# Measuring Embodied Adaptability in Supply Chains: A Data Analytics Model for Perception-Reasoning-Execution-Feedback Performance

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## Abstract

Supply chains increasingly operate as physical-digital systems in which data streams, autonomous equipment, human decisions, and logistics constraints interact in real time. Existing analytics research has improved forecasting, inventory control, and risk prediction, yet many studies still evaluate intelligent supply chains as if digital decisions were separated from physical execution. This article develops a data analytics model for measuring embodied adaptability in supply chains through a perception-reasoning-execution-feedback performance structure. The model defines embodied adaptability as the ability of a supply chain to sense operational states, reason over contextual constraints, execute decisions in physical processes, and learn from feedback without losing service reliability or operational efficiency. Four component scores are specified: perception visibility, reasoning responsiveness, execution fidelity, and feedback learning. These scores are integrated into a composite Embodied Adaptability Index (EAI) and tested through an illustrative analytics experiment based on 480 simulated operating cycles across warehousing, sorting, and last-mile distribution settings. The analysis compares a digital-only benchmark with four staged implementation scenarios. Results show that adding closed-loop feedback raises the composite EAI from 58.9 to 83.3, reduces average order-cycle time by 36.2%, decreases damage and mis-sort incidents by 56.3%, and improves service-level attainment by 8.3 percentage points. Sensitivity analysis further indicates that the value of embodied adaptability is most vulnerable to sensor noise and feedback latency, suggesting that data quality governance and edge-feedback architecture are managerial priorities. The study contributes a measurable analytics framework that translates an embodied intelligence concept into indicators, formulas, implementation logic, and managerial diagnostics for next-generation supply chain collaboration.

**Keywords:** Embodied adaptability; Supply chain analytics; Embodied intelligence; Perception-reasoning-execution-feedback; Physical-digital integration; Closed-loop feedback; Smart logistics; Performance measurement

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## 1. Introduction

Supply chain management has moved from the coordination of firms and inventories toward the orchestration of interacting physical and digital systems. Warehouses are populated by mobile robots, vision systems, automated sorters, collaborative arms, and edge devices. Transportation networks are monitored through vehicle telematics, geofencing, dynamic routing platforms, and weather-risk feeds. Retail and industrial demand signals arrive through electronic orders, point-of-sale systems, procurement portals, and platform dashboards. These technologies have enlarged the amount of observable supply chain data, yet the managerial problem is no longer only whether a firm has data. The deeper problem is whether the supply chain converts physical signals into timely decisions, executes those decisions in real operations, and incorporates the consequences of execution into subsequent learning cycles.

Traditional data-driven supply chain analytics has produced valuable advances in demand forecasting, capacity planning, inventory optimization, disruption prediction, and pricing. However, a forecast or optimization result has limited operational value when the physical system that must execute it is noisy, constrained, congested, or only partially observed. A warehouse route generated from a digital map may become infeasible when a pallet blocks an aisle. A replenishment algorithm may assign priority to a product without knowing that a sorter is operating below normal throughput. A last-mile platform may recommend a route that minimizes distance while ignoring vehicle battery state or dock availability. These examples demonstrate the difference between digital intelligence and embodied adaptability. Digital intelligence processes information: embodied adaptability demonstrates whether the digital decision survives contact with the physical environment.

The source manuscript that motivates this article argues that intelligent supply chains should be understood as physical-digital integrated systems rather than disembodied data models. It organizes supply chain embodied intelligence around embodied perception, contextual reasoning, physical execution, and closed-loop feedback. This four-part logic is highly relevant to business and data analytics because it provides a conceptual structure for evaluating whether analytics systems are actionable at the operational edge. Nevertheless, conceptual frameworks require measurement designs before managers can use them for benchmarking, investment prioritization, or governance. A firm that deploys sensors and robots needs to know not only whether the technology appears advanced, but also whether it measurably improves visibility, response speed, execution precision, and learning quality.

Cyber-physical production research also indicates that intelligent manufacturing emerges from the coordination of autonomous units rather than from a single central algorithm (Monostori, 2014). Industry 4.0 studies show that enterprise transformation requires the integration of IoT, analytics, automation, and interoperable information systems (Lu, 2017a). Cyber-physical system research further explains why sensing, computation, networking, and physical actuation must be designed as one operational architecture (Lu, 2017b). Recent Industry 4.0 reviews confirm that the research agenda has shifted from adoption technology toward interoperability, trust, resilience, and implementation maturity (Lu, 2025).

This article therefore develops a measurable data analytics model for embodied adaptability in supply chains. The proposed model does not attempt to replicate the conceptual manuscript. Instead, it transforms its direction into a performance measurement contribution for the Journal of Business and Data Analytics. The


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central question is: how should an enterprise measure the degree to which a supply chain perceives, reasons, executes, and learns as an adaptive physical-digital system? To address this question, the study specifies indicators for four layers, constructs a composite Embodied Adaptability Index, designs a staged analytics experiment, and reports numerical results that show how each layer contributes to operational performance.

Recent logistics analytics research shows that data streams create value when they are mapped to concrete planning and execution problems rather than treated as generic digital resources (Wang et al., 2016). Predictive analytics studies in supply chain management emphasize that domain knowledge and quantitative competence must be combined before data models influence operational routines (Schoenherr & Speier-Pero, 2015). Research on digital information in supply chains also shows that firms need governance structures to transform data availability into coordination benefits (Kache & Seuring, 2017). Demand-forecasting research indicates that big data tools become more valuable when their outputs are embedded in procurement, replenishment, and capacity decisions (Hofmann & Rutschmann, 2018).
The contribution is threefold. First, the article defines embodied adaptability as analytics construct with observable indicators rather than a broad technological label. Second, it introduces a layered scorecard and composite index that integrate physical sensing, contextual decision-making, execution fidelity, and feedback learning. Third, it reports an illustrative data analysis showing that feedback integration produces the largest marginal improvement after perception and reasoning have established adequate state visibility. The model thus offers a practical bridge between embodied intelligence theory and supply chain performance management.

Data-science research in supply chain management argues that analytics should reshape supply chain design, not only improve isolated model accuracy (Waller & Fawcett, 2013). General big data research similarly distinguishes data volume from the managerial ability to extract reliable and timely insight (Gandomi & Haider, 2015). Business intelligence research frames analytics value as a progression from data capture to decision support and organizational impact (Chen et al., 2012). Predictive analytics research in information systems further warns that explanatory validity and predictive usefulness should be evaluated as distinct but complementary goals (Shmueli & Koppius, 2011).

