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Autonomous Logistics and Real-Time Analytics in Disruption Mitigation: Evidence from Cross-Sectoral Secondary Datasets in Post-Pandemic Supply Networks

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Abstract

The post-pandemic supply-chain literature increasingly links autonomous logistics systems (ALS) and real-time analytics (RTA) with resilience, yet the evidence is fragmented across technologies and sectors and often interpreted causally from descriptive associations. This study revisits cross-sectoral secondary evidence for retail, pharmaceuticals, automotive, and food/agriculture over 2019-2024 and asks whether resilience is more strongly associated with isolated technologies or with an integrated digital-autonomy capability. The analytical unit is the sector-year, giving a maximum balanced panel of N = 24 observations (four sectors x six years). In addition to descriptive trend analysis, the revision reports Pearson correlations with 95% confidence intervals and false-discovery-rate adjusted p-values, a standardized multivariate OLS model reconstructed from the reported correlation matrix, multicollinearity diagnostics, and principal-component analysis (PCA). The four technology indicators are highly intercorrelated; their first principal component explains 79.3% of technology variance and is strongly associated with shorter recovery time ($r = -0.835$, $p < 0.001$) and lower disruption magnitude ($r = -0.624$, $p = 0.001$). In the multivariate recovery model, the four technologies jointly explain 70.7% of variance ($F(4,19) = 11.46$, $p < 0.001$), but no individual standardized coefficient remains statistically significant, consistent with shared variance and technological complementarity rather than a single dominant technology effect. The study therefore advances an Autonomous Resilience Architecture (ARA) in which sensing, interpreting, executing, and learning capabilities operate as a coordinated bundle. The evidence is explicitly associational, and ARA is presented as a theoretically grounded framework requiring future causal and formal validation.

Keywords: autonomous logistics; real-time analytics; supply chain resilience; digital capability complementarity; principal-component analysis; post-pandemic supply networks; explainable AI

1. Introduction

The COVID-19 shock exposed the fragility of globally dispersed and tightly synchronized supply chains. Factory shutdowns, port congestion, semiconductor shortages, abrupt demand shifts, and transport-capacity constraints propagated across multiple tiers and challenged the assumption that efficiency-oriented, just-in-time networks would remain stable under systemic disruption (Ivanov, 2020; Ivanov & Dolgui, 2021; Sarkis, 2021). The response accelerated investment in autonomous mobile robots, AI-supported planning, IoT-enabled visibility, digital twins, and other data-intensive technologies that promised faster sensing and response.

However, the empirical literature does not yet provide a clear answer to a more fundamental question: does resilience arise because a particular technology is superior, or because multiple digital and autonomous capabilities are deployed as an interdependent system? Existing evidence is commonly technology-specific, single-sector, single-country, or case-based. Such work is valuable for identifying mechanisms but offers limited basis for comparing the relative and joint associations of technologies across sectors. At the same time, strong correlations among digital technologies create a methodological problem: bivariate results can make several technologies appear independently important even when they represent one underlying digital capability bundle.

This distinction matters theoretically and managerially. Dynamic capability theory conceptualizes resilience as the ability to sense changes, seize or interpret opportunities and threats, and reconfigure resources (Teece et al., 1997). Digital supply-chain technologies map naturally onto these functions, but the theory does not imply that the technologies work independently. IoT sensing is of limited value without analytical interpretation; analytics has limited operational effect without execution capacity; and automation without high-quality data can merely accelerate poor decisions. A system-level test is therefore needed.

The present study addresses that gap by re-analysing a cross-sectoral 2019-2024 secondary-data matrix covering retail, pharmaceuticals, automotive, and food/agriculture. Rather than treating correlations as causal effects, the study evaluates the structure of the technology-resilience relationship and asks whether the joint pattern supports a complementarity interpretation. The analysis retains the original descriptive sector-year evidence but strengthens statistical reporting through confidence intervals, multiplicity adjustment, standardized multivariate regression, variance-inflation diagnostics, and PCA.

Research questions and main contributions

RQ1. How did disruption severity and recovery performance differ across the four sectors during 2019-2024?

RQ2. What are the magnitudes and uncertainty intervals of the associations between ALS/RTA-related capabilities and recovery time or disruption magnitude?

RQ3. Do the technology indicators retain independent associations in a multivariate model, or do they primarily reflect a shared integrated digital-autonomy capability?

This study makes four contributions. First, it clarifies the knowledge gap by shifting the unit of theoretical explanation from isolated technologies to digital-capability complementarity. Second, it reports transparent statistical uncertainty and multicollinearity diagnostics for the N = 24 sector-year analytical matrix, correcting the over-interpretation of simple correlations. Third, it introduces an integrated technology component whose empirical structure is directly recoverable from the reported correlation matrix; the component captures almost four-fifths of the variance shared by ALS, RTA, IoT, and AI forecasting. Fourth, it revises the Autonomous Resilience Architecture (ARA) as a conceptual mechanism linking sensing, interpretation, execution, traceability/coordination, and learning, while explicitly distinguishing theoretical development from empirical validation.

2. Literature Review

2.1 Supply-chain resilience, viability, and dynamic capabilities

Supply-chain resilience (SCRES) is commonly defined as the adaptive capacity to prepare for, respond to, and recover from disruption while maintaining an acceptable level of continuity (Ponomarov & Holcomb, 2009). Subsequent research broadened resilience beyond recovery to include anticipation, adaptation, and transformation (Hohenstein et al., 2015; Tukamuhabwa et al., 2015). Ivanov (2020) advanced this debate

through the concept of viability, emphasizing the ability of supply networks not merely to return to a prior state but to reconfigure under prolonged or structural shocks.

These perspectives overlap with dynamic capability theory. Sensing identifies threats and opportunities; seizing converts information into decisions; and reconfiguration changes processes and resource configurations (Teece et al., 1997). In supply networks, resilience therefore depends not only on redundancy or buffers but also on the speed and quality with which information is converted into coordinated action. This creates a theoretical role for real-time data, predictive models, and autonomous execution, but it also suggests that technological effects should be evaluated as interdependent capabilities rather than isolated assets.

