DIJEMSS: Dinasti International Journal of Education Management and Social Science
E-ISSN: 2686-6331
P-ISSN: 2686-6358
https://dinastipub.org/DIJEMSS dinasti.info@gmail.com +62 811 7404 455
DINASTI PUBLISHER
DOI: https://doi.org/10.38035/dijemss.v7i6

Maintaining Distribution Performance Amid Disruption Risks: The Role of Digital Logistics Agility in the Indonesian Trucking Industry

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Abstract: E-commerce growth has pushed last-mile trucking volumes in Indonesia higher year over year, raising a question prior research has left largely open: what happens to delivery performance when operations break down mid-route, and can a firm's agility actually absorb that damage? Prior studies have generally examined digital capability and route optimization in isolation, as positive drivers of logistics performance, while treating disruption risk as a separate resilience-oriented concern; few have tested whether digital logistics agility can convert a risk-laden operating environment into stable service outcomes within a single structural model, particularly in Indonesia's last-mile trucking segment. Grounded in Dynamic Capability Theory and Supply Chain Resilience Theory, this study tests the influence of digital logistics capability, route optimization, and disruption risk on distribution service performance, with digital logistics agility as the mediating mechanism. Using a quantitative explanatory design, data from 67 valid respondents, operational personnel at Indonesian trucking companies handling last-mile distribution, were processed with Partial Least Squares Structural Equation Modeling (PLS-SEM) in SmartPLS 4. Digital logistics capability and route optimization strengthen both agility and performance; disruption risk weakens both. Agility significantly and partially mediates all three relationships. The central finding: disruption risk keeps a significant direct negative effect on performance even after agility is accounted for, indicating that agility buffers disruption rather than neutralizing it, a distinction with direct implications for how trucking firms should allocate resilience investment.

Keywords: Digital Logistics Capability, Route Optimization, Disruption Risk, Digital Logistics Agility, Distribution Service Performance.

INTRODUCTION

Indonesia's archipelagic geography makes a working logistics system non-negotiable for economic competitiveness, yet the World Bank's 2023 Logistics Performance Index ranked the country 61st out of 140 nations, with a score of 3.0, trailing Vietnam and the Philippines at rank 43, India at 38, and Malaysia at 26 (Sudrajat et al., 2024). Trucking companies absorb much of that gap in practice: they are the ones translating national logistics targets into deliveries that actually arrive on time (Sudrajat et al., 2024). The pressure has only grown. Registered logistics companies in Indonesia grew roughly 10 percent in 2023, and express delivery volumes rose around 15 percent the same year (Sudrajat et al., 2024), leaving last-mile operators to hold punctuality, accuracy, and cost together under mounting load (Sawik, 2024).

Fragmented delivery points, tight time windows, and demand that shifts by the day, these are the conditions (Escudero-Santana et al., 2022) point to when explaining why last-mile routing keeps getting harder, not easier. Optimization and machine-learning methods cut cost and time when built properly into daily operations (Giuffrida et al., 2022), and multi-criteria frameworks for sustainable last-mile delivery show that economic, environmental, and social factors have to be weighed together, especially in a developing-economy setting like Indonesia's (Wang et al., 2023). Fleet size alone no longer decides who wins in last-mile trucking. The digital and analytical layer built into daily operations increasingly does (Sawik, 2024).

That digital layer- IoT connectivity, integrated platforms, process automation, and supply chain visibility- has become central to how logistics firms compete on efficiency and service quality (Zhang et al., 2023). (Atieh et al., 2025) found that automation and data integration lift supply chain performance further still once firms push deeper into digital transformation. Indonesian evidence points the same direction: (Muhammad Taufani & Anton Wachidin Widjaja, 2023) found digital transformation significantly improved logistics firm performance, with organizational innovation as a key precondition for successful adoption. (Ning & Yao, 2023) reached a related conclusion from a sustainability angle, digital transformation strengthens competitive performance by sharpening both internal process capability and external responsiveness.

Route optimization matters just as much. Algorithmic and heuristic route planning cuts total distance and travel time across a fleet meaningfully (Gasset et al., 2024). Feeding traffic-sensor data into vehicle routing problems makes route recommendations more reliable under changing road conditions (Almutairi & Owais, 2025), and pairing dynamic, heuristic-based routing with traffic flow analysis has measurably improved urban last-mile efficiency (Liu & Wang, 2026). The payoff shows up in punctuality too: electric-vehicle-enabled routing combined with AI optimization has been linked to real gains in on-time delivery in urban logistics settings (Ferreira & Esperança, 2025).

Disruption risk, meanwhile, keeps growing as a threat to reliable distribution, whether it comes from outside the firm- weather, congestion, regulatory shifts- or from inside it, breakdowns, driver shortages, system failures (Katsaliaki et al., 2022). A systematic review of pandemic-era disruption found demand volatility undermining resilience wherever anticipatory mechanisms were weak (Amio et al., 2024). Among Indonesian manufacturing SMEs, resource flexibility and supply chain ambidexterity together strengthened resilience against exactly this kind of disruption, evidence that internal capability matters as much as external exposure (Jamaludin et al., 2023). Firms without structured resilience strategies, a broader systematic review found, absorb disproportionately larger losses when disruption hits (Sultana et al., 2024).

Three gaps in this literature motivate the present study. First, digital logistics capability and route optimization tend to be studied as standalone, positively framed predictors, while disruption risk sits in a separate resilience literature; few studies place an enabling capability and a risk-based predictor in the same structural model to observe how they jointly shape performance (Gasset et al., 2024; Katsaliaki et al., 2022; Zhang et al., 2023). Second, digital logistics agility, theorized as the capacity to sense change, respond flexibly, and act quickly (Mutambik, 2024), and shown to strengthen sustainability outcomes when paired with machine learning (Pasupuleti et al., 2024), has rarely been tested as the connective mechanism linking heterogeneous antecedents, some enabling, some risk-based, to distribution performance, least of all in Indonesia's last-mile trucking sector. Third, distribution performance itself is often reduced to a single metric such as on-time delivery rate, when a fuller construct spanning reliability, operational efficiency, and service handling quality would tell a richer story (Adzhigalieva et al., 2022; Rashid & Rasheed, 2024).

Two theoretical lenses ground the hypothesized relationships in this study. Dynamic Capability Theory explains why digital logistics capability and route optimization translate into performance gains: firms compete not merely on the resources they hold but on their capacity to sense opportunities and threats, seize them through resource reconfiguration, and transform routines fast enough to stay ahead of a shifting environment (Alzate et al., 2022). Applied to logistics, digital infrastructure and route-planning systems function as the sensing and reconfiguration mechanisms the theory describes: they let a firm detect demand and road-condition changes and reallocate fleet and driver capacity accordingly (Tian & Cui, 2025). This is also the theoretical basis for treating digital logistics agility as a mediator rather than a parallel antecedent. Dynamic Capability Theory holds that resources and IT-based capabilities rarely convert into performance directly; the conversion happens through an intermediate organizational capacity to sense, seize, and reconfigure in real time (Barhmi et al., 2024). Digital logistics agility operationalizes that intermediate capacity in this study: it is the mechanism through which digital infrastructure and route-planning capability become realized performance, not merely a correlate of them.

