AI-Enabled Logistics Analytics, Operational Excellence, and Customer Satisfaction: A Multi-Industry Mediation Study

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Abstract

Artificial intelligence (AI) is reshaping how logistics functions sense demand, allocate resources, and serve customers, yet evidence on how AI-enabled analytics actually translates into customer outcomes remains fragmented across single industries and single links of the value chain. Drawing on the dynamic capabilities perspective, this study models operational excellence as the mechanism through which AI-enabled logistics analytics capability influences customer satisfaction, and tests whether the mechanism holds across industries. Survey data were collected from 512 logistics and operations decision-makers in manufacturing, retail and e-commerce, third-party logistics, and healthcare firms, and analyzed with partial least squares structural equation modeling, bootstrapped mediation tests, and permutation-based multi-group analysis. AI-enabled logistics analytics exerts a strong positive effect on operational excellence (beta = 0.612) and a modest direct effect on customer satisfaction (beta = 0.186), while the indirect path through operational excellence (0.316; 63.0 percent of the total effect) confirms complementary partial mediation. The mediation mechanism replicates in all four industries, although the capability-to-excellence link is strongest among third-party logistics providers and weakest in healthcare. Importance-performance analysis identifies algorithmic capability and analytics talent as the highest-leverage yet weakest-performing dimensions. The study contributes a cross-industry account of why AI investments pay off in customer terms chiefly when they are converted into disciplined operational routines.

Keywords: AI-enabled logistics analytics; operational excellence; customer satisfaction; mediation analysis; PLS-SEM; multi-group analysis; dynamic capabilities; multi-industry survey

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1. Introduction

Logistics has become one of the most data-saturated functions of the modern enterprise. Telematics streams from vehicles, scanner events from warehouses, order flows from commerce platforms, and service interactions from customer touchpoints generate a continuous record of how goods move and how customers experience that movement. Digital transformation research argues that value emerges not from the data itself but from the organizational ability to convert it into improved paths to value creation (Verhoef et al., 2021; Vial, 2019). Within logistics specifically, the label "Logistics 4.0" now denotes the fusion of connected assets, automation, and analytics into a qualitatively new operating system for physical flows (Winkelhaus & Grosse, 2020), while surveys of the field document a decisive shift from descriptive reporting toward machine-learning models that forecast, optimize, and increasingly decide (Choi et al., 2018; Duan et al., 2019; Toorajipour et al., 2021; Wang et al., 2016).

Investment has followed the promise. Industry consortia estimate that a majority of large shippers and logistics service providers now run at least one production AI application, spanning demand forecasting, dynamic routing, warehouse robotics coordination, exception prediction, and automated customer communication. Yet the managerial question that budgets ultimately answer to is not whether algorithms can be deployed but whether customers notice. The marketing literature is emphatic that customer satisfaction is among the most reliable intangible predictors of firm performance (Otto et al., 2020), and the AI literature is equally emphatic that many AI initiatives stall before producing business value (Dwivedi et al., 2021; Enholm et al., 2022). Between the algorithm and the satisfied customer lies a chain of operational activity that research has too rarely modeled explicitly.

Three gaps motivate this study. First, most empirical work links analytics capability directly to aggregate firm performance (Gunasekaran et al., 2017; Mikalef et al., 2019; Wamba et al., 2017), leaving the intermediate operational mechanism inside a black box; when mediators are examined, they are typically generic capabilities rather than the delivery-facing routines that customers actually experience (Akter et al., 2016; Mikalef et al., 2020; Wamba et al., 2017). Second, the customer side of the equation is usually measured from the consumer's viewpoint in a single retail setting, while the firm-level question, whether analytics-driven operations improve the satisfaction of the firm's own customer base, remains under-examined (Lemon & Verhoef, 2016; Vakulenko et al., 2019). Third, single-industry samples dominate, so it is unknown whether the analytics-to-satisfaction mechanism is a general regularity or an artifact of particular sectors (Adam et al., 2021; Prentice et al., 2020; Vakulenko et al., 2019).

This study addresses the three gaps jointly. It conceptualizes AI-enabled logistics analytics (AILA) as a higher-order organizational capability comprising data and technology infrastructure, algorithmic capability, analytics talent, and data-driven culture (Akter et al., 2016; Gupta & George, 2016; Mikalef & Gupta, 2021); it positions operational excellence (OE), understood as sustained superiority in delivery reliability, process efficiency, and operational agility, as the mediating mechanism (Bag et al., 2020; Carvalho et al., 2019; Srinivasan & Swink, 2018); and it tests the resulting mediation model on 512 firms drawn from four industries with deliberately different clock speeds and regulatory burdens. Three research questions guide the analysis. RQ1: Does AILA improve customer satisfaction, and how much of the effect travels through OE? RQ2: Is the mediation mechanism invariant across manufacturing, retail and e-commerce, third-party logistics, and healthcare? RQ3: Which capability dimensions deserve managerial priority given their importance and current performance?

The multi-industry design is not decorative; it is the identification strategy for a boundary question the literature has left open. Manufacturing embeds logistics inside production systems with long planning cycles;

retail and e-commerce expose logistics performance to end consumers within hours; third-party logistics providers sell operational performance as their entire value proposition; and healthcare distribution operates under validation and traceability regimes that deliberately slow process change. If the analytics-to-satisfaction mechanism survives contrasts of this severity, it can be treated as a general property of logistics organizations rather than a sector curiosity; if it bends, the pattern of bending itself is theoretically informative about what accelerates or brakes the conversion of digital capability into customer value. The study therefore contributes, beyond the mediation test itself, the first invariance-checked comparison of this mechanism across four structurally distinct industries.

The article proceeds as follows. Section 2 reviews the literature and develops the hypotheses summarized in the research model. Section 3 details the survey design, measures, and the partial least squares structural equation modeling (PLS-SEM) strategy. Section 4 reports measurement validation, structural estimates, mediation tests, multi-group comparisons, and an importance-performance analysis. Sections 5 through 7 discuss the findings, their implications, and the limitations, and Section 8 concludes.