2.2 Autonomous logistics and digitalisation

Autonomous logistics includes automated guided vehicles, autonomous mobile robots, automated storage and retrieval, AI-enabled transportation management, and other systems that execute physical or planning tasks with reduced manual intervention. Winkelhaus and Grosse (2020) show that Logistics 4.0 research increasingly integrates cyber-physical systems, automation, and data connectivity, while Bechtsis et al. (2017) emphasize that autonomous transport technologies create operational value only when embedded in sustainable and information-rich systems.

Aylak, Kayikci, and Tas (2020) provide an important pre-pandemic benchmark. Their survey of 65 companies operating across logistics-related sectors in Turkey identified autonomous logistics, robotics and automation, IoT, cloud logistics, big data, and e-commerce among the major digital trends. The study demonstrates that the technologies examined in the present paper were already diffusing as a cluster before COVID-19; however, its single-country and pre-pandemic design cannot establish whether the technologies improved disruption recovery. Aylak et al. (2021) further show how machine-learning methods can automate a specific logistics decision problem - pallet loading - illustrating operational automation but also the task-specific nature of much of the evidence.

2.3 Real-time analytics, AI, explainability, and blockchain

Real-time analytics (RTA) refers here to the capability to integrate current operational data with forecasting, exception detection, simulation, and decision support. Information integration and visibility have long been associated with agility and resilience (Brusset & Teller, 2017; Leuschner et al., 2013). Digital twin research extends this principle by linking physical operations with continuously updated virtual representations; Abideen et al. (2021), for example, systematize the literature on digital twins and reinforced learning and propose a data-driven framework for prescriptive supply-chain decision support.

Prediction quality is another critical element, but the literature cautions against assuming that complex models automatically deliver operational superiority. Carbonneau, Laframboise, and Vahidov (2008) compared machine-learning approaches with conventional forecasting in supply-chain demand prediction and found that advanced models performed well but were not uniformly statistically superior to regression. More recent explainable-AI studies demonstrate how predictive accuracy can be combined with interpretability. Cakiroglu et al. (2024), although working in wind-power prediction rather than supply chains, show how ensemble learners and SHAP can identify which inputs drive predictions. The methodological relevance is the transparency of high-performing predictive models. In a directly logistics-related application, Cakiroglu et al. (2026) used LightGBM and XGBoost to predict unloading hours and reported R-squared values above 0.99, with SHAP identifying the relative influence of load, truck weight, and distance. Such studies show the operational potential of explainable prediction but remain process-specific rather than resilience-level tests.

Blockchain research adds a coordination and traceability mechanism. Kayikci, Durak Usar, and Aylak (2022) examined blockchain in perishable-food supply chains during outbreaks and found that immutability, transparency, traceability, integration, smart contracts, and decentralisation can support responsiveness, flexibility, efficiency, and collaboration. Importantly, the authors also note the limits of statistical generalisation from a single use case. This reinforces a recurring limitation in the digital-resilience literature: strong mechanism evidence is often accompanied by restricted cross-sector generalisability.

Aylak (2025) extends the automation debate toward agentic AI through the SustAI-SCM framework, reporting improvements in cost, emissions, and warehouse efficiency in an experimental setting. The study is relevant to the learning-feedback element of ARA because agentic systems continuously update decisions rather than applying static rules. Yet, as with other technology-specific studies, the unresolved question is whether such capabilities have independent effects or derive value through orchestration with complementary sensing and execution systems.

2.4 Sustainability and cross-sector tensions

Resilience cannot be separated entirely from sustainability and sector context. Aylak (2022), using a systematic-review approach, links sustainability practices with procurement, manufacturing, and logistics performance while noting ambiguity about where the strongest effects occur. This matters because digitalization can create resilience benefits while also changing energy use, supplier relationships, compliance requirements, and capital intensity.

Sector characteristics may therefore change both adoption and payoff. Pharmaceutical supply chains face stringent traceability and service-criticality requirements; automotive networks are deeply tiered and component-specialised; retail has comparatively flexible fulfilment architectures; and food/agriculture combines perishability, biological variability, and fragmented producer structures. A single technology coefficient may consequently obscure sector-specific implementation constraints.

2.5 Critical synthesis and precise knowledge gap

Study	Design / focus	What it adds	Unresolved limitation
Aylak et al. (2020)	65-company survey; digital logistics trends	Shows ALS, IoT, cloud, big data, and automation diffuse together	Single country; pre-pandemic; no disruption outcome
Aylak et al. (2021)	ML for pallet loading	Demonstrates task-level logistics automation	Narrow decision problem; not resilience
Kayikci et al. (2022)	Blockchain in perishable food during outbreaks	Traceability/visibility mechanisms support operational excellence	Single use case; limited statistical generalisation
Cakiroglu et al. (2024)	Explainable ensemble learning	Shows high-performing prediction can be interpreted with SHAP	Outside supply-chain resilience domain
Aylak (2025)	Agentic AI supply-chain automation	Introduces continuous-learning automation with cost/sustainability outcomes	Framework/experimental focus; cross-sector resilience untested
Cakiroglu et al. (2026)	Explainable prediction of unloading hours	Direct logistics evidence for accurate, interpretable real-time prediction	Single operational process
Aylak (2022)	Systematic review of sustainability and SCM	Connects SCM performance with sustainability practices	Does not isolate digital resilience mechanisms

The literature therefore contains three competing interpretations. A technology-specific interpretation attributes resilience to particular tools such as AI forecasting or blockchain. A capability interpretation emphasizes sensing, visibility, and reconfiguration regardless of the specific tool. A complementarity interpretation predicts that value emerges when multiple technologies are jointly deployed and interoperable.

Existing empirical studies rarely distinguish these alternatives because they analyse one technology, one process, or one sector at a time. The precise knowledge gap addressed here is whether the cross-sectoral correlation structure supports independent technology effects or a common integrated digital-autonomy capability. That distinction is the paper's primary theoretical and empirical novelty.

3. Theoretical Development: Autonomous Resilience Architecture (ARA)

The revised ARA is grounded in dynamic capability theory, resilience/viability theory, and digital transformation research. It is not presented as a statistically validated framework. Instead, it is a theoretically derived architecture whose propositions are informed by the empirical structure of the cross-sectoral data and require formal validation in future primary studies.