Supply Chain Resilience Theory grounds the disruption risk relationships and, together with Dynamic Capability Theory, motivates the study's central question. Resilience theory frames a firm's capacity to anticipate, absorb, and recover from disruption as a function of redundancy, flexibility, and visibility built into the supply chain (Ma et al., 2025). Where much of the resilience literature treats agility-type capabilities as sufficient once developed to absorb disruption's consequences, this framing leaves open the possibility that a firm can be simultaneously agile and still exposed to residual performance loss, since flexibility reduces but does not eliminate the operational cost of an unplanned disruption event (Katsaliaki et al., 2022). This is precisely the boundary condition this study tests: whether digital logistics agility, understood through Supply Chain Resilience Theory as an absorptive rather than a preventive capacity, fully or only partially buffers disruption risk's negative effect on distribution performance.

Building on these two theoretical foundations, the novelty of this study is threefold; First, prior studies establish that digital capability and route optimization improve performance and, separately, that disruption undermines resilience, but rarely model an enabling capability and a risk-based predictor together to observe whether their effects on performance are symmetric or not (Gasset et al., 2024; Katsaliaki et al., 2022; Zhang et al., 2023). This study shows they are not: the three antecedents differ not only in direction but in how completely their effects travel through agility; Second, integrating digital logistics capability, route optimization, and disruption risk in one model, mediated by digital logistics agility, tests two theories against each other in a single empirical setting: Dynamic Capability Theory's claim that agility converts capability into performance, and Supply Chain Resilience Theory's implicit assumption that agility-type capacities are sufficient to absorb disruption. Third, while it appears to mediate the two enabling antecedents more completely, qualifies the resilience literature's assumption and extends Dynamic Capability Theory's logic to a risk-based antecedent rather than only capability-based ones; Why digital logistics agility is positioned as the mediator, not a parallel predictor. Because Dynamic Capability Theory specifies sensing-seizing-reconfiguring as the mechanism connecting resources to performance, and because Supply Chain Resilience Theory frames absorptive capacity as the mechanism connecting disruption exposure to performance loss, agility is modeled here as the shared conversion mechanism for both enabling and risk-based antecedents rather than as an independent driver alongside them.

The finding that emerges from testing this model, that digital logistics agility buffers disruption risk but does not neutralize it, is the study's central contribution and is treated as such throughout the remainder of this paper:

METHOD

This study uses a quantitative, explanatory design to test the hypothesized relationships among digital logistics capability, route optimization, disruption risk, digital logistics agility, and distribution service performance (Sekaran & Bougie, 2021). Because the data were collected at a single point in time, the design is cross-sectional; the relationships tested throughout this paper are therefore reported as hypothesized structural relationships rather than as causal claims, consistent with the inferential limits of cross-sectional survey data (Sekaran & Bougie, 2021). The unit of analysis is the individual: operational personnel at Indonesian trucking companies who work directly in last-mile transportation and distribution, drivers, dispatchers, fleet or logistics coordinators, and distribution supervisors. Respondents were selected through purposive sampling, with one screening criterion: at least six months of active involvement in day-to-day last-mile operations, so that responses reflect field experience rather than administrative distance from operations (Sekaran & Bougie, 2021).

Sample size followed the ten-times rule from (Hair et al., 2021) : the minimum sample equals ten times the largest number of structural paths pointing at any single construct. Distribution service performance (Y) receives four incoming paths in this model, from digital logistics capability, route optimization, disruption risk, and digital logistics agility, so the floor is $4 \times 10 = 40$ respondents. Data collection produced 82 questionnaires; after screening out incomplete responses, straight-lining patterns, and respondents below the six-month tenure threshold, 67 remained valid for analysis. Because a sample of 67 across five constructs and 60 indicators is still modest by conventional SEM standards, a post-hoc statistical power analysis was conducted rather than relying on the ten-times rule alone. Using the achieved R^2 for each endogenous construct converted to Cohen's f^2 and evaluated against an F-distribution at $\alpha = 0.05$ (Cohen, 1988), the omnibus test for both digital logistics agility ($R^2 = 0.727$, four predictors) and distribution service performance ($R^2 = 0.817$, four predictors) achieves power exceeding 0.999. At the level of individual paths, achieved power ranges from 0.68 for the weakest path in the model, disruption risk on distribution service performance ($f^2 = 0.095$), to above 0.99 for the strongest paths. Given $n = 67$ and four predictors, the design is powered at 0.80 to detect effects of $f^2 \geq 0.127$ or larger; effects below that threshold, such as the disruption risk to performance path, carry a correspondingly higher risk of Type II error even where they reach statistical significance, and this constraint is treated as an explicit limitation in this research.

Table 1 Profile of Respondents (N = 67)

Characteristic	Category	Frequency	Percentage (%)
Gender	Male	58	86.6
	Female	9	13.4
Age	< 25 years	8	11.9
	25 - 34 years	26	38.8
	35 - 44 years	21	31.3
	45 - 54 years	9	13.4
	> 54 years	3	4.5
Position	Driver	22	32.8
	Co-driver / Kernet	10	14.9
	Dispatcher / Operations Staff	15	22.4
	Fleet / Logistics Coordinator	12	17.9
	Distribution Supervisor	8	11.9
Work experience	< 2 years	9	13.4
	2 - 5 years	24	35.8

Characteristic	Category	Frequency	Percentage (%)
	6 - 10 years	21	31.3
	> 10 years	13	19.4
Total		67	100.0

Source: Primary data, processed (2026).

Each variable was measured with a self-administered questionnaire on a five-point semantic differential scale, from 1 (aligned with the negative statement pole) to 5 (aligned with the positive pole), a format common in PLS-SEM logistics research (Sekaran & Bougie, 2021). Digital logistics capability (X1) was conceptually derived from three theoretical dimensions, digital infrastructure, logistics automation, and supply chain visibility, drawn from (Atieh et al., 2025; Zhang et al., 2023) ; route optimization (X2) from route planning, dynamic routing, and digital navigation (Almutairi & Owais, 2025; Gasset et al., 2024) ; disruption risk (X3) from external risk, operational risk, and regulatory and policy risk (Katsaliaki et al., 2022) ; digital logistics agility (Z) from sensing capability, response flexibility, and decision and execution speed (Mutambik, 2024; Pasupuleti et al., 2024) ; and distribution service performance (Y) from delivery timeliness and reliability, distribution operational efficiency, and service handling and interaction quality (Ferreira & Esperança, 2025; Rashid & Rasheed, 2024). Each dimension contributed four indicators, for 12 indicators per construct and 60 indicators in total.

Although each construct was theoretically motivated by three underlying dimensions, all 12 indicators per construct were specified and estimated as reflective indicators of a single first-order latent construct, not as a reflective-reflective higher-order construct with three separate lower-order components (Sarstedt et al., 2019). This specification was chosen because the three dimensions within each construct are conceptually proximate facets of one coherent underlying capability rather than empirically or theoretically distinct sub-constructs requiring separate aggregation, and because a first-order specification with n = 67 preserves more degrees of freedom than a repeated-indicators or two-stage higher-order approach would (Hair et al., 2021; Sarstedt et al., 2019).

