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Reframing Modern Cargo Systems: Integrating Agility, Digital Intelligence, and Autonomy for Future-Ready Supply Chains

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Abstract:
Background: Contemporary supply chains face an unprecedented convergence of pressures: increasing demand variability, regulatory complexity, technological disruption, and the need for sustainability. Existing scholarship has separately examined agile manufacturing and supply chains, the economic feasibility of autonomous cargo transport, data-driven analyses of bulk cargo flows, and the application of intelligent sensing and IoT in warehousing. This article synthesizes these disparate strands into a coherent theoretical and operational framework for next-generation cargo and supply chain systems. The synthesis emphasizes how agility, digital intelligence (AI, data mining), and autonomy (low-manned/unmanned systems) interact to reshape tracking, inventory management, cargo handling, and the fate of complex cargo types. The article is grounded in the provided literature and integrates concepts from logistics, manufacturing theory, maritime engineering, and pharmaceutical cargo behavior to produce a cross-domain perspective (Gunasekaran, 1999; Gunasekaran et al., 2019; Kooij et al., 2021; Jörgensen et al., 2023).
Methods: Through a structured conceptual analysis, the paper constructs an integrative model by mapping theoretical constructs (agility capabilities, digital intelligence layers, autonomy spectrum) onto operational tasks (tracking, volume analysis, cargo handling, and decision-making). The approach combines task-based economic viability insights with empirical and methodological lessons from data-mining studies and IoT-enabled warehouse systems. The methods comprise systematic cross-referencing of theoretical propositions and operational evidence from the supplied references, followed by iterative model refinement through deductive elaboration (Gligor et al., 2015; Kim et al., 2021; Chowdhury, 2025).
Results: The analysis yields an operational taxonomy of agility-enabled digital systems, a layered architecture for cargo intelligence, and criteria for evaluating when to deploy low-manned or unmanned cargo systems. Key findings include: (1) explicit reconciliation of agility with digital sensing to maximize responsiveness while preserving stability (Gligor et al., 2015; Gunasekaran et al., 2019); (2) demonstration that bill-of-lading data-driven volume analytics can guide capacity and routing decisions when integrated with real-time IoT sensing (Kim et al., 2021; Chowdhury, 2025); (3) articulation of economic and safety thresholds that determine the viability of low-manned and unmanned maritime cargo concepts (Kooij et al., 2021); and (4) cross-domain insight that cargo chemical and physical behavior — illustrated by self-emulsifying drug delivery systems — can materially affect logistics handling and risk, requiring specialized digital monitoring strategies (Jörgensen et al., 2023).
Conclusions: The paper argues for an architecture that fuses agile governance, layered digital intelligence, and selective autonomy. The architecture improves supply chain resilience and responsiveness and supports sustainable performance when enacted with clear task-based economic criteria and rigorous cargo-specific sensing. Implementation requires organizational change, investment in digital skills, and policy alignment. Research implications include empirical validation of the model and development of decision-support algorithms that unify volume forecasting with autonomous routing and cargo-condition monitoring (Geyi et al., 2020; Gartner, 2021). Practical implications address managers aiming to balance agility investments against cost and safety constraints.

Keywords: Supply chain agility, digital intelligence, IoT, unmanned cargo, cargo analytics, SEDDS

INTRODUCTION:

The architecture of modern supply chains is experiencing a transformational phase marked by two interrelated forces. First is the persistent demand for agility — the capability to sense demand changes and to respond quickly and effectively (Hofman & Cecere, 2005; Gunasekaran, 1999). Second is the accelerating incorporation of digital intelligence — the application of data mining, AI, and pervasive sensing (IoT) — which creates new possibilities for visibility, prediction, and automated control (Jawahar et al., 2020; Chowdhury, 2025). Overlaying these forces is an emergent autonomy trend: proposals for low-manned and unmanned cargo ships and other autonomous logistics assets that aim to reduce labor costs and enable operational flexibility in constrained environments (Kooij et al., 2021). While these streams have been studied in isolation, they require an integrated theoretical treatment because operational decisions in one domain (for example, deploying unmanned vessels) have cascading implications for agility, digital investment, cargo handling, and risk management.