ARA separates four operational capability functions. Sensing uses IoT, event streams, and visibility data to detect changes in supply, demand, transport, and inventory conditions. Interpreting uses RTA, predictive models, and simulation to convert signals into forecasts and decision options. Executing uses autonomous logistics and workflow automation to implement responses at operational speed. Tracing/coordination uses interoperable data and traceability mechanisms, including blockchain where appropriate, to maintain shared state across organisational boundaries. A learning and reconfiguration loop updates models, thresholds, and resource allocations after disruption events.

The architecture adds a complementarity mechanism to conventional dynamic-capability reasoning. The empirical expectation is not that every technology will retain a large independent coefficient after adjustment for other technologies. Rather, high intercorrelation and a dominant common component are expected when the technologies form an integrated capability. Sectoral absorptive capacity, data governance, and disruption intensity are boundary conditions that affect how effectively the capability bundle translates into resilience outcomes.

ARA implies three propositions for future confirmatory testing. P1: an integrated digital-autonomy capability will explain more variation in recovery performance than any single technology indicator. P2: the resilience effect of digital autonomy will be stronger where data interoperability and organisational absorptive capacity are high. P3: integrated digital autonomy will affect recovery speed more consistently than initial disruption magnitude because technology can accelerate response even when exogenous shocks cannot be prevented.

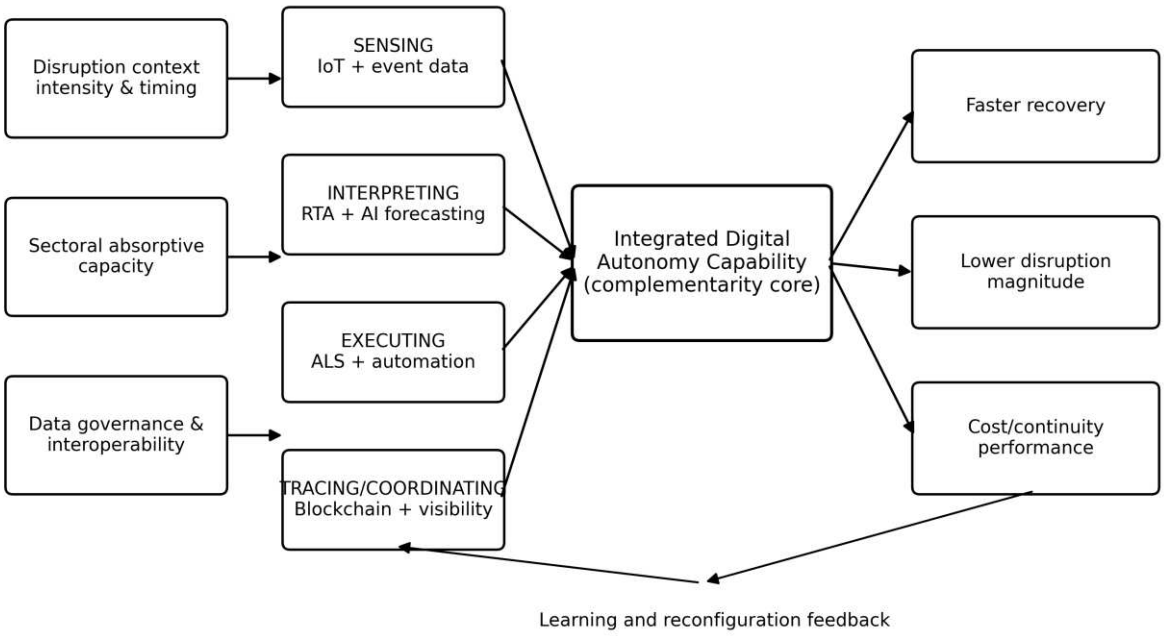


Figure 1. Revised Autonomous Resilience Architecture (ARA). The framework treats digital resilience as a coordinated sensing-interpretation-execution-learning system rather than a set of independent technologies.

4. Data and Methodology

4.1 Research design, observation unit, and scope

The study is an exploratory, associational secondary-data analysis. The principal analytical unit is the sector-year. Four sectors - retail, pharmaceuticals, automotive, and food/agriculture - are observed over six calendar years (2019-2024), yielding a maximum balanced analytical matrix of N = 24 sector-year observations. The study does not treat individual firms or countries as independent observations; therefore, firm-level and country-level sampling claims are not made.

Institutional and industry sources are used as aggregated inputs. Country-level logistics indicators, where present in a source, are used only as contextual or aggregate benchmark components and are not entered as separate rows in the inferential matrix. Accordingly, there is no country fixed effect and no claim that the N = 24 observations represent 24 countries. The inferential scope is limited to cross-sectoral sector-year associations.

4.2 Data sources and variable construction

Variable	Scale	Construction / source family	Direction
Disruption magnitude	Composite 0-100 index	Trade-flow disruption component plus logistics-cost pressure component from institutional trade/logistics indicators	Higher = more severe disruption
ALS adoption	Percent / standardized score	Aggregate industry and institutional technology-adoption indicators	Higher = greater active deployment
RTA depth	Standardized capability score	Aggregate measures of real-time visibility, predictive analytics, and decision-support depth	Higher = deeper analytics capability
IoT sensor density	Standardized score	Aggregate IoT deployment/visibility proxy	Higher = denser sensing infrastructure

Variable	Scale	Construction / source family	Direction
AI forecast accuracy	Standardized score	Source-reported forecasting accuracy indicator, harmonized to higher-is-better direction	Higher = greater forecast accuracy
Recovery time	Days; matrix coded higher = slower	Sector-level disruption recovery benchmark	Lower raw days = faster recovery
Resilience score	0-100 descriptive indicator	OECD/industry benchmark synthesis used in sector comparison	Higher = stronger resilience
Cost variance reduction	Percent descriptive indicator	Industry benchmark synthesis used in sector comparison	Higher = larger cost-variance reduction

The disruption-magnitude index is scaled from 0 to 100. For sector s in year t, the index is defined as DSI_st = 50 x [MM(TradeDisruption_st) + MM(LogisticsCostPressure_st)], where MM(.) denotes min-max normalization to the 0-1 interval across the analytic sample. Equal weights were selected a priori because the original secondary compilation did not provide an externally validated alternative weighting scheme. This explicit rule replaces the earlier unspecified aggregation description.