2. Literature Review and Hypothesis Development

2.1 AI-Enabled Logistics Analytics as an Organizational Capability

Research on big data analytics established early that competitive returns come from a bundled capability rather than from tools. Foundational work identified tangible resources, human skills, and intangible orientations as the joint ingredients of a big data analytics capability (Gupta & George, 2016), and demonstrated that such capability improves firm performance when aligned with business strategy (Akter et al., 2016) and when it feeds dynamic sensing and reconfiguration processes (Wamba et al., 2017). The AI wave extends this logic: an AI capability adds algorithmic assets, machine-learning talent, and governance routines to the analytics bundle, and its performance effects again run through organizational rather than purely technical channels (Enholm et al., 2022; Mikalef & Gupta, 2021). Reviews of AI-assisted decision-making similarly stress that value materializes where algorithmic outputs are embedded in decision processes rather than merely produced (Duan et al., 2019).

Applied to logistics, the capability takes concrete forms with well-documented technical substance. Machine-learning forecasting now routinely outperforms naive judgment, although careful benchmarking warns that its advantage over rigorous statistical baselines must be earned case by case (Makridakis et al., 2018); predictive analytics for supply chain demand has matured into a recognizable methodological repertoire (Seyedan & Mafakheri, 2020); robotized warehouse systems translate algorithmic scheduling into physical throughput (Azadeh et al., 2019); the Internet of Things supplies the sensing layer on which such models feed (Ben-Daya et al., 2019); and AI methods are increasingly applied to supply chain risk identification and response (Baryannis et al., 2019). These streams sit within the broader Industry 4.0 trajectory in which cyber-physical integration reorganizes production and distribution (Lasi et al., 2014). Following the resource-bundle tradition, this study therefore models AILA as a higher-order capability with four first-order dimensions: data and technology infrastructure, algorithmic capability, analytics talent, and data-driven culture, echoing classifications used in supply chain analytics reviews (Nguyen et al., 2018).

It is useful to be explicit about the value pathways this capability opens inside a logistics function, because they anchor the hypotheses that follow. At the planning level, learning-based demand and lead-time prediction narrows the uncertainty that safety stock and buffer capacity otherwise absorb. At the execution level, optimization over predicted states, dynamic routing, slotting, labor scheduling, converts information advantage into resource productivity. At the exception level, anomaly detection and estimated-time-of-arrival models move the operation from reactive firefighting to anticipatory intervention. And at the interface level, the same predictive assets feed promise dates, proactive notifications, and automated service dialogue. The first three pathways discharge into operational routines; only the fourth touches the customer without passing

through operations. This asymmetry is the structural reason to expect mediation rather than a dominant direct effect, and it is the reason the model must nevertheless retain a direct path.

2.2 Operational Excellence in Logistics Operations

Operational excellence denotes a durable state in which core processes outperform peers on the dimensions customers pay for: orders arrive when promised, resources are consumed frugally, and the operation adapts quickly when conditions shift. Scholarship links operational excellence to organizational culture and agility rather than to isolated improvement programs (Carvalho et al., 2019), and the analytics literature has begun to treat it as the proximate arena in which data capabilities do their work: big data analytics has been shown to function as an operational excellence approach that upgrades supply chain outcomes (Bag et al., 2020), to raise manufacturing performance when a supportive data culture is present (Dubey et al., 2019), and to strengthen the operational and dynamic capabilities that in turn produce competitive gains (Mikalef et al., 2020). Davenport and Harris (2007) describe how organisations embed analytics in routine managerial decisions.

The mechanisms are well specified in operations research. Analytics improves the information processing fit between task uncertainty and organizational capacity, with visibility and analytics acting as complements in performance production (Srinivasan & Swink, 2018); it converts data streams into faster and finer operational decisions across planning horizons (Choi et al., 2018); and, under disruption, digital twins and AI-driven analysis shorten detection and recovery cycles (Ivanov et al., 2019; Modgil et al., 2022). Complementary evidence shows that an AI-driven analytics culture fosters the agility and resilience that operations need under pressure (Dubey et al., 2022), and that the performance effect of analytics strengthens with the ambidexterity of the supply chain deploying it (Wamba et al., 2020). Viewed through the dynamic capabilities lens (Schilke et al., 2018), AILA is a sensing-and-reconfiguring capability whose most direct expression is the quality of everyday operating routines.

The three dimensions chosen to represent operational excellence deserve brief justification. Delivery reliability captures conformance to promises, complete orders arriving within committed windows, which is the single most customer-proximate operational attribute in logistics. Process efficiency captures the frugality of resource consumption per unit of service, the dimension that ultimately funds competitive pricing and reinvestment. Operational agility captures the speed and grace with which the operation absorbs volume swings, disruptions, and requirement changes, an attribute whose salience has risen sharply with recent supply chain turbulence. The three co-vary because they draw on shared underlying routines, standardized processes, visibility, and disciplined exception handling, which is why they are modeled as reflections of one higher-order excellence construct rather than as independent outcomes; the measurement results in Section 4 bear this specification out.

2.3 Customer Satisfaction as the Downstream Outcome

Customer satisfaction summarizes the customer's evaluation of a provider against expectations, and decades of evidence tie it to retention, share of wallet, and financial performance (Otto et al., 2020). In logistics-intensive settings, the operational core of the offer dominates that evaluation: research on online retail shows that the last-mile delivery experience mediates the link between the shopping experience and satisfaction (Vakulenko et al., 2019), and the customer journey perspective identifies fulfillment touchpoints as decisive moments of truth (Lemon & Verhoef, 2016). AI also reaches customers directly, through service automation and personalized interaction (Huang & Rust, 2018, 2021), with chatbot studies showing measurable effects on user responses (Adam et al., 2021) and service research finding that AI quality and human service quality jointly shape satisfaction and loyalty (Prentice et al., 2020). Direct channels notwithstanding, for physical-goods businesses the bulk of the customer's experience is manufactured in operations, which is precisely why the mediating role of operational excellence deserves explicit testing.

Two further properties of satisfaction in logistics-intensive markets sharpen the hypotheses. First, expectations ratchet: each improvement in delivery speed or visibility resets the reference point against which future performance is judged, so satisfaction advantages depend on sustained rather than episodic operational superiority, exactly what the excellence construct denotes. Second, in business-to-business relationships, which constitute the majority of the sampled firms' revenue, satisfaction is formed by professional buyers who monitor service-level attainment quantitatively; this tightens the coupling between measured operational performance and reported satisfaction relative to consumer contexts, and it justifies measuring satisfaction through informants' evidence-based assessments of their customer base rather than through general impressions.

