .88 | .62 |
| WIM | 3 | .79 | .83 | .56 |
| CESQ | 3 | .88 | .90 | .68 |
| RFD | 3 | .76 | .80 | .54 |
| SGL | 2 | .77 | .81 | .52 |
| EFF | 3 | .90 | .92 | .72 |

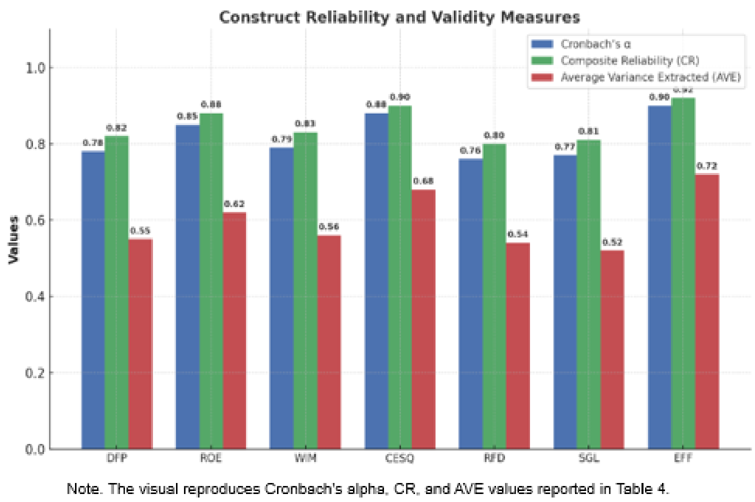



**Figure 3:** AMOS reliability and convergent-validity profile

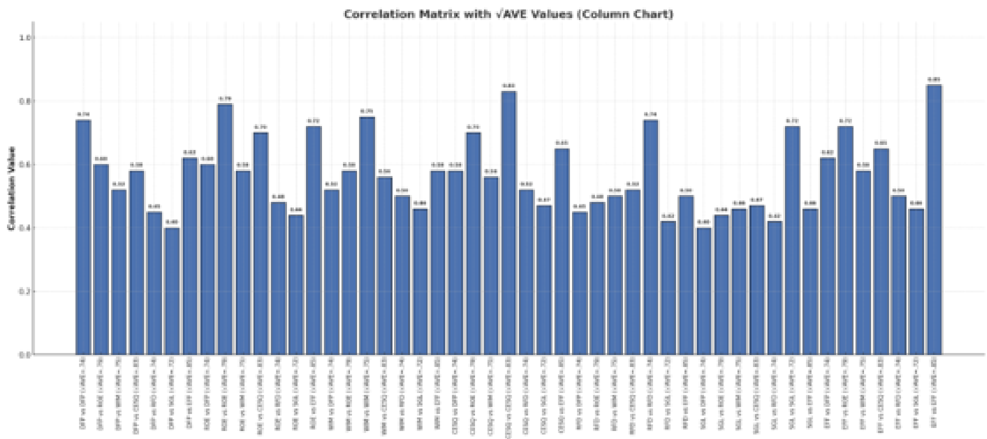
## 4.3. Discriminant validity

For each construct, the square root of AVE exceeded its correlations with the remaining constructs. The closest comparison was ROE with EFF (.72 versus square-root AVE values of .79 and .85), which remains within the reported Fornell-Larcker requirement. The constructs are therefore empirically related but distinguishable.

**Table 4:** Fornell-Larcker discriminant-validity matrix

| | DFP | ROE | WIM | CESQ | RFD | SGL | EFF |
|---|---|---|---|---|---|---|---|
| DFP | .74 | .60 | .52 | .58 | .45 | .40 | .62 |
| ROE | .60 | .79 | .58 | .70 | .48 | .44 | .72 |
| WIM | .52 | .58 | .75 | .56 | .50 | .46 | .58 |
| CESQ | .58 | .70 | .56 | .83 | .52 | .47 | .65 |
| RFD | .45 | .48 | .50 | .52 | .74 | .42 | .50 |
| SGL | .40 | .44 | .46 | .47 | .42 | .72 | .46 |
| EFF | .62 | .72 | .58 | .65 | .50 | .46 | .85 |

**Note.** Diagonal values are square roots of AVE; off-diagonal values are inter-construct correlations.




Note. The source visual is retained as a supplementary view of the Fornell-Larcker matrix; Table 5 should be used for exact comparisons.