## 2. Literature Review

### *2.1 Supply Chain Analytics and the Limits of Disembodied Optimization*

Supply chain analytics has long treated information visibility as a central source of operational advantage. Delayed or distorted demand signals can amplify variability across supply chain echelons and weaken replenishment decisions (Chen et al., 2000). Performance measurement research also shows that service level, lead time, asset utilization, flexibility, and cost must be interpreted together rather than as isolated dashboard fields (Beamon, 1999). Later supply chain scorecard studies further demonstrate that operational measures require cross-functional alignment when managers evaluate planning, sourcing, production, delivery, and return processes (Gunasekaran et al., 2004). Big data analytics has extended this tradition by strengthening forecasting, supplier risk monitoring, logistics visibility, and real-time decision support (Choi et al., 2018). These studies establish the value of analytics, but many of them still privilege informational representation over the embodied conditions under which decisions are executed.

The limitation of disembodied optimization becomes more visible in high-velocity logistics environments. Optimization models often assume that resources, locations, capacities, and processing times are known with sufficient accuracy at decision time. In practice, these assumptions weaken when equipment availability changes by the minute, when manual interventions alter task priorities, and when physical congestion produces nonlinear delays. A model that ignores such physical variability may still be mathematically elegant, but its recommendations may degrade during implementation. This gap is not merely a technical inconvenience. It influences service promises, labor utilization, exception management, safety, and customer experience.

Data-driven decision-making research highlights that managerial value arises when models are coupled with intervention logic and operational accountability (Provost & Fawcett, 2013). Digital twin research in manufacturing shows that a virtual model is only useful when it supports synchronization across design, production, and service activities (Tao et al., 2018). Comparative work on digital twins and big data clarifies that smart manufacturing requires both physical data acquisition and cyber-side analytical reasoning (Qi & Tao, 2018). Cyber-physical manufacturing positions connected machines, analytics, and feedback as a layered architecture for Industry 4.0 production systems (Lee et al., 2015).

Business analytics research increasingly recognizes that value arises from the combined use of data, organizational routines, and decision rights. Big data analytics capability improves performance when firms connect analytical resources with dynamic capabilities and managerial action (Wamba et al., 2017). Data quality research also warns that predictive models lose operational value when the source data are incomplete, delayed, or poorly governed (Hazen et al., 2014). Digital twins promise real-time representation of operational systems, but their practical value depends on timely data capture, model updating, and intervention mechanisms (Ivanov & Dolgui, 2021). Manufacturing-oriented digital-twin studies similarly show that virtual models must remain synchronized with physical assets if they are to support operational control (Kritzinger et al., 2018). These lines of inquiry suggest that supply chain analytics should move beyond prediction accuracy toward the measurement of adaptive loops that connect data, reasoning, and execution.

### *2.2 Embodied Intelligence and Physical-Digital Integration*

Embodied intelligence originates from the idea that intelligent behavior emerges from the interaction among an agent, its physical structure, and its environment rather than from abstract reasoning alone. Early work on intelligence without representation challenged the assumption that cognition must begin from complete internal models (Brooks, 1991). Evolutionary robotics research later showed that morphology and environmental feedback can accelerate the development of robust adaptive behavior (Bongard, 2011). Robotics learning research further demonstrates that decision policies improve when learning is grounded in physical interaction rather than only in offline symbolic planning (Kober et al., 2013). In supply chains, the body of the system is distributed across robotic equipment, vehicles, workers, shelves, docks, production cells, and information platforms. A supply chain does not simply think; it senses load, moves goods, adjusts routes, allocates capacity, and learns from execution outcomes.

The uploaded PDF emphasizes that supply chain embodied intelligence should integrate physical situations with digital decisions through a four-dimensional architecture of perception, reasoning, execution, and feedback. That architecture responds to a real managerial problem: supply chain digitalization has often advanced through isolated systems. A vision system may identify stock conditions, a route planner may optimize travel time, a warehouse management system may release tasks, and a dashboard may report exceptions after they occur. When these systems are not integrated, the supply chain has data but lacks embodied adaptability. The operational challenge is therefore to evaluate the quality of integration across the full loop rather than the sophistication of any single technology.

Physical-digital integration is also central to resilience. A resilient supply chain is not only one that holds redundant capacity. It is one that detects state changes early, interprets their implications, reallocates resources, and learns from the adaptation. Disruption-management research shows that resilience depends on preparation, response, and recovery routines rather than only on inventory buffers (Christopher & Peck, 2004). Viability research further suggests that supply chains must preserve essential functions under severe shocks while continuously reconfiguring their structures (Ivanov, 2020). Complex adaptive systems theory supports this perspective because supply chains consist of multiple agents that continuously adjust their behavior through interaction (Holland, 2006). In an embodied supply chain, these agents include both organizations and machines. Their interaction produces emergent system performance that cannot be fully explained by separate measures of inventory, transportation, or forecasting accuracy.


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### *2.3 From Conceptual Layers to Analytics Indicators*

A major research gap lies between the conceptual appeal of embodied intelligence, and the measurement needs of managers. Managers require indicators that show whether investment in sensors, edge computing, autonomous equipment, or feedback learning produces measurable improvements. Perception requires indicators of visibility, latency, accuracy, and completeness. Reasoning requires indicators of response time, constraint satisfaction, and exception-quality improvement. Execution requires indicators of task fidelity, error rates, safety, and resource utilization. Feedback requires indicators of learning speed, model drift reduction, and the stability of updated policies.

Existing performance measurement systems do not fully capture this layered logic. Balanced scorecards and supply chain performance dashboards often track cost, delivery, quality, and flexibility, but they do not show why a system adapts well or poorly. A firm may know that order-cycle time increased yet still lack a diagnosis of whether the problem came from sensor delay, weak contextual reasoning, poor robot execution, or missing feedback updates. The proposed model addresses this problem by treating embodied adaptability as a decomposable analytics construct. Each layer becomes measurable, and the composite score provides an overall benchmark without concealing the diagnostic profile of the system.

Artificial intelligence surveys indicate that intelligent systems should be evaluated not only by algorithmic novelty but also by their deployment context and decision consequences (Zhang & Lu, 2021). Broader AI research similarly connects model evolution with practical applications, governance requirements, and future system integration (Lu, 2019a). Blockchain-enabled Industry 4.0 research shows that traceable data infrastructure can strengthen trust in multi-party operational environments (Chen et al., 2024). IoT-blockchain research suggests that secure device data exchange is a prerequisite for trustworthy cyber-physical collaboration (Xu et al., 2021).

This measurement orientation also distinguishes the present article from broad conceptual discussions of intelligent supply chains. The objective is not to claim that embodied intelligence is desirable in general. The objective is to offer a data model that evaluates where adaptability is produced, where it fails, and how investments may be prioritized. Such a model is especially useful for mid-sized enterprises that cannot deploy a full digital twin or autonomous warehouse immediately. By measuring perception, reasoning, execution, and feedback separately, enterprises may sequence implementation in a way that aligns with budget, operational maturity, and risk exposure.