2.4 Hypotheses and Research Model

The argument yields four substantive hypotheses and one comparative expectation. Before stating them, two rival accounts deserve acknowledgment because the design must be able to adjudicate them. A substitution account holds that AI creates customer value chiefly by replacing human touchpoints at the interface, which would predict a dominant direct path and weak mediation. A slack account holds that both analytics adoption and customer satisfaction are symptoms of firm prosperity, which would predict that capability effects vanish once size and age are controlled. The hypothesized model embeds both alternatives as testable restrictions: mediation strength adjudicates the first, and control variables adjudicate the second.H1: AILA is positively associated with operational excellence, because analytics upgrades forecasting, scheduling, and exception handling, the routines that constitute excellence (Bag et al., 2020; Srinivasan & Swink, 2018).H2: Operational excellence is positively associated with customer satisfaction, because reliability, efficiency, and agility are the attributes customers experience and evaluate (Otto et al., 2020; Vakulenko et al., 2019).H3: AILA retains a positive direct association with customer satisfaction beyond the operational path, reflecting customer-facing AI applications such as proactive notifications, accurate promise dates, and intelligent service interaction (Huang & Rust, 2021; Prentice et al., 2020).H4: Operational excellence mediates the AILA-satisfaction relationship, consistent with mixed-method evidence that analytics affects performance through intervening capabilities (Mikalef et al., 2019; Mikalef et al., 2020).Finally, H5 anticipates that path strengths differ across industries, because AI adoption in operations is uneven in maturity, constraint, and use-case density across sectors (Grover et al., 2022). Figure 1 depicts the research model, its higher-order measurement structure, and the five hypotheses.

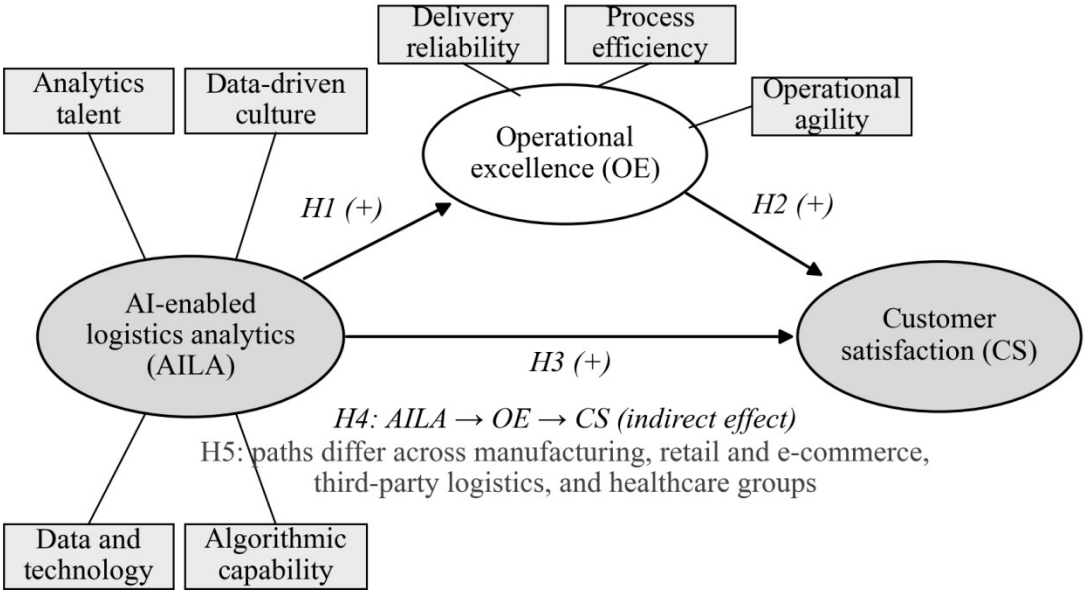


Figure 1. Research Model of AILA, Operational Excellence and Customer Satisfaction

Two features of Figure 1 warrant emphasis before the empirical test. First, both AILA and OE are modeled as reflective-reflective higher-order constructs, so the hypotheses concern capability bundles rather than any single technology or metric; this guards the test against idiosyncrasies of individual tools. Second, the model deliberately includes the direct path H3 alongside the mediated chain, which allows the analysis to distinguish full from partial mediation and to quantify how much of the total AILA effect on satisfaction is operational in origin, the quantity at the heart of RQ1.

The model includes firm size, firm age, and industry as controls for three reasons. Larger firms command more analytics resources and more complex networks simultaneously, so size could induce a spurious association in either direction. Older firms may carry legacy processes that dampen the conversion of capability into excellence. And industry membership bundles demand volatility, regulatory intensity, and customer expectations, which is precisely why it is treated twice: as a control in the pooled model and as the grouping variable for the H5 comparison. Any effect the hypotheses claim must therefore survive these alternative explanations.

3. Research Methodology

3.1 Research Design, Sampling, and Data Collection

A cross-sectional survey design was adopted with the firm as the unit of analysis and a single knowledgeable informant per firm. The sampling frame combined the membership directories of national logistics associations and a commercial business panel covering three Southeast Asian economies. Eligibility required that the firm operate a substantive logistics function, that it had used at least one AI or advanced analytics application in logistics for a minimum of twelve months, and that the informant held a managerial role with direct visibility into both operations and customer outcomes. Invitations were sent to 3,214 qualified contacts in two waves during late 2025; 561 questionnaires were returned, and after removing responses with excessive missing data, failed attention checks, or completion times under one third of the median, 512 usable responses remained, a 15.9 percent effective response rate that is typical for executive surveys in operations research.

Procedural remedies for common method concerns were designed into the instrument in line with current guidance for organizational research [Jordan & Troth, 2020]: predictor and criterion blocks were separated and counterbalanced across versions, item wording was pretested with twelve practitioners and four academics for clarity and neutrality, anonymity was guaranteed, and a theoretically unrelated marker variable was embedded. Non-response bias was assessed by comparing early and late respondents on firm size, industry, and all model constructs; no comparison was significant at the five percent level.

The questionnaire was administered online in English with professionally produced translations into two local languages; translation and back-translation by independent bilingual researchers ensured semantic equivalence, and discrepancies were reconciled in committee. A pilot with 38 respondents, excluded from the main sample, confirmed scale reliability and an acceptable median completion time of fourteen minutes. To anchor responses in evidence rather than aspiration, the instrument opened by asking informants to identify their firm's operating AI applications from a structured checklist and to answer all subsequent items with those applications and the most recent twelve months in mind. Firmographic answers were cross-checked against directory records for a random subsample of 60 firms with 96 percent agreement, supporting informant accuracy.