The agility literature established foundational principles: flexibility, visibility, rapid decision-making, and close coordination with demand signals (Gunasekaran, 1999; Gligor et al., 2015). More recent work expanded these concepts into manufacturing evolution, emphasizing how digital tools and organizational practices support agile behavior (Gunasekaran et al., 2019). Concurrently, research into digital cargo analytics has demonstrated that large administrative datasets — notably bill of lading records — can reveal structural patterns of cargo movement and volume that in turn inform routing and capacity decisions (Kim et al., 2021). IoT and AI applied in warehouse tracking have shown operational improvements in inventory accuracy and responsiveness, suggesting that agility can be materially enhanced through technology adoption (Chowdhury, 2025; Jawahar et al., 2020).

However, the cross-impacts and trade-offs among these domains are under-theorized. For instance, autonomy can reduce human oversight and thus potentially degrade the rapid judgment that defines agility unless compensated by superior digital sensing and decision-support. At the same time, certain cargo types pose unique handling requirements that technological interventions must address; the pharmaceutical literature on self-emulsifying drug delivery systems (SEDDS) draws attention to how material behavior and release dynamics can be governed by seemingly subtle factors (Jörgensen et al., 2023) — a lesson supply chains cannot ignore when handling sensitive chemical cargoes or liquid bulk. Furthermore, macro-level drivers such as the recognized need for resilience investments demonstrate that firms are planning capital allocations toward digital and agility capabilities (Gartner, 2021), but how those investments should be prioritized across sensing, analytics, and autonomy remains unclear.

This article responds to a clear literature gap: the absence of a comprehensive theoretical and operational framework that synthesizes supply chain agility, digital intelligence (data mining, AI, IoT), and the economic and task-based viability of autonomy in cargo systems. It also aims to translate cross-domain empirical insights — from big-data analyses of cargo volumes to task-based maritime economic models and pharmaceutical cargo behavior studies — into prescriptive guidance for managers and researchers. The research questions guiding this paper are:

1.How can agility and digital intelligence be architected together to support responsive, resilient cargo and supply chain operations?

2.What task-level criteria determine when low-manned or unmanned cargo assets are economically viable, and how do these criteria interact with digital sensing and agility demands?

3.How do cargo-specific material behaviors (e.g., the dynamics illustrated by SEDDS) influence monitoring and handling requirements, and what digital strategies best manage these risks?

To address these questions, the paper constructs a layered model integrating theoretical constructs and operational evidence, then elaborates decision rules and architectural principles for designing agile, digitally intelligent, and autonomous-capable logistics systems. The remainder of the article develops the methodology, presents the integrative results, discusses implications and limitations, and concludes with a synthesis of managerial and research recommendations.

METHODOLOGY

The methodological approach of this study is conceptual synthesis anchored in the supplied literature. Because the objective is theoretical integration and operational model building rather than empirical hypothesis testing on primary data, the methods emphasize careful cross-domain mapping and rigorous citation of established findings. The research proceeds through the following stages:

1.Construct Identification and Literature Mapping: Key constructs were identified from the provided references: agility capabilities and performance (Gunasekaran, 1999; Geyi et al., 2020; Gligor et al., 2015), digital intelligence and data-mining approaches in cargo analysis (Kim et al., 2021), IoT-enabled warehouse tracking (Chowdhury, 2025; Jawahar et al., 2020), economic viability and task-based analysis of autonomous vessels (Kooij et al., 2021), and cargo behavior exemplified by SEDDS (Jörgensen et al., 2023). Additionally, organizational intent to invest in resilience was incorporated as context (Gartner, 2021).

2.Task-Based Decomposition: Building on task-based economic analysis principles (Kooij et al., 2021), logistics operations were decomposed into discrete tasks (sensing, transport, handling, decision-making, exception management, and customer interface). Each task was mapped to agility requirements (speed, flexibility, visibility), digital intelligence roles (data collection, preprocessing, analytics, real-time decision-making), and autonomy implications (human-in-the-loop vs. automation).

3.Layered Architecture Synthesis: A layered architecture was conceptualized to capture the interactions among physical assets (ships, warehouses), sensing layers (IoT devices, administrative data), analytics layers (data mining, AI), and governance layers (agile decision-making, resilience planning). The architecture reflects the operational realities of cargo volume analytics — where administrative records like bills of lading provide crucial batch-level insight that complements continuous IoT sensing (Kim et al., 2021; Chowdhury, 2025).

4.Rule and Criterion Development: Drawing on the economic viability work of Kooij et al. (2021) and the performance outcomes literature on agility (Gligor et al., 2015), decision criteria were developed for autonomy deployment. These criteria include task repetitiveness, environmental volatility, safety/regulatory constraints, and the maturity of digital sensing and analytics.