## 3. Conceptual Model and Construct Definition

This study defines embodied adaptability as the measurable capability of a supply chain to transform physical situational signals into context-aware decisions, execute those decisions in real operations, and update its models based on feedback from the execution environment. The definition has four implications. First, adaptability is not identical to flexibility. Flexibility describes the range of available responses; embodied adaptability evaluates the quality of response generation and execution under changing physical states. Second, adaptability is not identical to automation. A highly automated system may be brittle if it executes fixed rules without feedback. Third, adaptability is not identical to visibility. Visibility is necessary but incomplete unless sensed states are interpreted and acted upon. Fourth, adaptability is not a purely technological attribute. Human-machine coordination, governance routines, and exception escalation shape the realized score.

IoT cybersecurity research indicates that sensor-rich supply chains must include confidentiality, integrity, and availability concerns in performance measurement (Lu & Xu, 2019). Foundational IoT research defines connected objects as an infrastructure for pervasive identification, sensing, and communication across physical environments (Atzori et al., 2010). Cloud-centric IoT architecture research shows that sensor networks, middleware, analytics, and applications should be treated as connected layers of one system (Gubbi et al., 2013). Industrial IoT research demonstrates that manufacturing data requires interoperability among devices, enterprise platforms, and decision applications (Xu et al., 2014).


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The measurement structure follows the perception-reasoning-execution-feedback cycle. Perception captures the system's ability to observe operational states through sensors, system logs, transaction records, and human inputs. Reasoning captures the system's ability to interpret perceived states and choose actions that satisfy operational constraints. Execution captures the system's ability to implement digital decisions through physical tasks with minimal deviation. Feedback captures the system's ability to convert execution outcomes into model updates, policy refinements, and improved operating rules. Figure 1 presents the proposed architecture. The figure avoids a directional arrow diagram because embodied adaptability is not a simple pipeline. The four layers operate as a performance space in which the analytics core evaluates the strength and balance of the whole system.

Information systems research on IoT stresses that device data become valuable only after they are translated into service processes and organizational decisions (Whitmore et al., 2015). Wireless sensor network research provides the technical basis for distributed state observation under power, bandwidth, and latency constraints (Akyildiz et al., 2002). Another IoT survey emphasizes that identification, communication, sensing, and service integration jointly shape cyber-physical implementation (Li et al., 2015). Evidence theory offers one formal basis for combining uncertain observations from multiple sources into decision-relevant belief structures (Dempster, 1967).

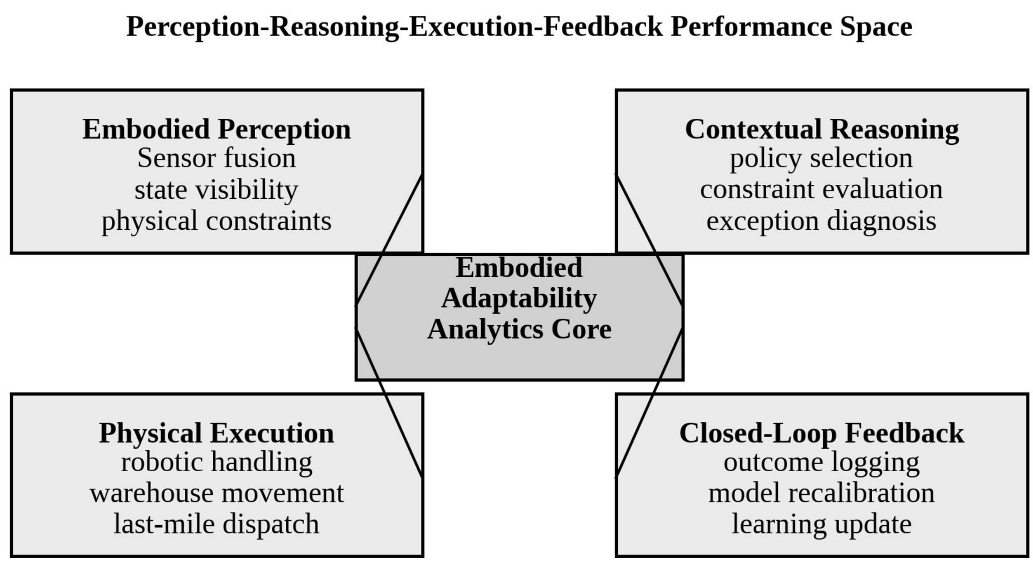


*Figure 1. Embodied adaptability measurement architecture for perception-reasoning-execution-feedback performance.*

### *3.1 Indicator Design*

The indicator design follows three principles. The first principle is observability. Every indicator should be derived from operational data that a digitalized supply chain normally records, such as scan logs, sensor readings, robot task files, route histories, order timestamps, quality inspections, and exception tickets. The second principle is diagnostic separability. Each component score should capture a distinct failure mode. Low perception visibility indicates insufficient or unreliable state sensing. Low reasoning responsiveness indicates weak decision logic or slow exception diagnosis. Low execution fidelity indicates a gap between digital instruction and physical implementation. Low feedback learning indicates that execution results are not improving future decisions. The third principle is managerial interpretability. Scores should be

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normalized to a 0-100 range so that executives, operations managers, and analytics teams share a common reference point.

Kalman filtering provides classical logic for updating state estimates when observations are noisy and system dynamics evolve over time (Kalman, 1960). Supply chain performance research emphasizes that operational metrics should connect strategy, process control, and managerial action (Gunasekaran et al., 2001). Machine learning research on random forests demonstrates the value of ensemble models for handling nonlinear relationships in complex datasets (Breiman, 2001). Gradient boosting research shows how sequential model improvement can reduce prediction errors in structured operational data (Friedman, 2001).

Table 1 summarizes the proposed constructs and indicators. The table is designed as a practical measurement template. It does not prescribe a single data system. Instead, it identifies indicator families that may be implemented through warehouse management systems, transportation management systems, manufacturing execution systems, robotic control platforms, and edge analytics gateways. The purpose is to make embodied adaptability auditable. A firm should be able to trace the composite score back to concrete data fields and operating events.