All constructs were measured with multi-item reflective scales on seven-point Likert response formats anchored at strongly disagree and strongly agree. AILA was operationalized as a higher-order construct with four dimensions adapted from validated analytics and AI capability inventories (Gupta & George, 2016; Mikalef & Gupta, 2021): data and technology infrastructure (four items, e.g., integration of logistics data across sources), algorithmic capability (five items, e.g., deployment of machine-learning models in forecasting and routing), analytics talent (four items), and data-driven culture (four items). Operational excellence comprised three dimensions grounded in the operations literature (Bag et al., 2020; Carvalho et al., 2019): delivery reliability (four items), process efficiency (four items), and operational agility (four items). Customer satisfaction was measured with five items capturing the informant' s evidence-based assessment of the firm's customer base, including satisfaction survey trends, complaint rates, and retention, adapted from service research (Otto et al., 2020; Prentice et al., 2020). Firm size, firm age, and industry served as controls.

Item development balanced fidelity to validated sources with fit to the logistics context. Representative items include, for algorithmic capability, "Our firm routinely uses machine-learning models to forecast demand or shipment volumes" and " Predictive models are embedded in our routing, scheduling, or inventory decisions"; for delivery reliability, "Compared with competitors, our orders arrive within the promised time window more consistently" ; and for customer satisfaction, " Our customer satisfaction indicators have improved over the past twelve months." Where source scales referenced generic information technology, wording was adapted to logistics referents and re-validated in the pretest. Two items, one infrastructure item and one agility item, were dropped after the pilot for redundancy, leaving the 34 indicators analyzed below.

3.2 Analytical Strategy

PLS-SEM was selected because the model contains higher-order constructs, the research goal mixes explanation with prediction, and the estimator is robust for complex models at moderate sample sizes (Hair et al., 2019). Higher-order constructs were estimated with the disjoint two-stage approach following current specification guidance (Sarstedt et al., 2019). Discriminant validity was examined with the heterotrait-monotrait ratio under the thresholds recommended by simulation evidence (Franke & Sarstedt, 2019). Mediation was tested with 10,000 bias-corrected bootstrap samples using the decision logic for PLS mediation analysis (Nitzl et al., 2016). Out-of-sample predictive power was assessed with the PLSpredict procedure (Shmueli et al., 2019). For the multi-industry comparison, measurement invariance was first established with the MICOM procedure (Henseler et al., 2016), after which path differences were evaluated with permutation-based multi-group analysis. Managerial prioritization used the importance-performance

map analysis (IPMA), which contrasts each construct's total effect on the target with its rescaled performance (Ringle & Sarstedt, 2016).

Three further analytical safeguards were specified in advance. Statistical power was verified prospectively: with the maximum number of predictors pointing at any endogenous construct, the smallest group (n = 84) provides power above 0.80 to detect medium effects at the five percent level, and the pooled sample detects even small effects. Significance testing used two-tailed percentile bootstrap intervals throughout, with effect sizes (f^2) reported alongside p-values so that magnitude, not mere detectability, carries the interpretation. Finally, robustness procedures were pre-registered internally: an endogeneity check using the Gaussian copula approach, an alternative-model comparison in which the causal ordering of excellence and satisfaction is reversed, and a test for quadratic effects of AILA, the results of which are reported with the structural model.4. Results

4.Empirical Analysis and Results

4.1 Sample Profile

The realized sample spans the four target industries in proportions broad enough to support group analysis, covers the full range of firm sizes, and draws on informants whose roles guarantee first-hand knowledge of both analytics deployments and customer outcomes. Table 1 reports the profile of the 512 responding firms and informants.

Table 1. Profile of Responding Firms and Informants (N = 512)

Characteristic	Category	Frequency	Percentage (%)
Industry	Manufacturing	168	32.8
	Retail and e-commerce	142	27.7
	Third-party logistics	118	23.0
	Healthcare and pharmaceuticals	84	16.4
Firm size (employees)	Fewer than 250	161	31.4
	250 to 999	195	38.1
	1,000 or more	156	30.5
Informant role	Logistics or supply chain director	211	41.2
	Operations manager	172	33.6
	Senior executive	129	25.2

Three sample properties matter for interpretation. The smallest industry group, healthcare and pharmaceuticals with 84 firms, still exceeds common minimum-size guidance for PLS group analysis of models with this path complexity, so H5 can be tested without pooling. The near-even split across firm-size bands limits the risk that any industry contrast merely proxies scale. And the informant mix, dominated by logistics directors and operations managers, matches the constructs being rated: these are the roles that see analytics deployments, operational metrics, and customer feedback simultaneously. Mean AI tenure in logistics was 3.4 years, indicating that respondents evaluate operating applications rather than pilots.

Descriptive statistics locate the sample on the response scales. The four AILA dimensions average between 4.61 (analytics talent) and 5.08 (data and technology infrastructure) on the seven-point scale, with standard deviations from 1.02 to 1.21, indicating meaningful dispersion rather than uniform enthusiasm; the ordering itself foreshadows the importance-performance findings, with infrastructure rated highest and talent lowest. The operational excellence dimensions average between 4.92 (operational agility) and 5.31 (delivery reliability), and customer satisfaction averages 5.17 (SD = 1.05). Inter-construct correlations range from 0.42 to 0.66, high enough to motivate the structural model and low enough to leave discriminant validity intact, as the formal tests in the next subsection confirm. Skewness and kurtosis remain within conventional bounds for all indicators, though the bootstrap inference used throughout does not depend on normality.

4.2 Measurement Model Assessment

The measurement model was evaluated at the first-order level before constructing the higher-order composites. All 34 retained indicators load above the 0.70 threshold on their intended constructs, and every construct exceeds conventional benchmarks for internal consistency and convergent validity. Table 2 summarizes the reliability and validity statistics.

Table 2. Reliability and Convergent Validity of First-Order Constructs

Construct	Items	Loadings range	Cronbach's alpha	CR	AVE
Data and technology infrastructure	4	0.78–0.88	0.86	0.90	0.70
Algorithmic capability	5	0.74–0.87	0.88	0.91	0.67
Analytics talent	4	0.79–0.89	0.87	0.91	0.71
Data-driven culture	4	0.76–0.86	0.84	0.89	0.68
Delivery reliability	4	0.77–0.88	0.85	0.90	0.69
Process efficiency	4	0.72–0.85	0.83	0.88	0.65
Operational agility	4	0.75–0.86	0.84	0.89	0.66
Customer satisfaction	5	0.79–0.90	0.90	0.92	0.70

Beyond the statistics in Table 2, discriminant validity holds throughout: the largest heterotrait-monotrait ratio is 0.78, comfortably below the conservative 0.85 criterion (Franke & Sarstedt, 2019). At the second stage, the four AILA dimensions load between 0.82 and 0.90 on the higher-order capability and the three OE dimensions between 0.84 and 0.89 on operational excellence, supporting the higher-order specification (Sarstedt et al., 2019). Full collinearity VIF values remain below 3.0 and the marker variable is uncorrelated with all substantive constructs, so common method variance is unlikely to account for the results; the structural model can be interpreted (Jordan & Troth, 2020).