Common method bias is a further concern in any study where all constructs are measured through a single self-reported instrument administered to the same respondent at one point in time. Two lines of defense were used. Procedurally, respondent anonymity was assured, items for different constructs were interspersed rather than grouped by variable, and the instrument was back-translated between English and Indonesian to reduce ambiguity that could otherwise inflate shared method variance (Sekaran & Bougie, 2021). Statistically, a full collinearity test was run following (Kock, 2015) : variance inflation factors were computed for every construct in the structural model, with values below the conservative threshold of 3.3 taken as evidence that common method bias is unlikely to be a serious concern. As reported in the Results, six of the seven structural paths meet this threshold; the exception (digital logistics agility on distribution service performance, VIF = 3.668) is discussed explicitly in the Results rather than omitted.

The data were processed with Partial Least Squares Structural Equation Modeling (PLS-SEM) in SmartPLS 4, a variance-based method suited to complex models with multiple latent constructs and mediating relationships at moderate sample sizes (Hair et al., 2021). Evaluation proceeded in two stages. The first stage checked the measurement model: convergent validity through outer loadings above 0.70 and average variance extracted above 0.50, reliability through Cronbach's alpha and composite reliability above 0.70, and discriminant validity through the Fornell-Larcker criterion and an HTMT ratio below 0.90 (Hair et al., 2021). The second stage checked the structural model: collinearity through VIF, explained variance through R^2, effect size through f^2, and path significance through bootstrapping with 5,000 resamples at a two-tailed 5 percent threshold, meaning t-statistics above 1.96 count as significant, with bias-corrected 95 percent confidence intervals reported for all direct, indirect, and total effects (Hair et al., 2021). Mediation was classified following (Zhao et al., 2010) : a significant indirect effect alongside a significant direct effect of the same sign is classified as complementary (partial) mediation, distinct from full mediation, in which the direct effect becomes non-significant once the mediator is introduced.

Figure 1 sets out the resulting conceptual framework: three direct paths from digital logistics capability, route optimization, and disruption risk to digital logistics agility (H1-H3); four direct paths from those same three predictors plus agility to distribution service performance (H4-H7); and three indirect paths running through agility (H8-H10), ten hypotheses in total.

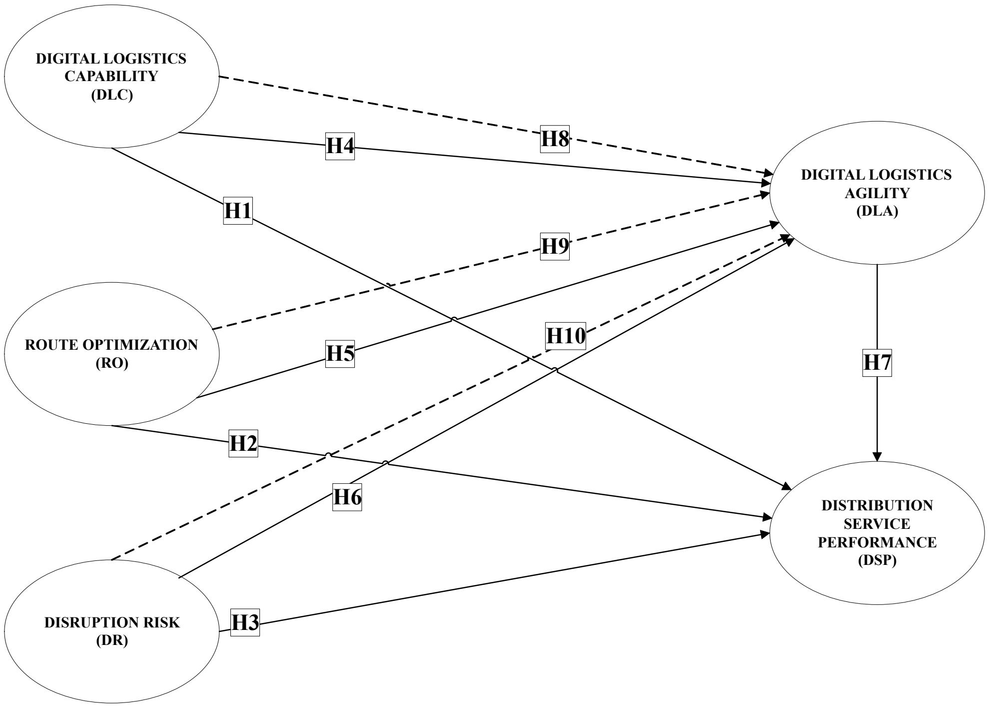

Figure 1 Conceptual Framework

Information:

⟶ : Direct Influence (H1, H2, H3, H4, H5, H6, H7)

- - ► : The Influence of Mediation (H8, H9, H10)

RESULTS AND DISCUSSION

Result

Before testing the structural relationships, the measurement model needed checking first: do the indicators actually reflect the constructs they are meant to measure? Path estimates only mean something once that question is answered (Hair et al., 2021).

Evaluation of the Measurement Model (Outer Model)

Convergent validity rests on two figures: outer loadings and average variance extracted (AVE). Across all 60 indicators and five constructs, standardized loadings fell between 0.727 and 0.953, clearing the 0.70 floor (Hair et al., 2021) recommend, so every indicator earns its place representing its construct. Table 2 lays out the full convergent validity and reliability picture, and Figure 2 shows the complete outer model with every indicator loading and structural path.

Table 2 Convergent Validity and Reliability

Construct	Loading Range	Cronbach's Alpha	Composite Reliability (rho_c)	AVE
Digital Logistics Capability (X1)	0.747 - 0.905	0.964	0.968	0.719
Route Optimization (X2)	0.727 - 0.895	0.958	0.963	0.687

Construct	Loading Range	Cronbach's Alpha	Composite Reliability (rho_c)	AVE
Disruption Risk (X3)	0.793 - 0.892	0.964	0.968	0.719
Digital Logistics Agility (Z)	0.849 - 0.901	0.973	0.976	0.770
Distribution Service Performance (Y)	0.909 - 0.953	0.985	0.986	0.859

Source: SmartPLS 4 Output (2026).

AVE values land between 0.687 and 0.859, comfortably above the 0.50 mark, so each construct accounts for more than half the variance in its own indicators (Hair et al., 2021). Reliability checks out too: Cronbach's alpha runs from 0.958 to 0.985, composite reliability (rho_c) from 0.963 to 0.986, both far past the 0.70 bar (Hair et al., 2021).

Values above 0.95 can signal item redundancy, indicators so similarly worded that they add reliability without adding conceptual information (Hair et al., 2021). Two things temper that concern here. First, each 12-item construct was built from four indicators under each of three distinct theoretical dimensions rather than 12 near-paraphrases of one idea, so the redundancy risk is structural, not merely linguistic, and the dimension-level content was deliberately varied during instrument design. Second, the discriminant validity results below show the five constructs remain empirically separable from one another despite this internal homogeneity: high reliability within a construct and clear separation between constructs are not in tension, and the latter is the more direct test of whether indicators are conflating distinct constructs rather than merely echoing each other within one.