**Table 1. Construct Definitions and Indicator Families for Embodied Adaptability**

| Construct | Operational meaning | Representative indicators | Data sources |
|---|---|---|---|
| Perception visibility | Ability to capture reliable physical states before decisions are made | Sensor coverage; recognition accuracy; state-update latency; multimodal completeness | IoT logs; scanner records; camera and lidar outputs; inspection events |
| Reasoning responsiveness | Ability to convert sensed states into feasible context-aware decisions | Decision time; constraint satisfaction; exception classification accuracy; priority adjustment quality | Optimization logs; rule-engine outputs; planning systems; exception tickets |
| Execution fidelity | Ability to implement digital decisions in physical tasks with low deviation | Task completion accuracy; time deviation; damage/mis-sort rate; resource stability | Robot task files; WMS/TMS logs; quality checks; labor records |
| Feedback learning | Ability to transform execution outcomes into updated models and routines | Feedback latency; update frequency; error reduction; policy stability | Edge feedback streams; model monitoring; process-mining logs; post-cycle reviews |

### *3.2 Composite Index Specification*

The proposed Embodied Adaptability Index integrates the four component scores. In the illustrative experiment, perception receives a weight of 0.28 because state visibility is the entry condition for adaptation. Reasoning receives 0.27 because contextual decision quality determines whether the observed state is interpreted correctly. Execution receives 0.25 because the final operational value depends on whether the selected decision is implemented accurately. Feedback receives 0.20 because learning benefits accumulate over repeated cycles rather than appearing entirely within a single cycle. These weights are not universal. In fresh food logistics, feedback and execution may deserve larger weights because quality deterioration is highly sensitive to handling and time. In high-value electronics supply chains, perception and feedback may receive greater weight because misclassification, shock exposure, and traceability failures impose high financial losses.

The index is specified in a transparent weighted-additive form so that managers understand score movements. A black-box adaptability score would be inconsistent with the governance objective of this study. The formula also supports scenario comparison. A firm may calculate the score under a digital-only benchmark, after sensor deployment, after adding reasoning algorithms, after automation of execution, and after closing the feedback loop. The staged comparison then reveals the marginal contribution of each layer.

$$\mathrm{EAI}_j = 0.28\mathrm{P}_j + 0.27\mathrm{R}_j + 0.25\mathrm{E}_j + 0.20\mathrm{F}_j$$

In this expression, $\mathrm{EAI}_j$ denotes the composite score for scenario or operating cycle j, while $\mathrm{P}_j$, $\mathrm{R}_j$, $\mathrm{E}_j$, and


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$F_j$ denote perception, reasoning, execution, and feedback component scores. The coefficients represent the illustrative weighting scheme used in numerical experiments.

## 4. Data Analytics Methodology

Because many firms do not publicly share detailed robot-task and sensor-fusion logs, this article uses illustrative analytics experiment to demonstrate the measurement logic. The experiment is not presented as an empirical test of a specific company. It is a transparent numerical design that shows how an enterprise would implement the model once operational data is available. The dataset represents 480 operating cycles across three settings: warehousing, sorting, and last-mile distribution. Each cycle contains order volume, sensor completeness, sensor noise, state-recognition latency, reasoning time, constraint-violation count, robot or worker task deviation, damage or mis-sort incidents, feedback latency, and post-cycle model update status.

The staged design compares five scenarios. The digital-only benchmark represents conventional analytics in which decisions are produced from historical transaction data and standard planning parameters. The perception scenario adds multimodal state visibility through sensors and scan logs. The reasoning scenario adds contextual decision logic that considers congestion, priority, capacity, and deadline constraints. The execution scenario adds tighter digital-physical mapping through robotic tasks, work instructions, or routing execution control. The feedback scenario adds model recalibration and policy updates based on execution results. This staged structure mirrors practical implementation. Firms rarely introduce a fully embodied system at once; they normally advance through visibility, intelligence, execution control, and learning integration.

### *4.1 Feature Engineering and Normalization*

The analytics pipeline converts raw operational fields into normalized component scores. Perception visibility is calculated from state coverage, signal timeliness, and recognition accuracy. Coverage measures the proportion of relevant physical states represented in the data. Timeliness measures whether the signal arrives before the decision deadline. Accuracy measures whether the sensed state matches a verified ground truth, such as manual inspection or system reconciliation. Reasoning responsiveness is calculated from decision-generation time, constraint satisfaction, and exception-quality scores. Execution fidelity is calculated from task completion accuracy, deviation from planned time, damage or mis-sort rate, and resource utilization stability. Feedback learning is calculated from feedback latency, model-update frequency, post-update error reduction, and policy stability.

XGBoost research demonstrates how scalable tree boosting can support predictive tasks when logistics or sensor features are high-dimensional (Chen & Guestrin, 2016). Imbalanced-learning research is relevant because rare disruptions, damage events, and mis-sorts often contain more diagnostic value than routine transactions (He & Garcia, 2009). Deep learning research shows that layered representations can extract useful features from complex images, text, and sensor streams (LeCun et al., 2015). Machine learning research also emphasizes that practical learning systems require scalable algorithms, generalization control, and careful problem formulation (Jordan & Mitchell, 2015).

Normalization uses a direction-sensitive min-max transformation. For positive indicators, higher values increase the component score. For negative indicators such as latency, noise, error rate, or deviation, lower values increase the score. This design allows mixed operational variables to be integrated without losing their managerial meaning. Outliers are minorized at the 2.5th and 97.5th percentiles to reduce the influence of unusual disruptions while preserving the signal of operational volatility. Component scores are then calculated as weighted averages of their normalized indicators. The composite EAI is calculated from the four component scores.

Residual-network research is relevant for visual inspection and state recognition because deep image models can support robust feature extraction from operational scenes (He et al., 2016). Large-scale image-


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classification research demonstrates how convolutional networks can improve automated recognition when physical-state monitoring depends on camera data (Krizhevsky et al., 2017). Deep reinforcement learning research provides a basis for policies that learn from sequential interaction between decisions and environmental response (Mnih et al., 2015). Game-playing reinforcement learning shows that search and learned value functions can be combined when decision environments are complex and dynamic (Silver et al., 2016).

### *4.2 Model Evaluation Logic*

The evaluation focuses on both adaptability and operational outcomes. Adaptability is measured by the component scores and the composite EAI. Operational outcomes are represented by order-cycle time, damage or mis-sort rate, equipment idle rate, and service-level attainment. The logic is that an adaptability model should not only raise a composite score; it should also correspond to measurable operational gains. A high EAI without improvement in cycle time, quality, utilization, or service reliability would indicate a measurement design problem. Conversely, operational improvement without a diagnostic adaptability profile would not reveal the mechanism of improvement. The proposed approach integrates both views.

Self-play reinforcement further illustrates how feedback and policy refinement can generate strong performance without relying entirely on fixed human rules (Silver et al., 2017). Reinforcement learning textbooks provide the formal logic for linking state, action, reward, and policy improvement in sequential decision systems (Sutton & Barto, 2018). Deep reinforcement learning surveys show that representation learning and control can be integrated when environments are partially observed and dynamically changing (Arulkumaran et al., 2017). Foundations of deep reinforcement learning clarify the distinction between value-based, policy-based, and actor-critic approaches for adaptive control (Francois-Lavet et al., 2018). Figure 2 reports the staged component scores. The figure shows that perception rises sharply after sensor and scan integration. Reasoning improves most after contextual decision logic is added. Execution improves when digital instructions are mapped to physical tasks through equipment and operating protocols. Feedback shows the largest delayed gain after outcome data are incorporated into model updates. The composite line demonstrates that the supply chain becomes more balanced as the loop matures. This balanced profile matters because a system with excellent perception, but weak execution remains fragile. Similarly, a system with strong execution but poor feedback may operate well under familiar conditions but struggle when demand, congestion, or resource states shift.