Additional diagnostics reinforce the measurement conclusion. The rho-A reliability coefficient, which brackets Cronbach's alpha and composite reliability, lies between 0.85 and 0.91 for all constructs; every indicator loads at least 0.15 higher on its own construct than on any other, so cross-loadings raise no concern beyond the HTMT evidence; and outer VIF values peak at 2.6, well below collinearity thresholds (Hair et al., 2019). Because the multi-group analysis in Section 4.5 requires comparable measurement across industries, it also bears noting here that all loadings remain above 0.70 within each industry subsample, an informal precursor to the formal MICOM tests reported there (Henseler et al., 2016).

4.3 Structural Model and Hypothesis Tests

The structural model was estimated on the full sample with 10,000 bootstrap resamples and controls for firm size, firm age, and industry. The model explains 41.2 percent of the variance in operational excellence and 43.4 percent in customer satisfaction, with a standardized root mean square residual of 0.052. Table 3 presents the path estimates and hypothesis decisions.

Table 3. Structural Path Estimates and Hypothesis Decisions

Structural path	β	t-value	p-value	f^2	Decision
H1: AILA → Operational excellence	0.612	14.87	< 0.001	0.60	Supported
H2: Operational excellence → CS	0.517	10.42	< 0.001	0.31	Supported
H3: AILA → CS (direct)	0.186	3.65	< 0.001	0.05	Supported
H4: AILA → OE → CS (indirect)	0.316	8.94	< 0.001	—	Supported

Table 3 tells a clear story about where the action is. The capability-to-operations link (H1) is by far the strongest relationship in the model, with a large effect size of 0.60, whereas the direct capability-to-satisfaction link (H3), though significant, carries only a small effect of 0.05. Neither control variable reaches significance (firm size beta = 0.07, firm age beta = 0.03), indicating that the modeled capabilities, not scale or longevity, drive the outcomes. In predictive terms, PLSpredict shows every customer satisfaction indicator with a lower RMSE than the naive linear-model benchmark [Shmueli et al., 2019], so the model generalizes beyond the estimation sample rather than merely fitting it.

The pre-registered robustness checks support the reported structure. The Gaussian copula terms for AILA and for operational excellence are both non-significant ($p > 0.10$), providing no evidence that unmodeled endogeneity inflates the focal paths. The alternative model that reverses the mediator and the outcome, routing AILA through satisfaction to excellence, fits decisively worse, with lower explained variance in both endogenous constructs and a Bayesian information criterion penalty of 214 relative to the hypothesized model, so the theorized ordering is empirically preferred even within cross-sectional data. A quadratic term for AILA on excellence is negligible ($f^2 = 0.003$), indicating no detectable saturation across the observed capability range: within this sample, additional analytics capability continues to purchase additional operational improvement at an approximately constant rate.

4.4 Mediation Analysis

The mediation test follows the bootstrap-based decision tree for PLS models [Nitzl et al., 2016]. The indirect effect of AILA on customer satisfaction through operational excellence equals 0.316 with a 95 percent bias-corrected confidence interval of [0.262, 0.373], which excludes zero, while the direct effect remains positive and significant. Both effects point in the same direction, so the pattern is complementary partial mediation: operational excellence transmits the dominant share of the influence, 63.0 percent of the total effect of 0.502, without exhausting it. Substantively, roughly two units of every three by which analytics capability raises customer satisfaction are delivered through better operations, and the remaining third flows through customer-facing channels such as accurate promises, proactive exception communication, and intelligent service interactions. H4 is therefore supported, and RQ1 receives a quantified answer.

Decomposing the mediator clarifies which face of excellence carries the effect. Re-estimating the model with the three first-order dimensions as parallel mediators shows that all three transmit significant indirect effects, with delivery reliability the largest conduit (0.118, 95 percent CI [0.079, 0.161]), followed by process efficiency (0.104, CI [0.066, 0.146]) and operational agility (0.094, CI [0.058, 0.135]); the three confidence

intervals overlap, so no single dimension monopolizes the mechanism. The ordering nevertheless matches the customer-proximity logic developed in Section 2: what customers reward most immediately is the promise kept, then the cost position that efficient processes enable, then the adaptability they experience mainly during disruptions. For managers, the decomposition warns against equating operational excellence with cost alone; the reliability channel is the single largest carrier of analytics value to customers.

4.5 Multi-Group Analysis Across Industries

Before comparing groups, the MICOM procedure established configural invariance and partial measurement invariance for all constructs across the four industries (Henseler et al., 2016), licensing path-level comparison. The mediation structure replicates everywhere: in each industry the indirect effect[object Object]Before comparing groups, the MICOM procedure established configural invariance is positive and its confidence interval excludes zero. Path magnitudes, however, are not uniform. Figure 2 compares the three structural paths across the four industry groups.