Technology measures originate from source-reported sector aggregates rather than firm-level microdata. Measures were re-oriented so that higher values consistently represent greater capability. Blockchain traceability remains part of the conceptual framework and literature synthesis but is not included as a predictor in the six-variable inferential matrix because a complete N = 24 sector-year series was not available in the reported analytical matrix. This distinction prevents descriptive evidence from being treated as a statistically tested predictor.

4.3 Harmonisation, missing values, and weighting

All variables used in the N = 24 inferential correlation matrix were harmonized to consistent directionality before analysis. Recovery time is expressed in days in descriptive tables but was coded such that higher values represent slower recovery in the correlation matrix; therefore, a negative correlation with a technology variable indicates faster recovery at higher technology capability.

No model-based imputation is used in the inferential matrix reported here. Variables without complete coverage for the 24 sector-year observations are excluded from the multivariate matrix rather than filled by interpolation. The descriptive sector tables retain source-reported values. No firm-level sampling weights are applied because the inferential unit is the sector-year and the input measures are already aggregated at that level. The disruption index alone uses the equal 0.50/0.50 component weighting specified above.

4.4 Statistical analysis and reproducibility

Analysis proceeds in five stages. First, longitudinal descriptive trends are reported by sector. Second, Pearson correlations are reported with N, two-sided exact p-values, and 95% confidence intervals obtained using Fisher's z transformation. Third, the eight pre-specified technology-outcome correlations are adjusted using the Benjamini-Hochberg false-discovery-rate procedure. Fourth, standardized multivariate OLS coefficients are reconstructed directly from the published correlation matrix using beta = R_xx^{-1} r_xy. This is algebraically equivalent to standardized OLS for the same complete data matrix and allows variance-inflation factors (VIFs) to be calculated from the diagonal of R_xx^{-1}. Fifth, PCA is applied to the four technology predictors to evaluate whether a dominant common capability underlies their correlations.

A fully saturated fixed-effects panel model is not estimated. With only 24 sector-year observations, four strongly correlated technology predictors, four sector effects, and six year effects, such a specification would be severely underpowered and unstable. Rather than present unreliable causal coefficients, the study reports a transparent pooled multivariate association analysis and limits all interpretation to association. Future

research with larger country-sector-year micro-panels should use fixed-effects, mixed-effects, generalized least squares, or quasi-experimental designs.

4.5 Statistical thresholds and interpretation

Two-sided alpha = 0.05 is used for nominal inference, with FDR-adjusted p-values reported for the planned technology-outcome correlation family. VIF values above approximately 5 are treated as a warning of substantial multicollinearity; values between 2 and 5 indicate meaningful shared variance that can still destabilize individual coefficients. Effect sizes and confidence intervals are prioritized over binary significance. No causal wording is used for the observational results.

5. Results

5.1 Cross-sectoral disruption dynamics, 2019-2024

Figure 2 reproduces the sector-level disruption trajectories used in the original descriptive analysis. Disruption increased sharply in 2020 across all four sectors, with pharmaceuticals reaching 85 and automotive 78, while automotive peaked at 82 in 2021. By 2024 the index had declined to 14 for pharmaceuticals, 19 for retail, 24 for automotive, and 18 for food/agriculture. These values show broad recovery but also distinct trajectories: automotive remained relatively elevated because of its specialised, multi-tier component structure, whereas pharmaceuticals recovered from the highest 2020 peak to the lowest 2024 score.

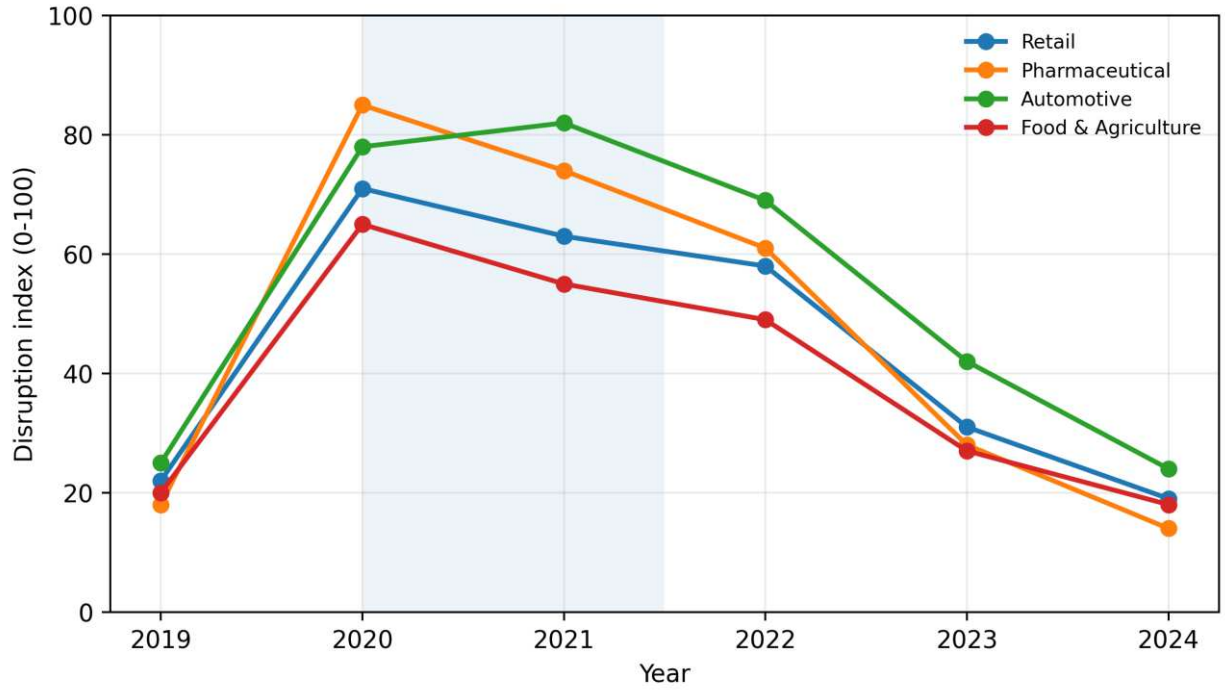


Figure 2. Cross-sectoral supply-chain disruption index, 2019-2024. Values reproduce the descriptive series reported in the original manuscript; higher values indicate more severe disruption.