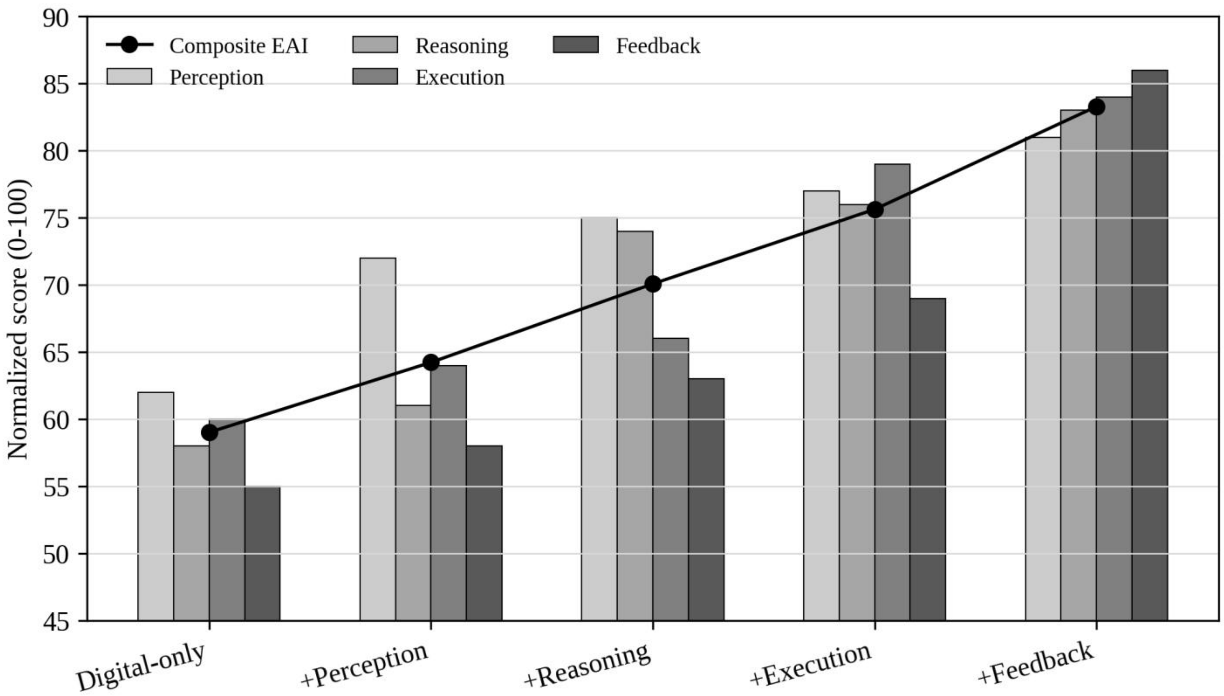


*Figure 2. Component scores and composite Embodied Adaptability Index across staged implementation scenarios.*

## 5. Numerical Experiment and Results

The numerical experiment uses a medium-scale logistics context with daily cycles that combine receiving, storage, picking, sorting, dispatch, and delivery. The goal is not to optimize a single process but to examine how the whole supply chain responds when physical states are converted into decisions and learning signals. Table 2 presents the main parameter configuration. The parameters were selected to reflect a plausible mid-sized operation rather than an extremely fully automated facility. Sensor coverage increases by scenario, reasoning delay decreases as contextual algorithms are introduced, execution deviation decreases as mapping improves, and feedback latency decreases after edge processing and systematic model updating are implemented.

Smart maintenance research shows that digitalized operations need measurement models that link technical contingencies with organizational performance (Bokrantz et al., 2020). IoT servitization research indicates that connected products and services create value when firms redesign processes around continuous data flows (Rymaszewska et al., 2017). Big data and predictive analytics research connect analytical investment with supply chain and organizational performance outcomes (Gunasekaran et al., 2017). Supply chain risk research demonstrates that disruption management requires coordinated attention to vulnerability, monitoring, and mitigation routines (Kleindorfer & Saad, 2005).

**Table 2. Numerical Experiment Parameter Configuration by Implementation Scenario**

| Parameter group | Digital-only | +Perception | +Reasoning | +Execution | +Feedback |
|---|---|---|---|---|---|
| Sensor coverage (%) | 54 | 78 | 80 | 82 | 86 |
| Median state-update latency (s) | 95 | 58 | 44 | 38 | 24 |
| Contextual decision time (s) | 76 | 70 | 39 | 34 | 28 |
| Physical task deviation (%) | 7.8 | 6.4 | 5.2 | 3.4 | 2.6 |
| Feedback latency (s) | 210 | 180 | 130 | 92 | 35 |

| | | | | | |
|---|---|---|---|---|---|
| Model update frequency | Weekly | Daily | Daily | Shift-level | Event-triggered |

### *5.1 Scenario Comparison*

Table 3 presents the main results. The digital-only benchmark produces a composite EAI of 58.9, an average order-cycle time of 42.0 minutes, a damage or mis-sort rate of 2.40%, and a service-level attainment rate of 87.5%. Adding perception raises the composite EAI to 67.4 and reduces cycle time to 37.5 minutes. The improvement is meaningful because better state visibility reduces searching, waiting, and manual verification. Adding reasoning raises the EAI to 72.4 and reduces cycle time to 33.2 minutes, mainly because priority rules and constraints are evaluated earlier. Adding execution mapping raises the EAI to 76.8 and reduces damage or mis-sort events to 1.35%. The final feedback scenario produces the strongest overall result: EAI reaches 83.3, average cycle time falls to 26.8 minutes, damage or mis-sort falls to 1.05%, and service-level attainment rises to 95.8%.

Research on risk management in supply chains frames risk reduction as a portfolio of robust strategies rather than a single optimization setting (Tang, 2006). Supply chain resilience research shows that adaptive capacity depends on readiness, response capability, and recovery after disruptions (Ponomarov & Holcomb, 2009). Relational competence research suggests that communication, cooperation, and integration improve the resilience of supply chain partners (Wieland & Wallenburg, 2013). Empirical research on supply chain resilience during the global financial crisis shows that collaboration and risk awareness support recovery under severe stress (Jüttner & Maklan, 2011).