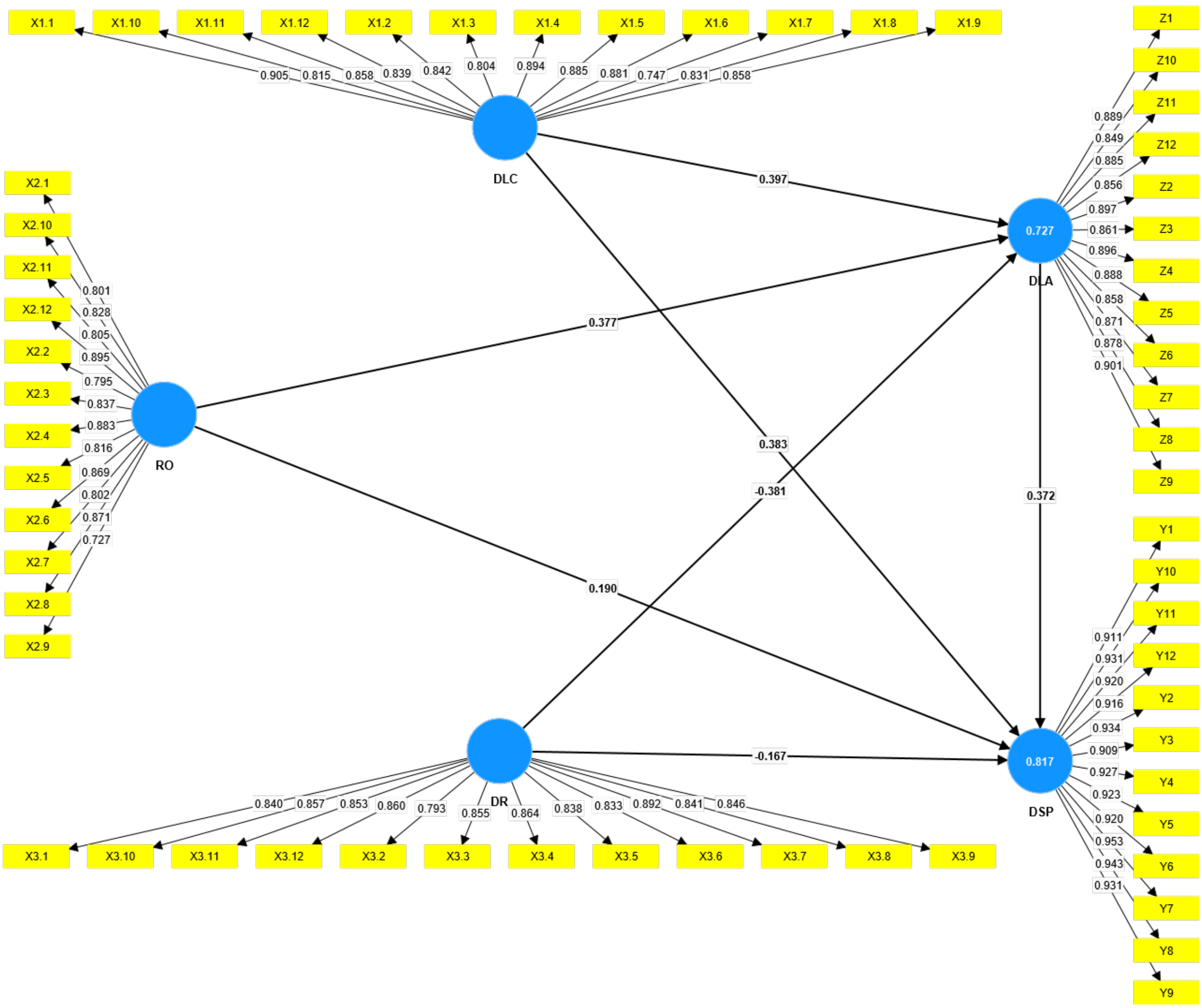

Figure 2 Full Outer Model

Based on the full outer model results presented in the figure, it is found that all indicators of the research variables have outer loading values above 0.70. Therefore, all indicators are declared valid and suitable for use in the study.

Discriminant Validity

Two tests check discriminant validity here: Fornell-Larcker and the heterotrait-monotrait ratio (HTMT). Fornell-Larcker asks whether the square root of a construct's AVE beats its correlation with every other construct (Hair et al., 2021). Table 3's diagonal values, the square roots of AVE, run from 0.829 to 0.927 and beat every corresponding correlation, so all five constructs pass.

Table 3 Fornell-Larcker Criterion

Construct	DLA	DLC	DR	DSP	RO
Digital Logistics Agility (DLA)	0.878				
Digital Logistics Capability (DLC)	0.665	0.848			
Disruption Risk (DR)	-0.544	-0.178	0.848		
Distribution Service Performance (DSP)	0.847	0.761	-0.483	0.927	
Route Optimization (RO)	0.680	0.529	-0.243	0.686	0.829

HTMT backs this up (Table 4). Every ratio stays under the 0.90 ceiling, the highest, between digital logistics agility and distribution service performance, reaches 0.864 (Hair et al., 2021).

Table 4 HTMT

Construct	DLA	DLC	DR	DSP	RO
Digital Logistics Agility (DLA)					
Digital Logistics Capability (DLC)	0,683				
Disruption Risk (DR)	0,559	0,192			
Distribution Service Performance (DSP)	0,864	0,779	0,491		
Route Optimization (RO)	0,698	0,549	0,248	0,701	

Source: SmartPLS 4 Output (2026).

The 0.864 ratio between digital logistics agility and distribution service performance is the highest in the matrix and close enough to the 0.90 ceiling to warrant a conceptual argument, not just a statistical pass. Agility and performance are theoretically distinct under Dynamic Capability Theory: agility is a process capability, the speed and flexibility with which a firm senses and responds, while performance is a realized outcome, the service levels actually delivered (Alzate et al., 2022). The two are expected to correlate strongly precisely because the study hypothesizes agility as a direct and mediating driver of performance (H7-H10); a high HTMT between a hypothesized antecedent and its outcome is consistent with that theoretical link rather than evidence the two instruments are measuring the same thing. The Fornell-Larcker result, where agility's own AVE-derived value (0.878) still exceeds its correlation with performance, reinforces that the two remain empirically separable even at this correlation strength.

Collinearity Assessment

Variance inflation factor (VIF) serves two purposes here: checking whether predictor constructs overlap too much with each other, and, following (Kock, 2015) full collinearity approach, screening for common method bias. Table 5 reports inner model VIF for all seven structural paths. Six of the seven fall below the conservative 3.3 threshold (Kock, 2015) recommended for ruling out common method bias, and all seven fall below the more permissive 5.0 threshold (Hair et al., 2021) use for general multicollinearity. The exception is digital logistics agility's path to distribution service performance (VIF = 3.668), which clears the multicollinearity threshold but sits above the stricter common-method-bias threshold. Combined with the procedural safeguards applied during instrument design, anonymity, interspersed items, and back-translation, this pattern suggests common method bias is unlikely to be driving the results broadly, but it cannot be fully ruled out for this specific path, and that caveat is carried into the interpretation of H7 and H8 in the Discussion.