5.2 Sector-specific 2024 performance

Sector	ALS adoption	RTA depth (0-10)	Recovery time (days)	Cost variance reduction	Resilience score
Retail	67%	7.8	48	41%	74

Sector	ALS adoption	RTA depth (0-10)	Recovery time (days)	Cost variance reduction	Resilience score
Pharmaceutical	58%	8.2	55	38%	79
Automotive	49%	6.9	72	29%	61
Food & agriculture	38%	5.4	61	27%	55

The 2024 descriptive evidence is not monotonic across every metric, which is important for avoiding over-generalisation. Retail combines the highest ALS adoption with the shortest recovery time, whereas pharmaceuticals achieve the highest resilience score and RTA depth despite lower ALS adoption than retail. Automotive has substantial technology adoption but the longest recovery time, consistent with structural exposure to highly specialised upstream components. Food/agriculture has the lowest ALS and RTA levels and the lowest resilience score, but its recovery time is shorter than automotive. These differences support sector-specific interpretation rather than a universal technology-performance ranking.

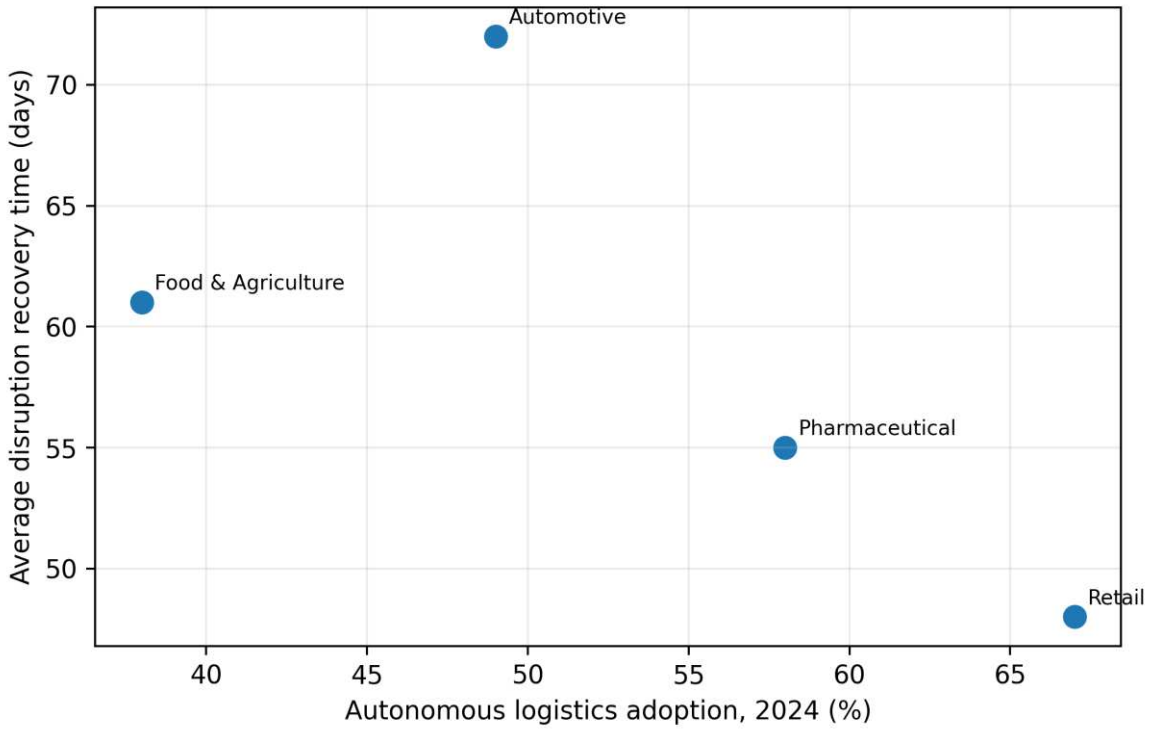


Figure 3. Descriptive 2024 association between autonomous-logistics adoption and average disruption-recovery time for the four study sectors. The figure is descriptive only (n = 4 sectors) and is not used for inferential testing.

5.3 Bivariate associations with uncertainty and multiplicity control

The full N = 24 correlation matrix is shown in Figure 4. ALS and RTA are strongly correlated (r = 0.82), as are RTA and AI forecast accuracy (r = 0.79). This degree of predictor correlation means that bivariate outcome correlations should not be interpreted as independent technology effects.