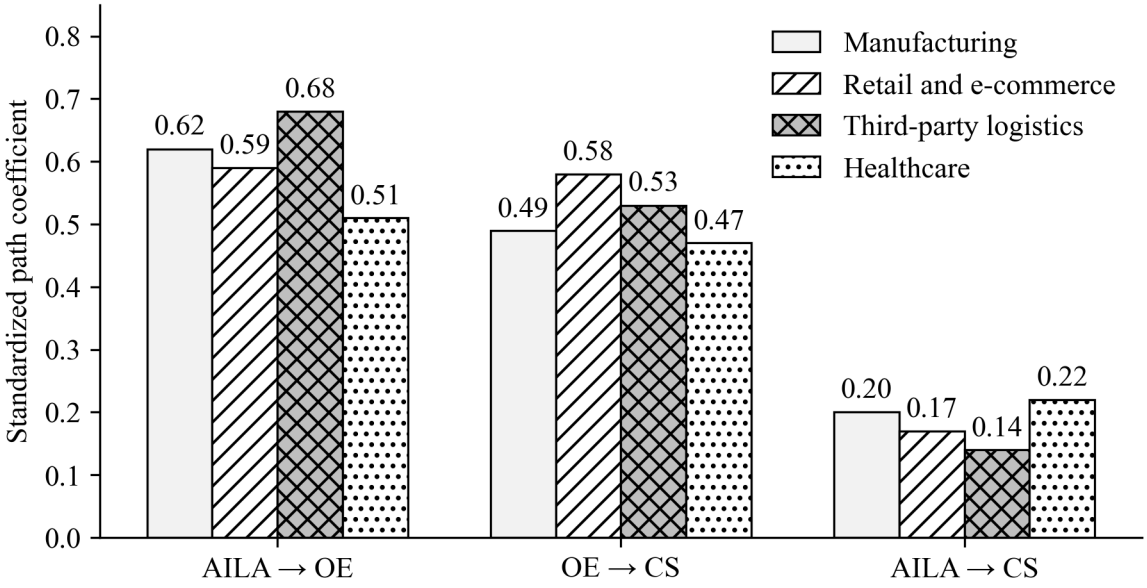


Figure 2. Standardized Path Coefficients across Industry Groups

Two contrasts in Figure 2 are statistically reliable under the permutation test. The AILA-to-excellence path is strongest for third-party logistics providers (0.68) and weakest in healthcare and pharmaceuticals (0.51), a difference of 0.17 ($p = 0.031$); and the excellence-to-satisfaction path peaks in retail and e-commerce (0.58) against the healthcare low of 0.47, a difference of 0.11 ($p = 0.048$). All remaining pairwise contrasts, including every comparison of the direct path, are non-significant. The pattern is interpretable: logistics is the entire product for third-party providers, so analytics feeds directly into their core routines, whereas regulatory validation requirements in healthcare slow the conversion of models into changed practice; and in retail and e-commerce the customer feels operational performance immediately through delivery experience [Vakulenko et al., 2019]. H5 is thus partially supported: the mechanism is general, its gain varies.

Group-level statistics round out the comparison. Explained variance in operational excellence is highest among third-party logistics providers ($R^2 = 0.48$) and lowest in healthcare (0.29), with manufacturing (0.40) and retail and e-commerce (0.38) in between; for customer satisfaction the ordering compresses (0.36 to 0.47), because the direct path partially offsets the weaker operational conversion in healthcare. The indirect effect is significant in every group, ranging from 0.240 in healthcare (95 percent CI [0.148, 0.334]) to 0.360 in third-party logistics (CI [0.281, 0.442]), and the proportion mediated stays between 55 and 68 percent across groups. In other words, industries differ in how much satisfaction a unit of analytics capability ultimately

buys, but not in the route by which it is bought; the operational channel dominates everywhere the study looked.

4.6 Importance-Performance Analysis

To translate the estimates into priorities (RQ3), an importance-performance map was computed at the dimension level, plotting each first-order dimension' s total effect on customer satisfaction against its performance rescaled to a 0–100 range Ringle & Sarstedt, 2016 . Figure 3 presents the map for the pooled sample.

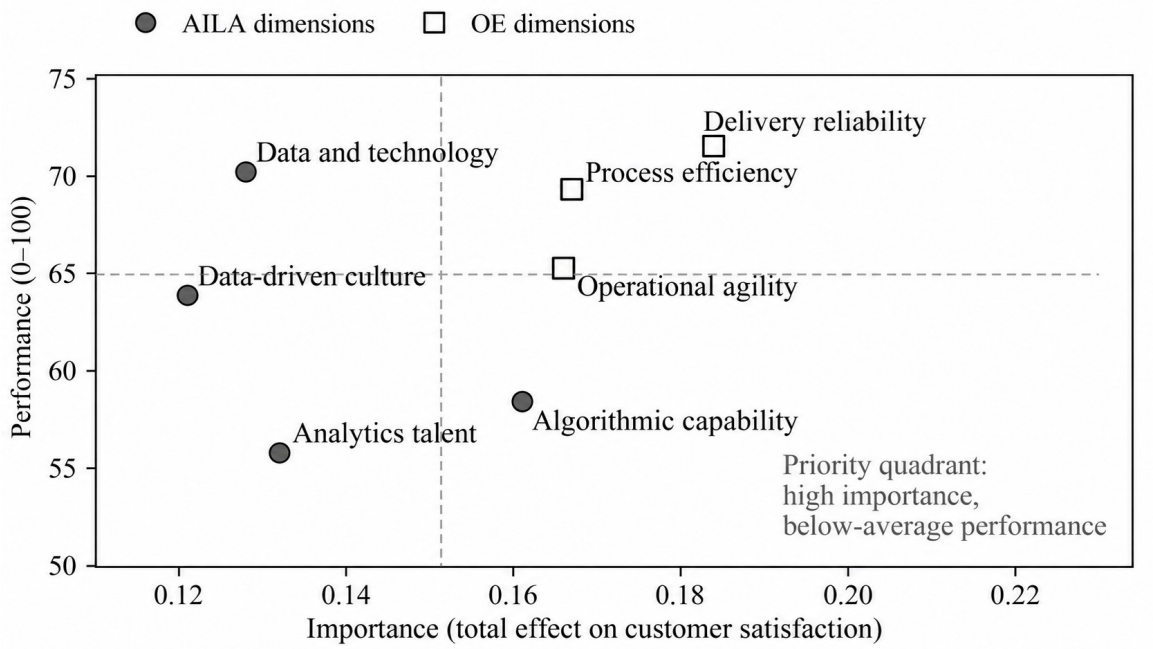


Figure 3. Importance-Performance Map of AILA and OE Dimensions

Figure 3 exposes an actionable asymmetry. Delivery reliability combines the highest importance (0.184) with the highest performance (71.5), confirming that firms already concentrate effort where customers are most sensitive. The priority quadrant, high importance with below-average performance, is occupied by algorithmic capability (importance 0.161, performance 58.4) and, just below the importance mean, analytics talent (55.7): the ingredients of AILA that are hardest to buy off the shelf are precisely those lagging furthest behind their leverage. Data and technology infrastructure, by contrast, performs well (70.2) but carries the lowest importance, suggesting that many firms have over-weighted the visible hardware of analytics relative to the models and people that convert it into operating advantage.