Table 5 Collinearity Statistics (Inner Model VIF) and Common Method Bias Screen

Structural Path	Inner VIF	Below 3.3 (Kock, 2015)	Below 5.0 (Hair et al., 2021)
Digital Logistics Capability -> Digital Logistics Agility	1.394	Yes	Yes
Route Optimization -> Digital Logistics Agility	1.434	Yes	Yes
Disruption Risk -> Digital Logistics Agility	1.067	Yes	Yes
Digital Logistics Capability -> Distribution Service Performance	1.973	Yes	Yes
Route Optimization -> Distribution Service Performance	1.954	Yes	Yes
Disruption Risk -> Distribution Service Performance	1.600	Yes	Yes
Digital Logistics Agility -> Distribution Service Performance	3.668	No	Yes

Structural Model Test Results (Inner Model)

With the measurement model cleared, the structural model comes next: explained variance (R^2), statistical power, effect size (f^2), overall fit, and the significance of each hypothesized path.

Table 6 R-Square Test Results and Statistical Power

Konstruk Endogen	R Square	R Square Adjusted	Achieved Power
Digital Logistics Agility (Z)	0,727	0,714	> 0,999
Distribution Service Performance (Y)	0,817	0,806	> 0,999

Source: SmartPLS 4 Output (2026).

Digital logistics capability, route optimization, and disruption risk together account for 72.7 percent of the variance in digital logistics agility (Table 6). Add agility to the mix and the four predictors together explain 81.7 percent of the variance in distribution service performance. (Hair et al., 2021) treat R^2 above 0.75 as strong, around 0.50 as moderate, around 0.25 as weak; both figures here land at or near the strong end. Two caveats temper this reading. Both R^2 values were computed from self-reported perceptual data collected from the same respondents at one point in time, so part of the shared variance may reflect measurement context rather than the underlying relationships alone, a concern the common method bias check above only partially resolves. And with $n = 67$, the omnibus F-tests behind these R^2 values are, as reported in Table 6, very highly powered (power > 0.999 for both constructs), but that headline power figure describes the model as a whole; individual paths, particularly the smaller ones, are considerably less well powered, as the next section shows.

Table 7 f-Square Effect Size and Statistical Power

Path	f Square	Effect Size	Achieved Power
Digital Logistics Capability -> Digital Logistics Agility	0.416	Large	> 0.99
Route Optimization -> Digital Logistics Agility	0.363	Large	> 0.99
Disruption Risk -> Digital Logistics Agility	0.500	Large	> 0.99
Digital Logistics Capability -> Distribution Service Performance	0.407	Large	> 0.99
Route Optimization -> Distribution Service Performance	0.101	Small-Medium	0.71
Disruption Risk -> Distribution Service Performance	0.095	Small	0.68
Digital Logistics Agility -> Distribution Service Performance	0.207	Medium	0.95

Source: SmartPLS 4 Output (2026).

Table 7 breaks down effect size (f^2) alongside the achieved power for each path, computed at $\alpha = 0.05$ with $n = 67$ and four predictors. Disruption risk hits digital logistics agility hardest ($f^2 = 0.500$), ahead of digital logistics capability (0.416) and route optimization (0.363), all three counting as large by (Hair et al., 2021) standard and all comfortably powered above 0.99. For distribution service performance, digital logistics capability again produces a large, well-powered effect (0.407), agility a medium effect at 0.95 power (0.207), while route optimization and disruption risk trail at 0.101 and 0.095, small effects whose achieved power (0.71 and 0.68, respectively) falls short of the conventional 0.80 benchmark.

Standardized root mean square residual (SRMR) came out to 0.058, under the 0.08 ceiling, so the model fits the data acceptably well (Hair et al., 2021).

Hypothesis Testing

Bootstrapping with 5,000 resamples in SmartPLS 4 tested the significance of each structural path, with a t-statistic above 1.96 and a p-value under 0.05 marking significance at the 5 percent level (Hair et al., 2021). Table 6 and Figure 2 lay out the full results, direct paths and mediation paths together.