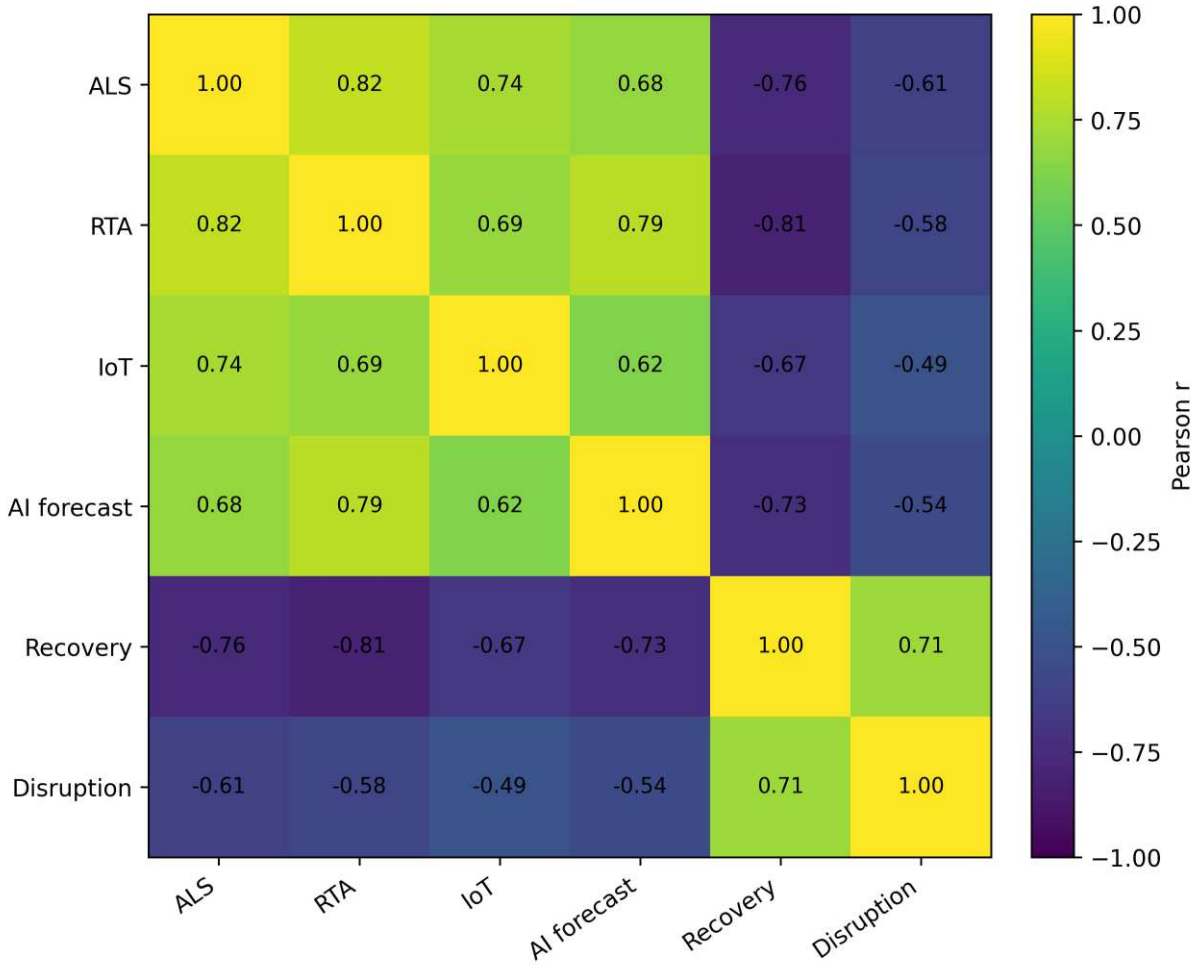


Figure 4. Pearson correlation matrix for the six reported variables (N = 24 sector-year observations). Recovery time is coded so that higher values indicate slower recovery.

Predictor	Outcome	r	95% CI	p	FDR-adjusted p
Autonomous logistics	Recovery time	-0.76	[-0.89, -0.51]	0.000016	0.000066
Real-time analytics	Recovery time	-0.81	[-0.91, -0.60]	0.000002	0.000013
IoT sensor density	Recovery time	-0.67	[-0.85, -0.37]	0.000341	0.000683
AI forecast accuracy	Recovery time	-0.73	[-0.88, -0.46]	0.000051	0.000137
Autonomous logistics	Disruption magnitude	-0.61	[-0.81, -0.27]	0.0016	0.0025
Real-time analytics	Disruption magnitude	-0.58	[-0.80, -0.23]	0.0030	0.0040
IoT sensor density	Disruption magnitude	-0.49	[-0.75, -0.11]	0.0151	0.0151
AI forecast accuracy	Disruption magnitude	-0.54	[-0.77, -0.17]	0.0065	0.0074

All eight pre-specified technology-outcome correlations remain statistically significant after FDR correction. The strongest bivariate association with recovery time is RTA depth (r = -0.81, 95% CI [-0.91, -0.60]), followed by ALS (r = -0.76), AI forecast accuracy (r = -0.73), and IoT sensor density (r = -0.67). Associations with disruption magnitude are smaller (absolute r = 0.49-0.61). This pattern is consistent with ARA Proposition 3: digital capability appears more closely associated with how quickly a sector recovers than with the initial magnitude of an externally imposed shock.

5.4 Multivariate model and multicollinearity

Predictor	Standardized beta	95% CI	p	VIF
ALS	-0.213	[-0.714, 0.288]	0.3847	3.71
RTA	-0.400	[-0.949, 0.148]	0.1430	4.45
IoT	-0.113	[-0.513, 0.287]	0.5619	2.37
AI forecast	-0.199	[-0.629, 0.231]	0.3452	2.74

The four technology predictors jointly explain 70.7% of the variance in recovery time (R-squared = 0.707; adjusted R-squared = 0.645; $F(4,19) = 11.46$, $p = 0.000067$). However, none of the four individual standardized coefficients is statistically significant at alpha = 0.05 once the other technologies are entered simultaneously. VIFs range from 2.37 to 4.45, confirming substantial shared variance, especially for RTA. This result materially changes the interpretation of the original bivariate findings: the data do not support a claim that one technology is uniquely the strongest predictor after adjustment. Instead, they support a system-level complementarity interpretation.

5.5 Principal-component analysis: integrated digital-autonomy capability

PCA provides a direct test of the complementarity interpretation. The first principal component (PC1) has an eigenvalue of 3.174 and explains 79.3% of total variance across ALS, RTA, IoT, and AI forecast accuracy. The loadings are balanced - ALS = 0.512, RTA = 0.522, IoT = 0.479, and AI forecasting = 0.486 - indicating that PC1 is not merely a renamed version of one predictor. Internal consistency of the four-indicator bundle is high (Cronbach's alpha = 0.913).