5.Cross-Domain Risk Integration: Cargo-specific handling risks were incorporated using the SEDDS literature (Jörgensen et al., 2023) as a representative case of cargo whose physical-chemical behavior imposes special monitoring needs. The methodology articulates how digital monitoring strategies (real-time sensors, predictive analytics) must adapt to cargo-level dynamics.

6.Iterative Deductive Elaboration: The above elements were synthesized iteratively with deductive reasoning, ensuring that each claim is anchored to one or more of the supplied references. Counter-arguments and alternative viewpoints from the literature were considered and integrated into the model.

This methodology is intentionally text-based and integrative. It privileges logical coherence, explicit citation of supporting literature, and the development of operationally actionable propositions rather than empirical generalizations unsupported by the references.

RESULTS

The synthesis produced three principal outputs: (A) an operational taxonomy linking tasks to agility and digital-intelligence requirements; (B) a layered architecture for integrating agility, digital intelligence, and autonomy; and (C) a set of decision criteria and operational thresholds for deploying low-manned or unmanned cargo assets. Each is presented in detailed descriptive form below.

A. Operational Taxonomy: Task-Level Mapping to Agility and Digital Intelligence

The taxonomy organizes logistics operations into six core tasks and specifies how each task benefits from agile capabilities and digital intelligence. Each task is illustrated with practical implications and linked to the literature.

1.Sensing and Data Acquisition

Role: Capture real-time and batch-level information about cargo, equipment, and environmental conditions.

Agility Link: Agility requires high-quality, timely information to sense demand and supply disruptions (Hofman & Cecere, 2005; Gligor et al., 2015).

Digital Intelligence: IoT devices and administrative data (e.g., bills of lading) form complementary streams. Bill-of-lading analytics provide macro-level volume patterns (Kim et al., 2021), while IoT provides micro-level real-time status (Chowdhury, 2025).

Implication: Systems must architect data pipelines that reconcile the temporal granularity of IoT data with the structural insights of administrative datasets.

2.Transport and Routing

Role: Movement of cargo across nodes and modes.

Agility Link: Rapid re-routing and mode switching are hallmark agile responses to demand shifts (Gunasekaran, 1999; Gligor et al., 2015).

Digital Intelligence: Data-mining volume forecasts from bills of lading can inform capacity planning and strategic routing; real-time traffic and weather sensing can support tactical adjustments (Kim et al., 2021).

Implication: Integrating predictive analytics with dynamic routing engines enhances responsiveness but requires governance for trust and override.

3.Handling and Stowage

Role: Physical manipulation of cargo in terminals, warehouses, and vessels.

Agility Link: Agile operations reduce lead time and error rates during handling (Gunasekaran et al., 2019).

Digital Intelligence: Cargo-specific monitoring — for instance, condition sensors for temperature, agitation, or chemical release — is necessary for sensitive cargo types (Jörgensen et al., 2023).

Implication: Handling systems must include cargo-aware protocols and sensors, with analytics to detect subtle risk patterns that could indicate release or degradation.

4.Inventory Tracking and Reconciliation

Role: Maintain accurate visibility of stock levels across the supply chain.

Agility Link: Inventory accuracy is essential for speedy replenishment and avoiding stockouts (Geyi et al., 2020).

Digital Intelligence: IoT-enabled tracking in warehouses improves the speed and accuracy of reconciliation (Chowdhury, 2025).

Implication: Tracking must be robustly integrated into planning systems so that real-time replenishment decisions reflect physical counts and predictive demand.

5.Decision-Making and Exception Management

Role: Rapid responses to disruptions, exceptions, and customer requests.

Agility Link: Agility is operationalized at the decision layer; rapid, cross-functional decisions drive performance (Gligor et al., 2015).

Digital Intelligence: AI and rule-based systems can support decisions but must be transparent and auditable. Administrative data (e.g., bill-of-lading trends) inform strategic exceptions such as capacity reallocation (Kim et al., 2021).

Implication: Human operators require decision-support tools that present clear trade-offs and grounded predictions, enabling swift action.

6.Customer Interface and Fulfillment

Role: Delivery promises, lead-time communication, and returns handling.

Agility Link: Customer-facing agility requires reliable lead-time predictions and flexible fulfillment options (Gunasekaran et al., 2019).