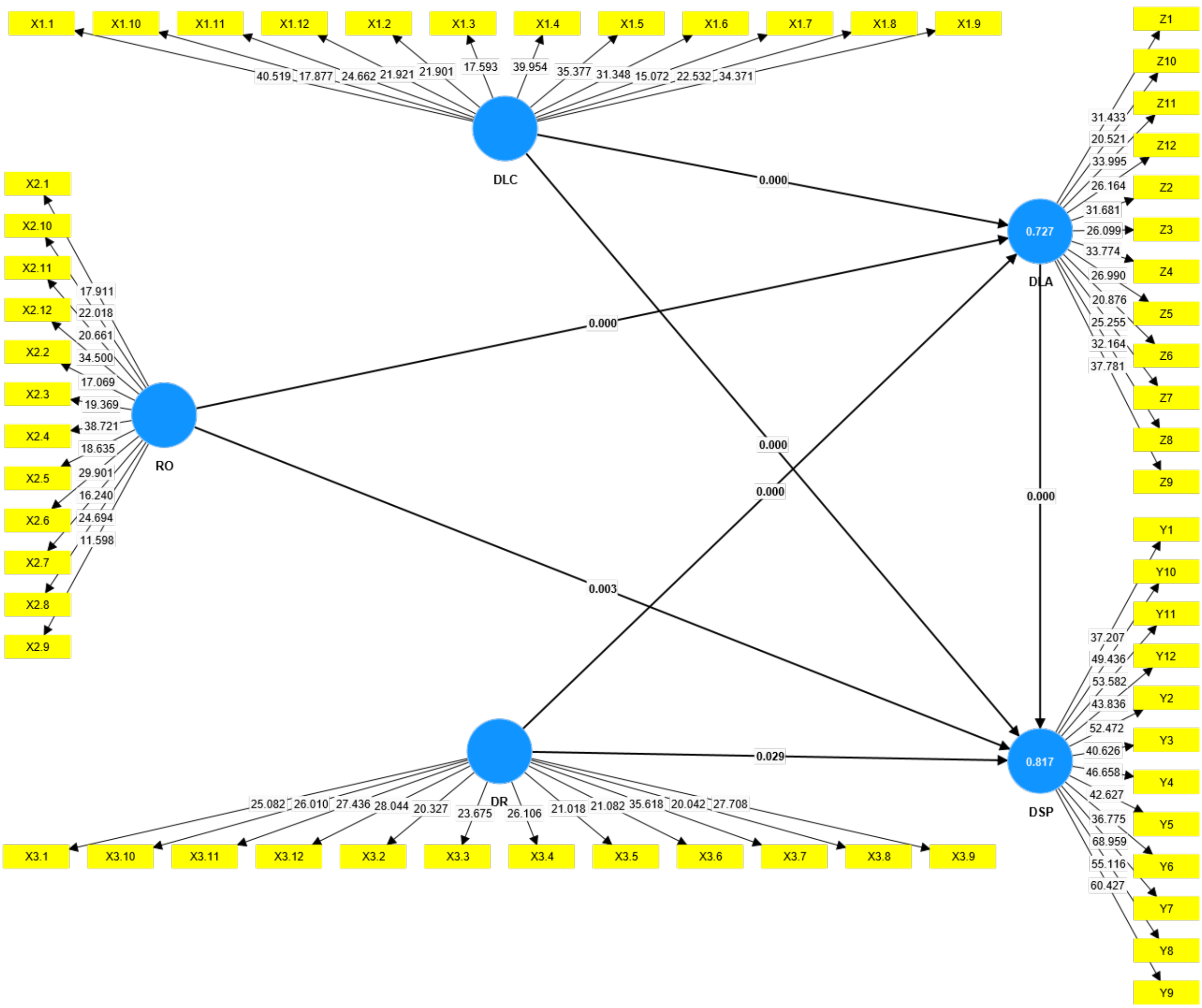

Figure 3 Structural Model Results (Bootstrapping)

Source: SmartPLS 4 Output (2026).

Table 8 Direct Effect (Hypothesis Testing)

Hyp.	Relationship	Original Sample (O)	T Statistics	P Values	Decision
H1	Digital Logistics Capability -> Digital Logistics Agility	0.397	5.298	0.000	Supported
H2	Route Optimization -> Digital Logistics Agility	0.377	4.461	0.000	Supported
H3	Disruption Risk -> Digital Logistics Agility	-0.381	4.572	0.000	Supported
H4	Digital Logistics Capability -> Distribution Service Performance	0.383	4.671	0.000	Supported
H5	Route Optimization -> Distribution Service Performance	0.190	2.975	0.003	Supported
H6	Disruption Risk -> Distribution Service Performance	-0.167	2.183	0.029	Supported
H7	Digital Logistics Agility -> Distribution Service Performance	0.372	3.567	0.000	Supported
H8	Digital Logistics Capability -> Digital Logistics Agility -> Distribution Service Performance	0.148	3.222	0.001	Supported
H9	Route Optimization -> Digital Logistics Agility -> Distribution Service Performance	0.140	2.589	0.010	Supported

Hyp.	Relationship	Original Sample (O)	T Statistics	P Values	Decision
H10	Disruption Risk -> Digital Logistics Agility -> Distribution Service Performance	-0.142	2.842	0.005	Supported

Source: SmartPLS 4 Bootstrapping Output, 5,000 resamples (2026).

All ten hypothesized in Table 8 relationships are statistically supported at the 5 percent significance level. The total effect of digital logistics capability on distribution service performance, combining its direct and indirect paths, reaches 0.531, the largest total effect among the three exogenous predictors, followed by route optimization at 0.330 and disruption risk at -0.309, indicating that although disruption risk is partially buffered through agility, its net effect on performance remains negative and, per the confidence interval in Table 9, reliably different from zero.

Table 9 decomposes each of the three mediated relationships into its direct, indirect, and total effect, with bias-corrected 95 percent bootstrap confidence intervals for all three, following Hair et al. (2021), and classifies each using the (Zhao et al., 2010) typology. In all three cases, the direct effect and the indirect effect are both statistically significant and share the same sign, direct and indirect effects for digital logistics capability and route optimization are both positive, and both are negative for disruption risk, which (Zhao et al., 2010) classify as complementary (partial) mediation: agility carries part of each antecedent's effect on performance without fully accounting for it. None of the three qualifies as full mediation, since a fully mediated relationship would show the direct effect losing significance once the mediator enters the model, and that does not happen here for any of the three antecedents.

Table 9 Mediation Analysis: Direct, Indirect, and Total Effects

Relationship	Direct Effect [95% CI]	Indirect Effect [95% CI]	Total Effect [95% CI]	Mediation Type
Digital Logistics Capability -> (Agility) -> Performance	0.383 [0.224, 0.549]	0.148 [0.073, 0.258]	0.531 [0.379, 0.673]	Complementary (partial)
Route Optimization -> (Agility) -> Performance	0.190 [0.066, 0.318]	0.140 [0.051, 0.267]	0.330 [0.191, 0.479]	Complementary (partial)
Disruption Risk -> (Agility) -> Performance	-0.167 [-0.323, -0.027]	-0.142 [-0.267, -0.062]	-0.309 [-0.434, -0.175]	Complementary (partial)

The disruption risk row is the one that carries the most theoretical weight. Its direct effect remains negative and significant (-0.167, CI excludes zero) even with the indirect path through agility (-0.142, CI excludes zero) already in the model; agility absorbs less than half of disruption risk's total effect on performance (-0.309), with the majority still travelling the direct route. By contrast, digital logistics capability's indirect effect (0.148) is a smaller share of a larger total effect (0.531), and route optimization's indirect effect (0.140) is nearly as large as its direct effect (0.190), both patterns consistent with agility doing comparatively more of the work for the two enabling antecedents than it does for the risk-based one. This asymmetry, not the mere presence of partial mediation, is the finding this study treats as its central contribution and returns to at length in the Discussion.

Discussion

Rather than restating each hypothesis in sequence, this discussion is organized around the four questions the empirical pattern raises most directly: why digital logistics capability carries the strongest effect, why route optimization's direct effect is comparatively modest, why disruption risk keeps a direct negative effect on performance despite agility's mediating role, and why agility buffers that effect without neutralizing it. Each section moves from the finding to its theoretical explanation, then to where it sits against prior research and why it may differ, before drawing out theoretical and practical implications.

1. Why Digital Logistics Capability Has the Strongest Effect

Digital logistics capability is the strongest predictor in the model on every relevant metric: the largest total effect on performance (0.531), a large effect size on both agility ($f^2 = 0.416$) and performance ($f^2 = 0.407$), and the only exogenous path whose direct effect exceeds its own indirect effect in absolute terms (Table 8). Dynamic Capability Theory explains why. Digital infrastructure, platform integration, and automation are not one-off resources; they are standing sensing and reconfiguration mechanisms that operate continuously, every dispatch decision, every tracked shipment, every automated exception alert draws on the same underlying capability (Alzate et al., 2022; Tian & Cui, 2025). Route optimization and disruption response, by contrast, are triggered capabilities: they activate when a specific routing decision or disruption event calls for them. A standing capability has more opportunities to influence outcomes than a triggered one, which is a plausible mechanism for why digital logistics capability outperforms the other two predictors on both paths.

This finding aligns with (Atieh et al., 2025; Ning & Yao, 2023), both of which found digital transformation's performance effect exceeding that of narrower operational capabilities, and with (Muhammad Taufani & Anton Wachidin Widjaja, 2023) in the Indonesian context specifically. Where this study adds nuance is in showing that capability's advantage holds on the indirect path as well as the direct one: capability's f^2 on agility (0.416) is the second-largest in the model, meaning the standing-capability advantage does not just produce performance directly, it also feeds the mediating mechanism more strongly than route optimization does. Theoretically, this suggests Dynamic Capability Theory's sensing-seizing-reconfiguring logic operates with different strength depending on whether the underlying capability is continuously active or event-triggered, a distinction the theory does not itself make explicit but that this data supports. Practically, it implies that of the three levers available to a trucking firm, investment in standing digital infrastructure, IoT connectivity, and platform integration offers the most reliable return, and it is the lever that should be funded first if resources are constrained.