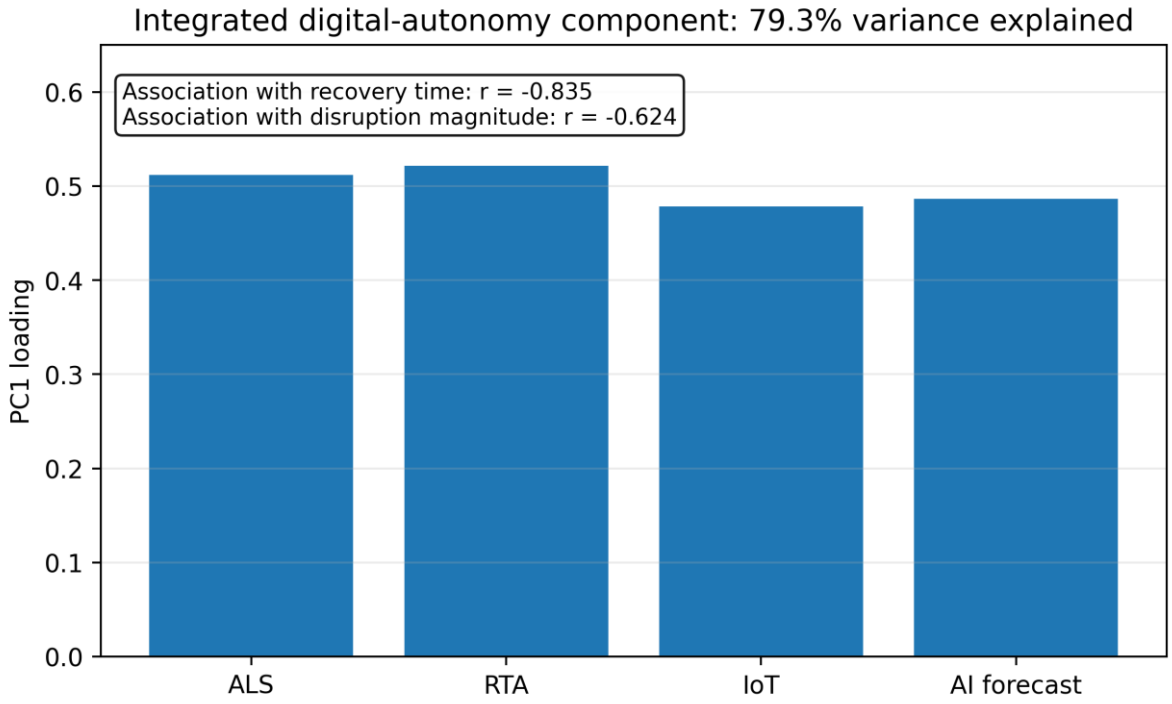


Figure 5. Loadings of the four technology indicators on the first principal component (PC1). PC1 is interpreted as an integrated digital-autonomy capability.

The integrated component is strongly associated with shorter recovery time ($r = -0.835$, 95% CI [-0.926, -0.651], $p < 0.001$) and moderately-to-strongly associated with lower disruption magnitude ($r = -0.624$, 95%

CI [-0.821, -0.295], p = 0.0011). The common component therefore provides a more parsimonious account of the evidence than competing claims that IoT, RTA, ALS, or AI independently dominate. This is the central new empirical result of the revision.

6. Discussion

6.1 What new knowledge is generated?

The main contribution is not another confirmation that digital technology correlates with resilience. The new knowledge lies in the structure of that relationship. Strong bivariate correlations coexist with weak unique multivariate coefficients because the technologies are themselves strongly correlated. PCA then shows that nearly four-fifths of their variance is captured by one balanced component. The evidence therefore supports a complementarity mechanism: sectors with deeper digital autonomy tend to deploy sensing, analytics, forecasting, and autonomous execution together, and resilience is associated with that bundle.

This result resolves an ambiguity in prior work. Technology-specific studies can correctly identify valuable mechanisms without demonstrating that the focal technology has an independent resilience effect. For example, blockchain can improve traceability in perishable-food chains (Kayikci et al., 2022), explainable gradient boosting can predict unloading time with very high accuracy (Cakiroglu et al., 2026), and agentic AI can improve operational efficiency in experimental supply-chain settings (Aylak, 2025). The present cross-sectoral evidence suggests that such technologies should be interpreted as components of an integrated capability architecture rather than as interchangeable stand-alone solutions.

6.2 Theoretical advancement of ARA

ARA extends dynamic capability theory by specifying a digital complementarity mechanism. Sensing, interpreting, executing, and learning are not only sequential organisational capabilities; in digitally intensive supply networks they are instantiated by distinct but interdependent technology layers. The PCA result provides empirical support for treating those layers as a shared latent capability, while the multivariate model shows why claims of isolated technology dominance are unstable.

The framework also distinguishes disruption magnitude from recovery speed. Exogenous shocks such as border closures, geopolitical events, or sudden shortages can affect a sector regardless of its digital maturity. Digital capabilities may therefore have a more reliable association with response and recovery than with whether the shock occurs or how large its first-order impact is. The stronger PC1 association with recovery time than disruption magnitude is consistent with this mechanism.

Finally, ARA introduces sectoral absorptive capacity and data interoperability as boundary conditions. Automotive networks may have advanced automation yet remain exposed to specialised components and long tier structures. Pharmaceutical networks can extract high value from analytics and traceability because regulatory and service requirements incentivise end-to-end visibility. Food/agriculture may face fragmented adoption and biological variability. Thus, the same technology bundle can produce different realised resilience depending on sector structure.

6.3 Sector-specific interpretation

Retail: High ALS adoption and relatively short recovery are consistent with flexible fulfilment, e-commerce infrastructure, and the ability to re-route inventory across nodes. The sector appears well positioned to convert real-time signals into execution, but resilience should not be attributed to automation alone.

Pharmaceuticals: The highest RTA depth and resilience score, despite lower ALS adoption than retail, illustrate the importance of analytical depth, traceability, and service-critical visibility. This sector is a strong example of the sensing-and-interpreting layers of ARA.

Automotive: The longest 2024 recovery time despite moderate-to-high digital capability indicates that structural network complexity can dominate technology benefits. Highly specialised components, multi-tier dependence, and long qualification cycles limit substitutability. This is a clear boundary condition against universal digital-resilience claims.

Food and agriculture: Lower technology adoption and lower resilience scores suggest a digital-capability gap, but the sector also faces perishable inventory, biological production risk, weather exposure, and fragmented producers. Blockchain and traceability evidence from perishable-food supply chains (Kayikci et al., 2022) suggests promising mechanisms, but implementation must account for interoperability and small-firm constraints.

6.4 Managerial and policy implications

Managers should avoid a "single best technology" investment logic. The data favour coordinated portfolios in which sensing infrastructure, analytical capability, decision automation, and execution systems are interoperable. The highest marginal value may come from closing missing links in the capability chain rather than maximising one technology score.