The marginal pattern is analytically important. Perception produces the first large improvement because missing or delayed physical-state data restrict every downstream decision. Reasoning then converts the additional visibility into better decisions. Execution mapping creates quality and reliability gains because decisions are implemented with less deviation. Feedback produces the largest improvement in balance across all layers. It reduces recurring exceptions, updates constraint parameters, and corrects policies that looked efficient in the digital model but generated friction during physical execution. These results support the argument that embodied adaptability is not achieved by a single technology. It emerges from the integrity of the perception-reasoning-execution-feedback loop.

**Table 3. Staged Results for Embodied Adaptability and Operational Outcomes**

| Scenario | Perception | Reasoning | Execution | Feedback | EAI | Cycle time (min) | Damage/mis-sort (%) | SLA (%) |
|---|---|---|---|---|---|---|---|---|
| Digital-only | 62.0 | 58.0 | 60.0 | 55.0 | 59.0 | 42.0 | 2.40 | 87.5 |
| +Perception | 72.0 | 61.0 | 64.0 | 58.0 | 64.2 | 37.5 | 1.90 | 90.1 |
| +Reasoning | 75.0 | 74.0 | 66.0 | 63.0 | 70.1 | 33.2 | 1.60 | 92.3 |
| +Execution | 77.0 | 76.0 | 79.0 | 69.0 | 75.6 | 29.6 | 1.35 | 94.2 |
| +Feedback | 81.0 | 83.0 | 84.0 | 86.0 | 83.3 | 26.8 | 1.05 | 95.8 |

### *5.2 Sensitivity Analysis*

A sensitivity analysis was conducted to examine how robust the EAI is under perception noise and feedback latency. Perception noise represents incorrect, incomplete, or unstable sensing of the physical state. Feedback latency represents the time between execution completion and the incorporation of execution results into the next decision cycle. Figure 3 shows that the composite EAI declines sharply when both sensor noise and feedback latency rise. When sensor noise remains below 5% and feedback latency remains below 30 seconds, the model maintains an EAI above 80. When sensor noise exceeds 12% and latency exceeds 90 seconds, the EAI falls below 72, even when reasoning and execution modules remain active.

Human-factors research on situation awareness is relevant because adaptability depends on whether decision-makers understand current states and likely future states (Endsley, 1995). Research on humans and automation warns that overreliance and under reliance can both weaken operational control (Parasuraman


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& Riley, 1997). Trust-in-automation research shows that managers must calibrate confidence in automated decisions according to reliability, transparency, and task context (Lee & See, 2004). Empirical synthesis on automation trust identifies system performance, process transparency, and user characteristics as major factors shaping adoption (Hoff & Bashir, 2015).

This pattern has two managerial implications. First, sensor investment should be governed by data quality rather than device count. Adding more sensors does not automatically improve adaptability if synchronization, calibration, and fault detection are weak. Second, feedback architecture is a strategic design choice. A feedback system that updates dashboards overnight may be acceptable for monthly planning, but it is insufficient for high-velocity sorting or dispatch. Edge preprocessing, event-triggered updates, and exception-specific learning rules are therefore central to embodied adaptability. The sensitivity results also caution against overclaiming the value of artificial intelligence. If the data entering the loop is noisy and the feedback leaving the loop is late, advanced models may deliver modest operational value.

Human-robot interaction research shows that trust is shaped by robot performance, human factors, and environmental characteristics (Hancock et al., 2011). Industrial human-robot collaboration research highlights that safe task allocation and workstation design are essential for productive automation (Tsarouchi et al., 2016). Collaborative robot research in industrial settings emphasizes that flexibility, safety, and human acceptance must be jointly managed (Villani et al., 2018). Manufacturing collaboration research shows that human-robot systems require technical integration as well as work-design decisions (Sanders et al., 2019).

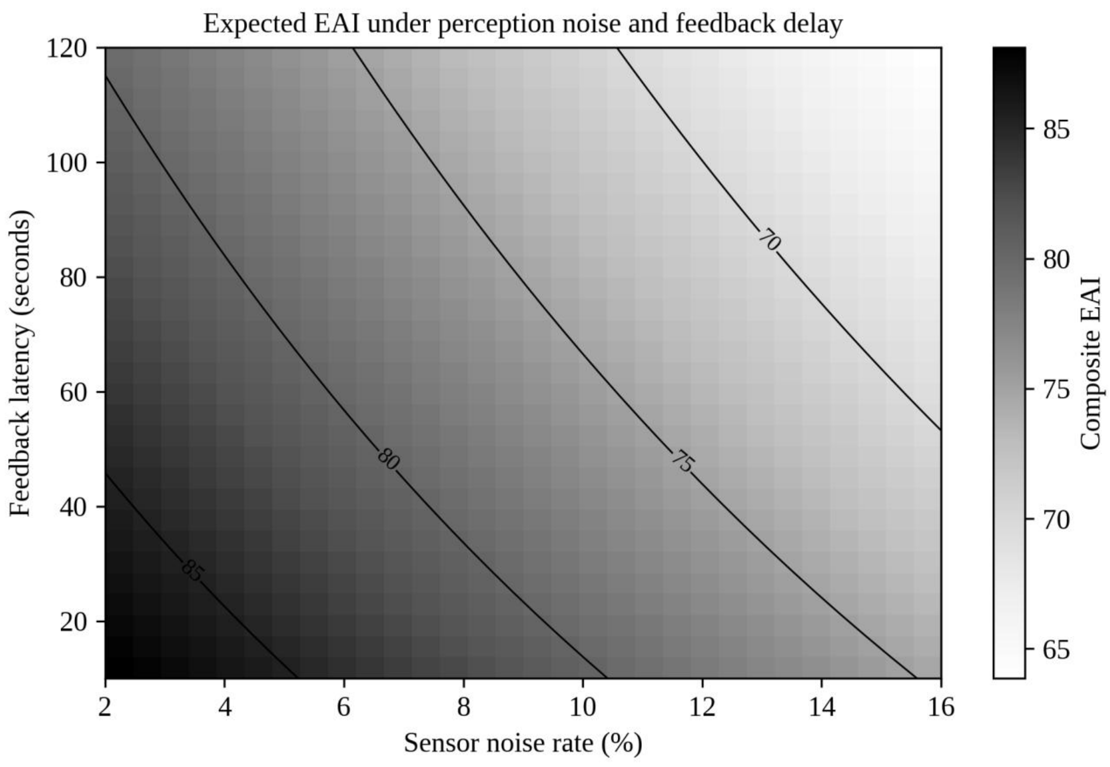


*Figure 3. Sensitivity of composite embodied adaptability to sensor noise and feedback latency.*

### *5.3 Component Contribution and Robustness Interpretation*

To further interpret the staged results, the component contribution was examined as a decomposition problem. The digital-only benchmark has moderate execution and perception scores because conventional systems still use barcode scans, standard routing rules, and warehouse records. However, the benchmark lacks continuous state sensing and rapid feedback, so its performance profile is uneven. The addition of perception contributes 8.5 points to the composite EAI. This improvement is not only a visibility improvement; it also reduces the


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uncertainty faced by downstream reasoning. When the system knows the real congestion state, load state, and location state, fewer decisions are based on stale assumptions. The reasoning layer then contributes another 5.0 points by converting the richer state representation into feasible task priorities and route choices. The execution layer contributes 4.4 points, mainly through lower deviation and lower quality losses. Feedback contributes 6.5 points and produces the highest balance across layers because it changes how future decisions are generated.