2. Why Route Optimization's Direct Effect Is Comparatively Modest

Route optimization's direct effect on performance ($\beta = 0.190$, $f^2 = 0.101$, power = 0.71) is the smallest of the three significant positive predictors, even though its effect on agility ($\beta = 0.377$, $f^2 = 0.363$) is large and close to digital logistics capability's. The gap between these two numbers is the finding worth explaining: route optimization builds agility about as strongly as digital logistics capability does, but converts far less of that into performance directly.

A plausible dynamic-capability explanation is that route optimization operates at a narrower scope than digital logistics capability. It reconfigures one decision, the sequence and timing of a specific delivery run, whereas digital infrastructure reconfigures the firm's capacity to sense and respond across every operational decision simultaneously. A narrower-scope capability can still build the broader sensing-and-response capacity captured by agility (hence the large f^2 on agility), while contributing less on its own to the wide range of outcomes that distribution service performance actually measures: delivery timeliness, operational efficiency, and service handling quality together. (Ferreira & Esperança, 2025; Wang et al., 2023) both report route optimization's performance gains concentrated specifically in punctuality and on-time delivery rather than across the full performance construct, which is consistent with a narrower direct footprint. Where this study differs from that prior work is in showing route optimization's total contribution (0.330) is still substantial once the indirect path through agility is counted, nearly double its direct effect alone, so studies that measure only the direct path risk understating route optimization's real contribution to performance. The practical implication follows directly: trucking firms should not expect route optimization software to move performance metrics on its own; its return is realized mainly by first strengthening the organization's broader responsiveness, and should be evaluated on that basis rather than on direct delivery-time savings alone.

3. Why Disruption Risk Retains a Direct Negative Effect on Performance

Disruption risk is the only predictor in the model whose direct effect on performance ($\beta = -0.167$, CI [-0.323, -0.027]) survives fully alongside a significant indirect effect through agility (-0.142, CI [-0.267, -0.062]) without either one dominating, a genuinely complementary partial mediation pattern rather than a case where one path clearly carries most of the effect. Supply Chain Resilience Theory anticipates exactly this kind of split. The theory frames resilience capacities like agility as absorptive, not preventive: they reduce the operational cost of a disruption event after it occurs, but they do not prevent the event's occurrence or eliminate its immediate operational consequences, a stranded truck is still stranded regardless of how quickly the firm can reroute around it (Ma et al., 2025). The direct path from disruption risk to performance plausibly captures those immediate, structural consequences, lost time, damaged goods, missed windows, that no amount of organizational responsiveness fully undoes after the fact.

This reading departs in an important way from (Amio et al., 2024; Katsaliaki et al., 2022), both of which frame resilience capacity as the primary explanatory mechanism connecting disruption to performance outcomes and treat the direct path largely as unexplained residual variance rather than a substantively meaningful channel. This study's data do not support treating it as residual: the direct effect's confidence interval excludes zero by a comfortable margin, and its magnitude ($f^2 = 0.095$, admittedly modest, power = 0.68) is smaller than the indirect path's but not negligible relative to it. Jamaludin et al. (2023) come closer to this study's reading, finding that resource flexibility among Indonesian SMEs reduced but did not eliminate disruption's performance cost, a pattern consistent with what this study documents for digital logistics agility specifically. Theoretically, the implication is that Supply Chain Resilience Theory's absorptive framing of agility-type capacities should be read literally: absorption is not elimination, and models that omit the direct disruption-to-performance path may overstate how much resilience capacity actually protects. Practically, this is the strongest argument in the paper for treating disruption risk as something to be managed on two fronts simultaneously, both through the organizational agility that partially buffers it and through direct exposure reduction that the next section develops.

4. Why Agility Buffers Disruption Risk but Does Not Neutralize It

Agility itself is a significant, positive, and well-powered driver of performance ($\beta = 0.372$, $f^2 = 0.207$, power = 0.95, H7 supported), and it significantly and partially mediates all three antecedents (H8-H10 supported). The question this section addresses is why that mediation is partial specifically for disruption risk, given the theoretical expectation, common in the broader resilience literature, that developing sufficient agility should be enough to absorb a disruption's consequences.

The answer follows from the distinction drawn in the section above: agility, as operationalized here through sensing capability, response flexibility, and decision and execution speed, describes how fast and how well a firm reacts once a disruption is already underway. It does not describe whether the disruption's initial impact, the missed window, the idle truck, the rerouted driver, can be avoided altogether. Digital logistics capability and route optimization, by contrast, act mostly upstream of any single disruptive event, building sensing and planning capacity that shapes performance whether or not a disruption occurs in a given period, which is consistent with why their mediation, while also classified as complementary rather than full, shows agility carrying a comparatively larger share of their total effect (Table

8) than it does for disruption risk. (Amio et al., 2024; Katsaliaki et al., 2022) implicitly assume resilience capacity operates the same way regardless of whether the antecedent is an enabling capability or a risk exposure; this study's data suggest it does not; the mediating mechanism is asymmetric, doing more work for capability-building antecedents than for a risk-based one.

This is the study's central theoretical implication: Supply Chain Resilience Theory's treatment of agility as a general-purpose resilience mechanism needs a boundary condition distinguishing what agility can and cannot absorb, and this study's data suggest that boundary falls between preventing an event's occurrence and managing the response to one already underway. The practical implication is equally direct. A trucking firm that treats agility-building, sensing tools, flexible dispatch, faster decision cycles, as sufficient risk management is very likely leaving a residual, measurable performance cost on the table. Closing that gap requires investment that operates on the exposure itself rather than only on the response to it.

Theoretical Contribution

This study contributes to four bodies of literature. To Dynamic Capability Theory, it extends the sensing-seizing-reconfiguring logic beyond capability-based antecedents to a risk-based one, showing the theory's conversion mechanism, here operationalized as digital logistics agility, operates with different strength depending on whether the antecedent is a standing capability, a triggered capability, or a risk exposure, a distinction the theory does not itself specify but that this study's comparative effect sizes make visible. To Supply Chain Resilience Theory, it supplies a boundary condition the literature has largely assumed rather than tested: agility-type resilience capacities are absorptive rather than preventive, and the empirical gap between an antecedent's direct and indirect effect is a measurable way to see how much of a disruption's cost resilience capacity actually removes versus how much remains structurally unavoidable. To the digital logistics and logistics agility literature, it offers a rare within-model comparison of an enabling and a risk-based antecedent operating through the same mediator, rather than studying each in isolation, which is the condition needed to observe the asymmetry this study documents. To the last-mile logistics literature specifically, and to Indonesian last-mile trucking in particular, it provides one of the few structural models to jointly test digital capability, route optimization, and disruption risk against a multidimensional performance construct rather than a single delivery-time metric, in a segment of the logistics sector that has received comparatively little PLS-SEM attention relative to manufacturing or general supply chain contexts.