For analytics investments, explainability should be treated as an operational requirement rather than a research add-on. The SHAP-based studies by Cakiroglu et al. (2024, 2026) illustrate how predictive models can disclose the features driving output, which is especially important when supply-chain planners must justify re-routing, inventory, or scheduling decisions under disruption.

Policymakers should calibrate support by sector. Digital infrastructure and interoperability standards can have broad value, but sector-specific constraints differ. Food/agriculture may require shared platforms and support for smaller firms; pharmaceuticals require trusted traceability and compliance integration; automotive may benefit more from multi-tier mapping and supplier substitution capacity than from additional warehouse automation alone.

6.5 Limitations and future research

First, the analysis remains observational and cannot establish causal effects. Reverse causality is plausible: resilient sectors may have more resources to invest in technology. The revised paper therefore uses associational language throughout.

Second, $N = 24$ is small for panel modelling, and the predictor correlations are high. The multivariate coefficients should be interpreted as diagnostic rather than definitive causal parameters. Larger country-sector-year datasets would permit sector and year fixed effects, hierarchical mixed-effects models, generalized least squares, dynamic panels, or quasi-experimental designs.

Third, technology inputs are aggregated secondary indicators assembled from institutional and industry sources with different definitions and reporting frequencies. The revision makes the transformation rules and inferential matrix explicit, but source-level proprietary industry microdata cannot be independently reconstructed from the manuscript alone. Future work should archive the complete extraction sheet and source-specific metadata as a machine-readable supplement.

Fourth, ARA is a conceptual framework and has not been scientifically validated through Delphi consensus, structural equation modelling, confirmatory factor analysis, or an independent primary sample. Formal validation should test the proposed capability layers, moderators, and propositions. Fifth, the 2019-

2024 window captures an exceptional disruption-and-recovery cycle; the persistence of the observed complementarity pattern under more stable conditions remains unknown.

7. Conclusion

This study revises the interpretation of cross-sectoral evidence on autonomous logistics and real-time analytics in post-pandemic supply networks. The descriptive data show distinct sectoral recovery paths, while the inferential matrix confirms strong associations between digital capabilities and both recovery time and disruption magnitude. Yet the multivariate results also show that ALS, RTA, IoT, and AI forecasting do not behave as independent predictors. Their shared covariance is substantial, and a single principal component explains 79.3% of their variance. That integrated digital-autonomy component is strongly associated with faster recovery and lower disruption magnitude.

The theoretical implication is that resilience is better understood as an architectural capability than as the payoff from a single technology. ARA therefore conceptualizes resilience formation through coordinated sensing, interpretation, execution, traceability/coordination, and learning, moderated by sector structure, interoperability, and absorptive capacity. The paper does not claim causal identification or formal validation of ARA. Instead, it provides a more transparent and statistically rigorous foundation for future confirmatory and longitudinal work.

Declarations

Funding: The authors received no specific funding for this work.

Conflict of interest: The authors declare no conflict of interest.

Ethics: The empirical analysis uses secondary aggregated data and does not analyse identifiable human or animal participants.

Data availability: All values required to reproduce the descriptive disruption series, the 2024 sector comparison, the N = 24 correlation matrix, the confidence intervals, standardized multivariate regression, VIFs, and PCA results are reported in the manuscript and Appendix A. Proprietary source-level industry microdata are not redistributed.

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Appendix A. Reproducibility and Sensitivity Details

A1. Descriptive disruption-index values used in Figure 2

Sector	2019	2020	2021	2022	2023	2024
Retail	22	71	63	58	31	19
Pharmaceutical	18	85	74	61	28	14
Automotive	25	78	82	69	42	24
Food & Agriculture	20	65	55	49	27	18

The table above makes the descriptive longitudinal figure numerically reproducible. The index is a 0-100 composite; higher values represent more severe disruption.

A2. Complete correlation matrix used for inferential re-analysis

	ALS	RTA	IoT	AI forecast	Recovery	Disruption
ALS	1.00	0.82	0.74	0.68	-0.76	-0.61
RTA	0.82	1.00	0.69	0.79	-0.81	-0.58
IoT	0.74	0.69	1.00	0.62	-0.67	-0.49
AI forecast	0.68	0.79	0.62	1.00	-0.73	-0.54
Recovery	-0.76	-0.81	-0.67	-0.73	1.00	0.71
Disruption	-0.61	-0.58	-0.49	-0.54	0.71	1.00

N = 24 for the complete matrix. Recovery is coded so that a higher value means slower recovery. Therefore negative technology-recovery correlations imply faster recovery at higher technology capability.

A3. Matrix-based regression and PCA formulas

Standardized OLS coefficients are reproduced from beta = inverse(R_xx) x r_xy, where R_xx is the 4 x 4 predictor correlation matrix and r_xy is the vector of predictor-outcome correlations. With N = 24 and k = 4, residual degrees of freedom equal 19. VIF_j is the j-th diagonal element of inverse(R_xx).

PCA is performed by eigen-decomposing R_xx. The first eigenvalue is 3.174, which represents 79.34% of the total standardized predictor variance. The normalized first-component eigenvector is [0.512, 0.522, 0.479, 0.486] for ALS, RTA, IoT, and AI forecast accuracy, respectively.

The reported confidence intervals for Pearson r use Fisher's z transformation. The family of eight technology-outcome p-values is corrected using the Benjamini-Hochberg false-discovery-rate procedure. These steps allow independent reproduction of all statistical quantities reported in Sections 5.3-5.5 from the matrix above.

A4. Sensitivity interpretation

The complementarity conclusion does not depend on a single outcome. PC1 is associated with both recovery time ($r = -0.835$, $p < 0.001$) and disruption magnitude ($r = -0.624$, $p = 0.0011$). At the same time, individual standardized technology coefficients become non-significant in the joint recovery model while the model itself remains strongly significant. The combined pattern - high predictor intercorrelation, a dominant first principal component, significant omnibus regression, and weak unique coefficients - is the statistical basis for interpreting digital technologies as a shared capability bundle rather than independent causal drivers.