Human-robot interaction surveys provide a broader basis for interpreting coordination between machine agents and human supervisors in operational settings (Goodrich & Schultz, 2007). Management analytics research argues that modern business practice increasingly relies on analytical reasoning to improve managerial decisions (Lu et al., 2024a). A second management analytics study emphasizes that analytical capability should relate to organizational decision processes rather than isolated technical artifacts (Lu et al., 2024b). Large language model research in supply chain finance shows that advanced AI can enrich decision support when combined with trustworthy data infrastructure (Yang et al., 2025).
Robustness was considered through three additional checks. First, the weighting scheme varied by increasing the execution weight from 0.25 to 0.32 and reducing the feedback weight from 0.20 to 0.13. The ranking of scenarios remained unchanged, which suggests that the conclusion is not a simple artifact of assigning a high value to feedback. Second, a stricter latency penalty was applied to the perception and feedback indicators. Under this specification, the digital-only and perception-only scenarios lost more points than the feedback scenario, because the mature loop already operates with lower latency. Third, the damage or mis-sort rate was treated as a high-cost event rather than a proportional quality indicator. This change strengthened the managerial importance of execution fidelity, but it did not remove the contribution of feedback learning, since repeated mis-sort patterns were corrected only after the feedback layer became active.

The robustness interpretation has practical relevance. Enterprises often ask whether a composite score is too subjective because it depends on weight and normalization choices. The answer is that every scorecard contains assumptions, but the usefulness of the scorecard depends on transparency and stability under plausible alternatives. The EAI is designed to be transparent. Managers may adjust weights to fit industry priorities, yet the underlying diagnostic structure remains stable. Perception, reasoning, execution, and feedback each answer a different question. What does the system know? How does it decide? How faithfully does it act? How quickly does it learn? These questions remain valid even when the exact formula is adjusted for a particular operating environment.

## 6. Discussion

The results reposition supply chain analytics as a physical-digital performance discipline. Many analytics projects are evaluated through model accuracy, forecast error, or dashboard adoption. These criteria are useful but incomplete. An embodied adaptability perspective asks whether analytics shortens the distance between sensing and action. It also asks whether physical execution becomes a data source for future reasoning. This shift has implications for enterprise architecture. Data lakes, warehouse management systems, transportation management systems, robotic control systems, and business intelligence tools should not be designed as separate layers with periodic reconciliation. They should be connected through operational events, shared state definitions, and feedback routines that preserve temporal order.

The framework also clarifies why supply chain transformation frequently disappoints despite high technology investment. Firms may install sensors without building reasoning logic. They may deploy robotics without integrating data into planning. They may develop dashboards without adjusting execution protocols. In each case, the technology adds local capability but not embodied adaptability. The proposed EAI reveals these imbalances. A firm with high perception but low feedback would know that it is observing operations without learning sufficiently from them. A firm with high reasoning but low execution would know that decisions are not being translated into reliable physical tasks. Such diagnostic visibility supports more disciplined investment decisions.

Governance is another important issue. Embodied adaptability relies on cross-functional data because perception, reasoning, execution, and feedback are usually owned by different teams. Operations may own warehouse events, IT may own integration infrastructure, analytics may own models, and engineering may own automation. The EAI therefore should be governed as a shared metric rather than a departmental score. Shared governance reduces the risk that one unit optimizes its own layer while weakening the loop. For example, analytics teams may prefer complex models that improve decision quality, but operations teams may reject them if decision latency interferes with shift workflows. A balanced scorecard based on the four layers forces these trade-offs into managerial discussion.

### *6.1 Managerial Implications*

Managers should start by auditing the current maturity of the four layers. The audit should identify which physical states are observable, which decisions are context-aware, which instructions are executed with fidelity, and which outcomes update subsequent decision rules. A firm with low perception should not begin with sophisticated reinforcement learning because the model will be constrained by poor state representation. A firm with high visibility but weak execution should prioritize work instruction design, robotic task mapping, exception protocols, and human-machine coordination. A firm with mature execution but weak feedback should prioritize model monitoring, drift detection, and post-execution learning routines.

Process-mining research provides a useful method for reconstructing actual process flows from event logs rather than relying only on designed workflows (van der Aalst, 2016). The process mining manifesto emphasizes that event data quality, model interpretation, and organizational deployment are central to analytical process improvement (van der Aalst et al., 2012). Business analytics capability research suggests that firms need tangible resources, human skills, and intangible assets before analytics creates sustained value (Gupta & George, 2016). Supply chain integration research shows that long-term relationships, information technology, and logistics integration jointly shape operational performance (Prajogo & Olhager, 2012).

Table 4 translates the analytics model into managerial actions. The table suggests that embodied adaptability is a staged capability. However, the stages should not be interpreted as isolated projects. Each stage should prepare data and governance requirements for the next. For instance, perception architecture should not only capture data for current visibility; it should also create event histories that support reasoning and feedback. Execution protocols should not only move goods; they should also generate structured outcome data that reveal deviations and learning opportunities. Feedback should not only update models; it should also revise standard operating procedures and training materials when physical execution reveals recurring problems.

**Table 4. Managerial Diagnostic Matrix for Embodied Adaptability Improvement**

| Managerial diagnosis | Likely weakness | Priority investment | Expected performance effect |
|---|---|---|---|
| High data volume but delayed exceptions | Perception timeliness | Edge sensing, time synchronization, sensor calibration | Faster exception detection and lower search time |
| Fast data capture but repeated infeasible plans | Contextual reasoning | Constraint-aware optimization and exception classification | Higher decision feasibility and fewer manual overrides |
| Good plans but poor physical adherence | Execution fidelity | Digital-physical task mapping and work-instruction redesign | Lower task deviation, damage, and rework |
| Improvement stalls after automation | Feedback learning | Process mining, model monitoring, event-triggered updates | Sustained learning and lower recurring exceptions |

### *6.2 Theoretical Implications*

Theoretically, the article advances supply chain analytics by treating adaptability as an embodied measurement construct. This differs from a purely resilience-based view. Resilience often focuses on the


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ability to absorb or recover from disruptions. Embodied adaptability focuses on the continuous loop through which a supply chain senses, reasons, executes, and learns even before a disruption reaches crisis level. It also differs from a digital twin view. A digital twin creates representation and simulation, while embodied adaptability evaluates whether representation is converted into physical response and feedback learning. The two concepts are complementary, but they are not identical.