Practical Implications

The findings translate into a reasonably specific set of actions for trucking company management, organized by which lever they strengthen.

1. Upgrade digital infrastructure first. Because digital logistics capability shows the strongest total effect on performance and a large effect on agility, IoT connectivity, platform integration, and automated exception handling are the highest-return investment among the three levers tested and should be prioritized when resources are constrained.
2. Build real-time logistics visibility. Visibility is the specific dimension of digital capability most directly tied to the sensing function Dynamic Capability Theory describes; dashboards and tracking systems that surface disruption signals early feed both the direct performance path and the agility-mediated one.
3. Treat route optimization as an agility investment, not a standalone efficiency tool. Because route optimization's return travels mainly through agility rather than direct delivery-time savings, it should be evaluated, and budgeted, on its contribution to organizational responsiveness rather than judged narrowly against fuel or time savings alone.

4. Maintain contingency fleet capacity. Since agility only partially buffers disruption risk's direct effect, spare vehicle capacity that can be activated when a primary route or vehicle fails addresses the structural, not merely the responsive, side of disruption exposure.
5. Establish a backup driver pool. Driver unavailability is one of the internal risk sources this study's disruption risk construct captures; a backup pool shortens the gap between a disruption occurring and a company's ability to act on it, complementing rather than substituting for agility.
6. Build route redundancy into network planning. Alternative routing options prepared in advance reduce the direct operational cost of a blocked or congested route before agility-driven rerouting even needs to engage.
7. Integrate digital capability investment with disruption management planning rather than treating them as separate budget lines. Since capability and disruption risk both operate substantially through agility, and disruption risk retains a direct effect capability-building does not touch, the two workstreams address different parts of the same performance equation and should be planned together, not competed against each other for resources.

Table 8 and the discussion above converge on a single empirical fact that anchors this study's contribution: digital logistics agility significantly mediates disruption risk's negative effect on distribution service performance (H10 supported, indirect effect = -0.142, CI excludes zero), but the direct path from disruption risk to performance remains significant and substantial in its own right (H6 supported, -0.167, CI excludes zero), and the total effect stays firmly negative (-0.309, CI [-0.434, -0.175]). Agility buffers disruption. It does not neutralize it. That distinction, developed theoretically in section 4 above and translated into the resource-allocation implications in the Practical Implications section, is this study's central and most defensible claim, and the one on which its contribution to the resilience literature rests.

CONCLUSION

Conclusion

Based on the findings of this study, the following conclusions can be drawn:

1. Digital logistics capability strengthens digital logistics agility. Stronger infrastructure, automation, and data integration give a trucking company more room to sense and respond to operational change.
2. Route optimization strengthens digital logistics agility. Algorithm-based, dynamic route planning sharpens a company's ability to catch and respond to disruption along the delivery route.
3. Disruption risk weakens digital logistics agility. As external and internal operational risks mount, sensing, response, and execution capacity erodes measurably.
4. Digital logistics capability improves distribution service performance directly. Infrastructure and automation translate into more reliable, more efficient last-mile delivery on their own, not only through agility, and this is the single strongest relationship in the model.
5. Route optimization improves distribution service performance directly, though modestly relative to its effect on agility; most of its contribution to performance travels through the agility it builds rather than through this direct path.
6. Disruption risk damages distribution service performance directly. Operational disturbance degrades reliability and service quality even when agility is accounted for, and this direct channel is not a statistical residual but a substantively meaningful part of disruption's total cost.
7. Digital logistics agility improves distribution service performance. The capacity to sense, respond, and act quickly is a substantive, well-powered driver of last-mile outcomes in its own right.

8. Digital logistics agility significantly and partially (complementarily) mediates the effect of digital logistics capability on distribution service performance, per the Zhao et al. (2010) typology; capability strengthens performance both directly and through the agility it builds.
9. Digital logistics agility significantly and partially (complementarily) mediates the effect of route optimization on distribution service performance; route optimization strengthens performance both directly and, more substantially, through the agility it builds.
10. Digital logistics agility significantly but only partially (complementarily) mediates disruption risk's negative effect on distribution service performance, since disruption risk keeps a significant, non-trivial direct negative effect regardless. This is the study's central finding: agility buffers operational disruption in Indonesia's last-mile trucking sector, it does not neutralize it, a boundary condition this study contributes to Supply Chain Resilience Theory.

Limitations

Five limitations bound these findings, each carrying a specific interpretive consequence rather than serving as a general disclaimer. The cross-sectional design means every relationship reported here is a hypothesized structural association, not a demonstrated causal effect; the language used throughout this paper reflects that limit deliberately, and readers should resist a causal reading even where the statistical pattern is strong. The valid sample of 67, while clearing the (Hair et al., 2021) ten-times-rule minimum, leaves the two smallest paths in the model, route optimization and disruption risk on performance, powered at only 0.71 and 0.68 respectively; their statistical significance in this sample is real, but their precise magnitude should be treated as provisional until replicated with a larger sample. All constructs were measured through a single self-reported instrument administered to the same respondent at one time, and while the full collinearity test in the Results found common method bias unlikely to be a serious concern for six of seven paths, the seventh (agility to performance) could not be fully cleared, which tempers confidence in that specific path's magnitude. No objective operational metrics, GPS-tracked delivery time, system-logged disruption frequency, entered the model, so the performance and disruption constructs reflect perception rather than directly observed operational records. And the sample covers only operational personnel in Indonesian last-mile trucking, so generalizing to line-haul, warehousing, sea or air freight, or to trucking industries outside Indonesia would require further testing rather than being assumed.

Recommendation

Future research could widen the scope to other logistics segments and regions across Indonesia, grow the sample specifically to strengthen power on the two underpowered paths identified above, and move to a longitudinal design that tracks how agility develops across successive disruption events rather than at one point in time. A reflective-formative higher-order respecification of the three-dimension constructs, following (Sarstedt et al., 2019), would test whether the first-order specification used here understates dimension-specific effects that a full higher-order model might reveal. Adding variables such as organizational resilience, digital leadership, or driver-level psychological capital would round out the explanatory model, and pairing self-reported data with objective metrics like GPS-based delivery tracking would address the common-method and self-report limitations directly. Given that agility only partially buffers disruption risk here, a natural next step is testing direct mitigation strategies, contingency fleet capacity, multi-carrier partnerships, route redundancy planning, as complements to agility-building investment rather than substitutes for it. Longitudinal SEM, system dynamics simulation, or AI-based predictive modeling could each add a layer of insight into how disruption risk and distribution performance interact over time.

Author Contribution

Both authors contributed substantially to this study. The first author led conceptualization, theoretical framework development, data collection, PLS-SEM analysis, and manuscript drafting. The second author developed the operational variable framework, interpreted the structural model results, and led critical review and revision. Both authors read and approved the final manuscript.

Acknowledgment (Opsional)

The authors thank the management and operational personnel of the participating Indonesian trucking companies for their time and candor during data collection, and colleagues at Universitas Logistik dan Bisnis Internasional for feedback during the development of this study.

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