Industry-specific maps, computed as a supplementary analysis, preserve the pooled pattern with instructive local accents. Algorithmic capability sits in the priority quadrant for all four industries, but its performance deficit is deepest in healthcare (52.9), where validation burdens slow model deployment, and shallowest in third-party logistics (62.7), consistent with that sector's stronger conversion path. Analytics talent is a priority in manufacturing and healthcare but approaches the performance mean in retail and e-commerce, where labor markets for data roles are deeper. Delivery reliability remains the top-right anchor in every industry, confirming that the reliability channel identified in the mediation decomposition is not an artifact of pooling.

Because IPMA importance values are total effects on the rescaled target, they support a direct ceteris-paribus reading that managers can use for expectation setting. A one-point improvement in the performance of algorithmic capability, on the 0–100 scale, is associated with a 0.161-point gain in customer satisfaction on the same scale, holding the remaining dimensions constant; closing that dimension's 13-point gap to the

delivery-reliability benchmark would therefore be worth roughly 2.1 satisfaction points, the largest single improvement available anywhere on the map. Comparable arithmetic for analytics talent yields about 2.0 points, while further investment in already-strong infrastructure offers less than half of either figure. These are associational projections, not experimental guarantees, but they order the improvement agenda on a common customer-denominated scale, which is precisely the decision support that separates an importance-performance analysis from a list of significant paths.

5. Discussion

The central finding is that the customer value of AI in logistics is manufactured mainly on the shop floor and the road, not at the interface. Nearly two thirds of the total effect of analytics capability on customer satisfaction travels through operational excellence, and the capability's largest single consequence is the upgrading of operational routines themselves ($f^2 = 0.60$). This places the study's results in continuity with the capability-mediation tradition, which finds analytics acting through intervening organizational capabilities rather than directly on outcomes [Mikalef et al., 2020; Mikalef et al., 2019], while extending it in two ways: the mediator is specified as the delivery-facing excellence customers actually experience, and the outcome is the satisfaction of the firm's customer base rather than self-reported firm performance.

The surviving direct path is theoretically informative rather than residual noise. Its magnitude (0.186) is consistent with the growing body of service research in which AI touches customers without any change in physical operations, through anticipatory communication, precise promise dates, and automated service recovery [Huang & Rust, 2018; Adam et al., 2021; Prentice et al., 2020]. A model that forced full mediation would misdescribe firms whose analytics investments are weighted toward the customer interface; the complementary partial mediation observed here accommodates both routes and quantifies their relative weight.

The industry contrasts discipline the generalization. That the capability-to-excellence conversion is strongest in third-party logistics supports an absorptive interpretation: where logistics is the core business, analytics meets dense use cases, short decision loops, and undivided managerial attention [Grover et al., 2022]. The healthcare attenuation is equally instructive; validation and compliance requirements insert deliberate friction between model output and practice change, so identical capability produces less immediate operational movement. Importantly, the mediation mechanism itself held in every group, which argues that the theory travels across sectors even while its exchange rate varies, the pattern multi-industry research is designed to detect.

Finally, the importance-performance results speak to a familiar imbalance in digital investment. Infrastructure scores high on performance but low on leverage, while algorithmic capability and talent, the classic intangible complements identified since the earliest capability studies [Gupta & George, 2016; Wamba et al., 2017], remain the binding constraints. The finding echoes field evidence that AI value realization stalls on organizational rather than technical grounds [Enholm et al., 2022; Dwivedi et al., 2021] and gives that diagnosis a quantitative, satisfaction-anchored form.

The magnitudes reported here are plausible against the wider evidence base rather than outliers. The capability-to-performance associations in prior firm-level analytics studies typically fall in the 0.3 to 0.6 range for proximate outcomes and decay for distal ones [Wamba et al., 2017; Mikalef et al., 2019]; the present estimates reproduce exactly that gradient, 0.612 for the proximate operational outcome, 0.502 total and 0.186 direct for the distal customer outcome, which is the signature of a genuinely mediated system. Two design features likely sharpen the estimates relative to earlier work: restricting the sample to firms with at least a year of operating AI applications removes pilot-stage noise, and anchoring satisfaction in evidence-based informant assessments reduces the halo that purely perceptual outcome measures invite.

Neither feature manufactures the mediation structure, but both reduce the attenuation that has muddied earlier direct-effect designs.

The design also speaks to the rival accounts posed in Section 2.4. The substitution account, under which AI's customer value is primarily interfacial, is contradicted by the effect decomposition: the direct path carries barely a third of the total effect, and its effect size is an order of magnitude smaller than the operational path's. The slack account, under which prosperity produces both analytics and satisfaction, is weakened on three fronts: size and age controls are non-significant, the copula terms detect no endogeneity, and the reversed-ordering model fits decisively worse. Cross-sectional data cannot eliminate every causal alternative, but the surviving interpretation, capability improving operations improving satisfaction, is the one the data consistently prefer over its articulated competitors.

6. Theoretical and Managerial Implications

6.1 Theoretical Implications

Three contributions follow for theory. First, the study specifies and validates a mediating mechanism, operational excellence, that converts a digital capability into a customer outcome, thereby opening the black box left by direct capability-performance designs. Second, by modeling AILA as a four-dimensional higher-order capability and demonstrating measurement invariance across industries, it supplies a transferable measurement apparatus for AI capability research in operations contexts. Third, the cross-industry replication with calibrated differences refines dynamic capabilities theory: the sensing-to-reconfiguration conversion is general, but its rate is governed by industry clock speed and regulatory friction, a boundary condition that single-sector studies cannot observe. A methodological corollary deserves mention: reporting the proportion mediated (63 percent here) alongside path coefficients gives future studies a comparable quantity for meta-analysis, which coefficient-only reporting does not, and the dimension-level mediation decomposition offers a template for locating mechanisms inside higher-order mediators rather than treating them as monoliths.

6.2 Managerial Implications

For executives, the results reorder the AI business case. Because two thirds of the customer payoff arrives through operations, AI programs in logistics should be owned jointly by analytics and operations leadership and should be evaluated on operational metrics, on-time delivery, cost per order, and recovery time, before customer metrics are expected to move. The importance-performance map converts this into budget language: incremental spending shifts from infrastructure, which is already performing, toward model development and analytics talent, the high-leverage laggards. For third-party logistics providers, the strong conversion rate justifies aggressive analytics differentiation; for healthcare logistics, managers should pair every model deployment with a validation pathway so that regulatory necessity does not become organizational inertia. Finally, the significant direct path warns against a purely internal focus: promise accuracy, proactive notification, and intelligent service interaction are satisfaction levers in their own right and can be activated while deeper operational transformation matures (Huang & Rust, 2021; Lemon & Verhoef, 2016; Prentice et al., 2020; Vakulenko et al., 2019).