Digital Intelligence: Predictive analytics based on cargo flows and warehouse status enable accurate ETAs and dynamic fulfillment choices (Chowdhury, 2025).

Implication: Systems must expose trustworthy data to customers and integrate customer requests into operational plans without destabilizing core processes.

This taxonomy specifies that agility is not a single capability but an emergent property of coordinated capabilities across tasks, underpinned by digital intelligence. Each task benefits from both administrative analytics (e.g., bill-of-lading analysis, which supplies structural patterns) and continuous sensing (IoT), and their integration is fundamental for reliable responsiveness (Kim et al., 2021; Chowdhury, 2025).

B. Layered Architecture for Agile, Digitally Intelligent, and Autonomous Cargo Systems

From the taxonomy, a layered architecture emerges that organizes components into four interacting layers: Physical Assets, Sensing & Data Layer, Analytics & Decision Layer, and Governance & Agility Layer.

1.Physical Assets Layer

Composition:Vessels(including low-manned/unmanned), warehouses, trucks, handling equipment.

Function: Provide the actuation — movement and manipulation — necessary for logistics.

Relevance: The economic viability of certain asset modalities (e.g., unmanned vessels) depends on task profiles and digital readiness (Kooij et al., 2021).

2.Sensing & Data Layer

Composition: IoT devices (sensors for temperature, vibration, location), administrative datasets (bills of lading, manifests), and environmental feeds.

Function: Capture both batch and real-time data; bills of lading supply structural and historical volume patterns while IoT provides stateful telemetry (Kim et al., 2021; Chowdhury, 2025).

Relevance: The duality of batch and streaming data necessitates architectural patterns that handle heterogeneity in latency, volume, and veracity.

3.Analytics & Decision Layer

Composition: Data preprocessing, predictive models (volume forecasting, failure prediction), prescriptive algorithms (routing, scheduling), and human-in-the-loop decision interfaces.

Function: Convert raw data into actionable insights; reconcile batch-derived forecasts with real-time anomalies.

Relevance: Effective analytics are necessary for substituting human judgment in autonomous operations and for enhancing the speed of agile decision-making (Gligor et al., 2015; Kim et al., 2021).

4.Governance & Agility Layer

Composition: Organizational rules, exception protocols, resilience planning, performance metrics, and regulatory compliance frameworks.

Function: Translate analytical recommendations into accepted actions; ensure alignment with resilience investment priorities (Gartner, 2021) and agile practices (Gunasekaran, 1999).

Relevance: Governance ensures that agility does not devolve into instability and that autonomy deployment adheres to safety and economic thresholds (Kooij et al., 2021).

The architecture emphasizes that autonomy can only substitute for human roles where sensing fidelity and analytic robustness are sufficient to replicate or exceed human situational awareness. Where cargo behavior introduces high uncertainty — as with certain chemical release dynamics documented in SEDDS research — the sensing and analytics layer must be enhanced to preserve safety and compliance (Jörgensen et al., 2023).

C. Decision Criteria for Autonomy and Low-Manned Operations

Leveraging task-based economic analysis and agility performance findings, the synthesis identifies decision criteria for whether to deploy low-manned or unmanned cargo assets. These criteria are presented as threshold questions, each grounded in the literature.

1.Task Repetitiveness and Standardization

○ Criteria: Tasks that are highly repetitive and standardized (e.g., bulk route legs with stable port procedures) are better candidates for autonomy.

○ Rationale: Standardization reduces the need for ad hoc human judgment; Kooij et al. (2021) show economic advantages when tasks have low variability.

2.Environmental and Operational Volatility

Criteria: Environments with high variability (e.g., ports with unpredictable congestion or extreme weather) raise the bar for autonomy unless compensated by superior sensing.

Rationale: Agility literature emphasizes responsiveness to change; where volatility is high, human flexibility remains beneficial (Gligor et al., 2015).

3.Digital Sensing and Analytics Maturity

Criteria: Autonomy requires mature sensing (IoT) integrated with predictive and prescriptive analytics. Low maturity implies retained human oversight.

Rationale: Chowdhury (2025) and Kim et al. (2021) demonstrate that data-driven systems materially improve operational outcomes; autonomy depends on such systems.

4.Cargo Sensitivity and Risk Profile

Criteria: Sensitive cargo (chemical, pharmaceutical, perishable) with complex physical behaviors should only be transported autonomously when cargo-condition monitoring and fail-safe responses are proven reliable.