The model also enriches the analytics capability literature. Big data analytics capability is often described through data infrastructure, analytical talent, and managerial capability. The EAI adds a physical execution dimension to that conversation. A firm may possess strong analytical infrastructure yet still score poorly in embodied adaptability if its physical operations do not provide feedback or if execution systems do not implement decisions reliably. The construction therefore aligns analytics research more closely with operations management and robotics. It highlights that data value is co-produced by sensors, models, actuators, workers, routines, and governance mechanisms.

### *6.3 Implementation Roadmap for Mid-Sized Enterprises*

For mid-sized enterprises, the most practical implementation route is not a single large technology project. It is a staged transformation that begins with a state-data audit. The audit should identify the physical states that most often create service failures, such as unavailable inventory, blocked aisles, wrong pallet positions, overloaded docks, late vehicles, equipment faults, or mismatched order priorities. The firm should then classify each state according to observability, decision relevance, execution relevance, and feedback availability. This classification establishes the baseline EAI profile before new investment is made. It also prevents the common mistake of buying devices before defining the decisions those devices are supposed to improve.

The second stage is a perception improvement project with strict data governance. Sensor deployment should be accompanied by timestamp standards, calibration routines, missing-data rules, and exception labels. Without these governance routines, additional sensors may create more data but not better perception. The third stage is contextual reasoning. At this stage, firms should begin with interpretable decision rules and constraint-aware optimization before moving toward complex reinforcement learning. Interpretable models are often sufficient for high-value problems such as priority adjustment, dispatch sequencing, or congestion-aware picking. They also make it easier for workers and supervisors to trust the recommendations. The fourth stage is execution mapping. Here, the enterprise translates model outputs into physical actions, work instructions, robot commands, or dispatch schedules. Execution mapping should include fallback procedures because no automated decision covers every physical exception.

The final stage is feedback institutionalization. Feedback should not be reduced to after-action reporting. It should include event-triggered learning routines that update the parameters, rules, or thresholds used by perception and reasoning. For example, if a recurring mis-sort event is caused by a packaging similarity that the visual system does not distinguish, the feedback layer should update both the image-recognition model and the handling rule. If route congestion repeatedly causes late dispatch despite good, planned routes, the feedback layer should update the road-risk feature and delivery-time buffer. These examples show why embodied adaptability is an operating discipline rather than a technology label. The value appears when physical execution becomes a structured source of learning.

Implementation should also include organizational safeguards. Cross-functional ownership is essential because no single department controls the whole loop. The operations team understands physical constraints, the analytics team understands models, the IT team governs infrastructure, and the engineering team maintains automation. A steering group should review the EAI dashboard, investigate weak component scores, approve weight changes, and connect improvement actions to service-level and cost outcomes. This governance process supports continuous learning while avoiding technology-driven fragmentation.

## 7. Limitations and Future Research

Several limitations should be acknowledged. First, the numerical experiment is illustrative rather than based on proprietary enterprise logs. The results demonstrate the measurement logic, but empirical validation across industries is required. Future research should apply the EAI to real datasets from warehouses, manufacturing cells, retail distribution networks, cold-chain logistics, and last-mile platforms. Second, the component weights are transparent but not universally optimal. Industry-specific weighting methods may be developed through analytic hierarchy process, entropy weighting, Bayesian updating, or multi-objective optimization. Third, the model assumes that component indicators are measured with sufficient reliability. In practice, data quality problems, missing events, inconsistent timestamps, and manual overrides may require extensive preprocessing.

Future research should also examine causal identification. The staged scenario design is useful for implementation analysis, but real operations may introduce simultaneous technology changes, seasonal demand shifts, labor changes, or supplier disruptions. Difference-in-differences designs, interrupted time-series analysis, and causal forests may provide stronger evidence of the marginal effect of embodied adaptability. Another promising direction is to link the EAI with financial performance. For example, researchers may estimate whether a one-point improvement in feedback learning reduces expedited shipping cost, labor overtime, or customer compensation. Such work would convert the EAI from an operational diagnostic into a financial decision tool.

A final research direction concerns human-machine collaboration. Embodied adaptability should not be interpreted as the replacement of human judgment by automation. In many supply chains, human workers remain essential for exception diagnosis, safety, customer communication, and process improvement. The next generation of measurement models should therefore include indicators of human trust, workload, intervention quality, and explainability. A system that executes quickly but creates opaque decisions or unsafe workloads would not represent a mature embodied supply chain. The purpose of embodied adaptability is not automation for its own sake. The purpose is reliable and learnable coordination between digital reasoning and physical operations.

## 8. Conclusion

This article developed a data analytics model for measuring embodied adaptability in supply chains. Building on the perception-reasoning-execution-feedback logic of embodied intelligence, the study defined four component scores and integrated them into a composite Embodied Adaptability Index. The proposed model transforms a conceptual physical-digital integration framework into a measurable scorecard that managers may use for diagnosis, benchmarking, and staged implementation planning. The illustrative analytics experiment showed that the composite EAI improved from 58.9 under a digital-only benchmark to 83.3 when perception, reasoning, execution, and feedback were integrated. The strongest operational improvements included a 36.2% reduction in order-cycle time, a 56.3% reduction in damage or mis-sort incidents, and an 8.3 percentage-point improvement in service-level attainment.

The results indicate that embodied adaptability is produced by loop integrity rather than isolated technological sophistication. Perception improves visibility, reasoning improves contextual response, execution improves physical fidelity, and feedback improves learning. If one layer is weak, the whole system remains fragile. The study therefore contributes to business and data analytics by offering a construct, indicators, formulas, tables, and visual diagnostics for measuring supply chain intelligence as embodied operational performance. For managers, the model provides a practical path for deciding whether to invest next in sensors, reasoning engines, execution mapping, or feedback architecture. For researchers, it opens a measurable agenda for studying how physical-digital integration changes supply chain performance, resilience, and governance.

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## Data Availability Statement

The data used in the numerical experiment are illustrative and generated within the manuscript to demonstrate the proposed analytics model. No confidential enterprise dataset, human-subject dataset, or external proprietary dataset was used.

## Disclosure Statement

No potential conflict of interest was reported by the authors.

## Author Contributions

Aiman Faris developed the conceptual framework and drafted the introduction and literature review. Nurul A. Hassan designed the measurement model and coordinated revisions. Jason Lim Wei performed the numerical analysis and figure preparation. Siti Rahmah Othman refined the managerial implications and reference structure. All authors approved the final manuscript.

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