**Figure 4:** AMOS discriminant-validity correlation profile

## 4.4. Structural model and hypothesis tests

The structural model showed good fit: chi-square(165) = 365.50, chi-square/df = 2.21, CFI = .961, TLI = .954, RMSEA = .048 (90% CI [.041, .055]), and SRMR = .038. The six predictors explained 65% of the variance in EFF, indicating substantial explanatory power within the sample.

Route optimization was the strongest predictor, followed by demand forecasting. These two capabilities directly affect daily delivery and capacity decisions, explaining their comparatively large effects. Warehouse and inventory management and customer experience also made meaningful contributions. Risk and sustainability paths were smaller but significant, suggesting that they complement rather than replace the core operational capabilities.

# 5. Discussion

## 5.1. Operational AI creates the largest immediate returns

The dominance of ROE and DFP indicates that AI produces its clearest efficiency gains where decisions are frequent, data-rich, and directly connected to resource movement. Dynamic routing can influence each delivery cycle, while improved forecasting shapes labor, inventory, vehicle, and facility requirements before execution begins. This result is consistent with the broader argument that AI-driven supply chain solutions create value through faster and better coordinated decisions *(Nagaraju et al., 2024)*.

## 5.2. Efficiency is multi-dimensional rather than purely technical

WIM and CESQ show that efficiency is not limited to transport speed. Warehouse error reduction, inventory visibility, accurate tracking, and effective exception communication can prevent rework and failed delivery attempts. Research on technology-enabled customer experience similarly indicates that service quality depends on reliability and ease across digital touchpoints *(Nagaraju & Subbarayudu, 2017)*. The results therefore support an end-to-end view in which operational and customer information flows are designed together.

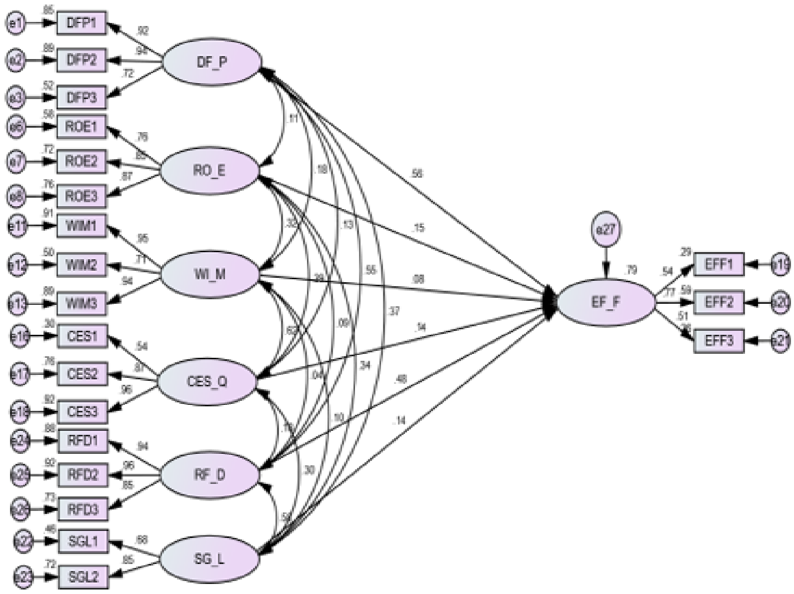



**Figure 5:** AMOS structural model of AI-integrated practices and supply chain efficiency

**Table 5:** Structural paths and hypothesis decisions

| Hypothesis | Path | Standardized beta | t | p | Decision |
|---|---|---|---|---|---|
| H1 | DFP → EFF | .28 | 5.60 | < .001 | Supported |
| H2 | ROE → EFF | .32 | 5.33 | < .001 | Supported |
| H3 | WIM → EFF | .21 | 4.20 | < .001 | Supported |
| H4 | CESQ → EFF | .19 | 3.80 | < .001 | Supported |
| H5 | RFD → EFF | .12 | 3.00 | .003 | Supported |
| H6 | SGL → EFF | .10 | 2.50 | .013 | Supported |

### 5.3. Risk and sustainability are complementary capabilities

RFD and SGL had smaller standardized effects, but both remained significant. Their contribution may be indirect or longer-term: fraud prevention protects resources and trust, while emissions and fuel optimization can improve cost and regulatory performance over time. Their effects should not be dismissed merely because they are smaller in a cross-sectional efficiency model. A mature AI portfolio balances immediate throughput gains with resilience, integrity, and environmental performance.