Rationale: Jörgensen et al. (2023) show that cargo behavior can be governed by subtle chemical interactions; such dynamics mandate specialized monitoring.

5.Economic Trade-offs and Cost Structure

Criteria: The cost of human labor, capital for autonomy, and potential cost-saving must be computed at the task level; where savings outweigh risks and capital costs, autonomy is viable.

Rationale: Kooij et al. (2021) use task-based models to calculate viability; Gartner (2021) mentions broad investment plans in resilience that could fund autonomy.

6.Regulatory and Safety Constraints

Criteria: Regulatory frameworks and safety imperatives may preclude full autonomy in certain corridors or cargo types.

Rationale: Deployments must adhere to national and international regulations; even economic viability is subordinate to legal compliance (Kooij et al., 2021).

These criteria function as a decision checklist. Importantly, they highlight chicken-and-egg dependencies: autonomy requires digital maturity, which in turn benefits from the capital freed by autonomy gains — a dynamic that organizations must manage carefully through staged investments and pilots (Gunasekaran et al., 2019).

DISCUSSION

The synthesized architecture and decision criteria provide a framework for integrating agility, digital intelligence, and autonomy. This discussion elaborates the theoretical implications, practical applications, counter-arguments, and limitations, and outlines future research directions.

Theoretical Implications

1.Agility as an Emergent System Property

The findings reaffirm that agility is not reducible to single practices but emerges from the coordinated functioning of sensing, decision-making, and governance (Gunasekaran, 1999; Gligor et al., 2015). Digital intelligence operates as an enabler — increasing the speed and accuracy of sensing and decision-making — but does not automatically confer agility without organizational redesign and governance mechanisms that permit rapid action (Gunasekaran et al., 2019). This reconceptualization situates agility as a socio-technical achievement requiring alignment across layers of the architecture.

2.Complementarity of Batch and Real-Time Data

The integration of batch administrative data (bills of lading) with streaming IoT telemetry creates a complementarity:administrative datasets reveal structural, systemic patterns, while streaming data supplies real-time state awareness needed for tactical adjustments (Kim et al., 2021; Chowdhury, 2025). This complementarity suggests hybrid analytics architectures: long-term forecasting models driven by structural patterns and short-term anomaly detection models from streaming data. The theoretical implication is that predictive models must be context-aware about data provenance and temporal granularity.

3.Task-Based Autonomy Thresholds

Adopting Kooij et al.'s (2021) task-based approach, autonomy is reframed not as an all-or-nothing attribute but as a spectrum determined by task profiles. This nuance avoids binary debates and provides a framework for staged automation. The theoretical contribution is a decision-theoretic view of autonomy that ties economic viability to observable task characteristics and digital readiness.

4.Cargo-Specific Monitoring as a Systems Constraint

By highlighting cargo-behavior complexity via the SEDDS case (Jörgensen et al., 2023), the analysis emphasizes that logistical architectures must be cargo-aware. This extends traditional logistics theory, which often treats cargo as passive mass, by introducing a demand for integrated chemical/physical sensing and domain-specific analytics. The implication is a multi-disciplinary integration of supply chain engineering with materials science and pharmaceutical logistics.

Practical Applications and Managerial Implications

1.Investing in Dual Data Pipelines

Firms should invest in both administrative-data analytics (to capture volume patterns and inform strategic decisions) and IoT infrastructure (for tactical control). Kim et al. (2021) show how bill-of-lading analytics yield volume insights, which can inform capacity planning for fleets and terminals. Combining these insights with IoT-based inventory and condition monitoring (Chowdhury, 2025) allows a firm to translate strategic forecasts into operational plans and to react in real time.

2.Pilot and Staged Autonomy Deployment

Using the task-based criteria, managers should identify low-variability route legs and standardized terminal procedures as pilot zones for autonomy (Kooij et al., 2021). Successful pilots yield both operational savings and data to refine decision rules for broader rollout. This staged approach mitigates regulatory and safety concerns while allowing iterative learning.

3.Cargo-Aware Sensor Strategies

Sensitive cargo requires bespoke sensors. For pharmaceutical consignments whose behavior resembles SEDDS dynamics, monitoring must extend beyond simple temperature and location to include indicators of chemical stability or release dynamics, wherever feasible (Jörgensen et al., 2023). These sensors feed analytics that produce early warnings and trigger exception-handling protocols in the governance layer.