### 5.4. Theoretical contribution

The study validates a seven-construct architecture for AI-integrated logistics. It extends a simple technology-adoption argument by showing that performance is produced through a portfolio of interrelated capabilities. The strong R-squared and discriminant-validity results indicate that the six practices share a common technological orientation while retaining distinct operational roles. The model also provides a basis for future mediation and moderation tests involving organizational readiness, employee digital capability, data quality, and leadership support.

## 6. Managerial Implications

Managers should sequence investment around the strongest pathways while building shared data and governance foundations. Forecasting and routing pilots can create visible benefits, but scale should depend on stable integrations, employee training, validation, exception handling, and model monitoring. Cloud or serverless components may improve scalability, yet architectural choices should follow workload, security, cost, and audit requirements rather than novelty *(Vanisree et al., 2025)*.

The findings also imply that employee engagement is part of implementation quality. Operational staff should participate in model design, exception definitions, and post-deployment review because they observe conditions that training data may omit. Performance dashboards should distinguish technical accuracy from business outcomes and adverse effects.

## 7. Limitations and Future Research

The study has several limitations. Purposive sampling and concentration on three Bengaluru organizations limit population generalization. The cross-sectional design and self-reported measures do not establish temporal or causal effects. Common-method bias may inflate relations because predictors and outcomes were collected from the same respondents. The source material does not report missing-data treatment, normality diagnostics, estimator choice, bootstrapping, marker-variable tests, or multi-group invariance. Company-level objective outcomes were unavailable.

Future research should use longitudinal designs and objective measures such as delivery time, route distance, fuel use, forecast error, inventory dwell, complaint resolution, and cost per shipment. Multi-group SEM could compare firms, roles, and adoption maturity. Mediation models should test whether data quality, process integration, or employee capability translate AI use into performance, while moderation models could examine leadership support, technology readiness, and environmental uncertainty. Additional constructs may include robotics, autonomous delivery, predictive maintenance, and circular-logistics capability.

**Table 6:** Priority roadmap for logistics managers

| Priority | Managerial action | Performance evidence |
|---|---|---|
| 1. Forecast and route | Integrate demand signals with capacity plans and dynamic dispatch | Forecast error, on-time delivery, distance per stop |
| 2. Connect warehouse | Link inventory, sortation, picking, and dispatch exceptions | Pick accuracy, dwell time, rework, throughput |
| 3. Close service loop | Use trusted tracking data for notifications, chatbots, and escalation | First-contact resolution, failed deliveries, complaints |
| 4. Protect operations | Embed anomaly detection, access controls, and human review | Fraud loss, false alerts, incident recovery time |
| 5. Optimize sustainably | Include fuel, emissions, packaging, and reverse-flow objectives | Fuel per delivery, emissions, material recovery |
| 6. Govern and learn | Maintain model owners, monitoring, change control, and staff training | Drift, override rate, adoption, realized benefits |

**Note.** Metrics should be baselined before deployment and monitored by route, facility, customer segment, and model version.

# 8. Conclusion

AI-integrated supply chain practices are positively associated with perceived logistics efficiency in the Bengaluru sample. Route optimization and demand forecasting deliver the strongest effects, but warehouse, customer-service, risk, and sustainability capabilities collectively strengthen the model. The results support a holistic implementation strategy: organizations should prioritize high-impact operational use cases while connecting them to reliable data, employee judgment, customer communication, risk controls, and environmental objectives. The retained AMOS evidence demonstrates that the proposed seven-factor measurement and structural models fit the reported data well, while the study's design requires cautious interpretation beyond the sampled organizations.

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