4.Aligning Resilience Investments with Agility

Gartner (2021) reports widespread intent to invest in resilience — managers should calibrate these investments to prioritize those that yield agility dividends (rapid sensing, analytics) and that remove bottlenecks to autonomous operations. Investments should be assessed not only on cost but on the extent to which they improve cross-layer coordination.

Counter-Arguments and Critical Reflections

1. Over-Reliance on Digital Systems

One critique is that increasing reliance on digital systems introduces new fragility: cybersecurity risks, data integrity issues, and overfitting of predictive models to historical patterns that may not hold under regime shifts. While digital intelligence enhances agility, organizations must guard against substituting data-driven automation for strategic oversight and maintain human expertise for exceptions (Gligor et al., 2015).

2.Equity and Labor Displacement

Autonomy-led cost reductions could lead to workforce displacement in ports, warehouses, and marine operations. The literature calls for socially responsible transitions that include retraining and role redefinition, consistent with the broader agility literature that emphasizes organizational change (Gunasekaran et al., 2019). Practically, staged deployments and human-in-the-loop operations can soften labor shocks.

3.Regulatory and Ethical Constraints

Regulatory frameworks for unmanned vessels and automated cargo handling are evolving and may impose constraints inconsistent with near-term autonomy economics. Policymakers must balance innovation with safety and environmental protections (Kooij et al., 2021). Organizations should proactively engage regulators to shape pragmatic frameworks that allow safe innovation.

4.Data Quality and Integration Challenges

Integrating administrative datasets with streaming IoT data presents technical challenges — heterogeneous formats, missingness, and synchronization problems. Overcoming these challenges requires investment in data engineering and governance, which can be substantial (Kim et al., 2021; Chowdhury, 2025).

Limitations

This research is intentionally conceptual and synthesizes findings from the provided literature. Key limitations include:

1.Lack of Primary Empirical Validation: The models and criteria proposed require empirical testing across diverse operational contexts — from containerized ports to bulk-liquid supply chains and pharmaceutical logistics.

2.Reference Scope Constraints: The synthesis relies solely on the supplied references; while these are diverse, they do not exhaustively cover all relevant empirical or theoretical work on autonomy regulation, advanced sensing technologies, or AI methodologies.

3.Generality vs. Specificity Trade-off: The framework aims to be broadly applicable, which necessarily means some specificity is sacrificed. Exact thresholds for autonomy viability, sensor specifications, and algorithmic architectures will vary by context and require local calibration.

4.Rapid Technology Evolution: The pace of AI, IoT, and autonomy technology change means that some tactical recommendations may become dated; however, the overarching theoretical principles of layered integration and task-based decisioning should remain applicable.

Future Research Directions

1.Empirical Pilots and Comparative Studies: Conduct multi-site empirical studies that implement the layered architecture in varied cargo contexts (container, bulk liquid, pharmaceuticals) to measure impacts on agility, cost, and safety.

2.Algorithmic Decision Support Development: Design and test prescriptive algorithms that fuse bill-of-lading derived forecasts with real-time IoT anomalies to produce routing and handling recommendations.

3.Cargo-Specific Sensor Design: Research sensor modalities tailored to specific cargo classes, particularly chemicals and biologics, and develop analytics that interpret multi-modal signals to predict degradation or release.

4.Regulatory and Socio-Economic Studies: Investigate regulatory pathways for maritime and terminal autonomy, and research socio-economic transition strategies to mitigate labor displacement.

5.Resilience and Stress-Testing Frameworks: Develop resilience stress tests that simulate regime shifts (pandemics, trade disruptions) to evaluate how the integrated architecture performs under extreme but plausible scenarios (Gartner, 2021).

CONCLUSION

This article offers a cross-disciplinary synthesis that integrates supply chain agility, digital intelligence, and autonomy considerations into an operationally actionable framework. The contributions are threefold: an operational taxonomy mapping tasks to agility and digital needs; a layered architecture that reconciles physical assets, sensing, analytics, and governance; and decision criteria for the viability of low-manned and unmanned cargo systems. The analysis emphasizes that neither agility nor autonomy can succeed in isolation; both require robust digital sensing and analytics, governance mechanisms that permit rapid yet safe decisions, and cargo-aware strategies that account for material behavior. The framework provides managers with a roadmap to stage investments and pilots and researchers with a conceptual basis for empirical validation. As organizations invest in resilience and digital capabilities, the integrated approach outlined here can guide the responsible deployment of autonomy and the maturation of truly agile, intelligent supply chains.

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