The findings also translate into a sequencing logic for AI programs. In the near term, effort is best spent wiring existing models into the routines the mediation analysis identified as the widest conduits: promise-date setting, exception detection, and recovery workflows that protect delivery reliability. Over a medium horizon, the priority-quadrant deficits argue for building model-development capacity and analytics staffing ahead of further infrastructure expansion, including rotation programs that seat analysts inside operations teams so that data-driven culture is practiced rather than proclaimed. Progress should be instrumented as a chain, capability measures feeding operational metrics feeding customer indicators, because the study's core

result is precisely that these links are where AI value is created or lost; a program that tracks only endpoints will not see failures of conversion until customers do.

7. Limitations and Future Research

The design imposes qualifications. The data are cross-sectional, so the paths carry theoretical rather than demonstrated temporal direction; panel designs tracking firms through AI scale-up would strengthen causal claims. Single informants rated all constructs; although procedural remedies, marker-variable tests, and collinearity diagnostics indicate that method variance is not driving the results (Jordan & Troth, 2020), matched dyads pairing operations informants with actual customer-side satisfaction data would be more stringent. Customer satisfaction was assessed as the informant's evidence-based summary of the customer base; linking firm surveys to transaction-level or survey-based customer data is a natural extension. The sample is drawn from three Southeast Asian economies, and institutional differences may condition the exchange rates observed here. Future work should also decompose the mediator, testing whether reliability, efficiency, and agility transmit different shares of the effect, examine disruption periods where AI-enabled resilience becomes salient (Ivanov et al., 2019; Modgil et al., 2022), and follow the technology frontier as generative and autonomous AI enter planning and customer interaction (Duan et al., 2019; Huang & Rust, 2021; Toorajipour et al., 2021).

Measurement itself offers a further frontier. The AILA scale treats algorithmic capability as a single dimension, yet forecasting, optimization, and interaction models may convert into excellence at different rates; item-level archives collected for this study suggest heterogeneity worth modeling explicitly. Likewise, operational excellence was measured perceptually against competitors; pairing the survey with audited service-level data for a subsample would allow calibration of perceptual bias, and satisfaction measured directly from customers of the responding firms would close the remaining inferential gap in the chain.

8. Conclusion

This study asked whether, how, and where AI-enabled logistics analytics turns into satisfied customers. Across 512 firms in four industries, the answer is consistent: analytics capability raises customer satisfaction primarily by producing operational excellence, which transmits 63 percent of the total effect, while a smaller direct route operates through customer-facing intelligence. The mechanism replicated in every industry examined, with its strength calibrated by sector characteristics, strongest where logistics is the business itself and most attenuated where regulation slows the conversion of models into practice. The dimension-level analysis located the binding constraints in algorithmic capability and analytics talent rather than infrastructure. For research, the study delivers a validated cross-industry mediation model of AI value creation in logistics; for practice, it delivers a simple ordering principle: in logistics, AI earns customer loyalty by first earning operational discipline.

As AI systems continue to migrate from decision support toward autonomous execution, the mechanism documented here is likely to strengthen rather than fade: the more directly algorithms operate the logistics system, the more completely their quality will be expressed as operational performance before customers ever encounter it. Firms that build the conversion machinery now, talent, models, and the routines that absorb them, will therefore compound their advantage as the technology frontier advances.

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Author Contributions

Conceptualization, J.H.D. and S.B.H.; Methodology, J.H.D. and S.B.H.; Formal Analysis, J.H.D. and S.B.H.; Investigation, J.H.D. and Z.Q.W.; Data Curation, J.H.D. and Z.Q.W.; Software, J.H.D. and Z.Q.W.; Validation, J.H.D. and S.B.H. and Z.Q.W.; Resources, Z.Q.W.; Visualization, J.H.D. and Z.Q.W.; Writing – Original Draft, J.H.D.; Writing – Review & Editing, J.H.D. and S.B.H. and Z.Q.W.; Supervision, S.B.H.; Project Administration, J.H.D. and S.B.H. We have read and approved the final manuscript and take responsibility for the work.

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Conflicts of Interest

The authors declare no financial or professional conflicts of interest that could affect the objectivity of the research design, data analysis and conclusions.

Ethical Approval and Consent

This study adopted a questionnaire survey method. All respondents participated voluntarily with informed consent, and all response data were anonymized and aggregated for analysis without involving identifiable personal or sensitive business information, conforming to ethical norms of social science research.

Data Availability Statement

Core scale items, structural model parameters, path coefficients and effect sizes are fully presented in the tables and figures of the main text. The raw survey data cannot be publicly disclosed due to confidentiality commitments with participating enterprises. The statistical analysis code is available from the corresponding author upon reasonable request, subject to data use specifications.

Declaration of Generative AI Use

Generative AI tools were used to assist with language polishing of the manuscript and initial drafting of diagrams, including the research model diagram, cross-industry path coefficient chart, and importance-performance map. All AI-assisted content has been carefully reviewed and verified by the authors, who take full responsibility for the final content of the manuscript.

References

Adam, M., Wessel, M., & Benlian, A. (2021). AI-based chatbots in customer service and their effects on user compliance. Electronic Markets, 31(2), 427–445. https://doi.org/10.1007/s12525-020-00414-7

Akter, S., Wamba, S. F., Gunasekaran, A., Dubey, R., & Childe, S. J. (2016). How to improve firm performance using big data analytics capability and business strategy alignment? International Journal of Production Economics, 182, 113–131. https://doi.org/10.1016/j.ijpe.2016.08.018

Azadeh, K., De Koster, R., & Roy, D. (2019). Robotized and Automated Warehouse Systems: Review and Recent Developments. Transportation Science, 53(4), 917–945. https://doi.org/10.1287/trsc.2018.0873

Bag, S., Wood, L. C., Xu, L., Dhamija, P., & Kayikci, Y. A. (2020). Big data analytics as an operational excellence approach to enhance sustainable supply chain performance. Resources, Conservation and Recycling, 153, 104559. https://doi.org/10.1016/j.resconrec.2019.104559

Baryannis, G., Validi, S., Dani, S., & Antoniou, G. (2019). Supply chain risk management and artificial intelligence: state of the art and future research directions. International Journal of Production Research, 57(7), 2179–2202. https://doi.org/10.1080/00207543.2018.1530476

Ben-Daya, M., Hassini, E., & Bahroun, Z. (2019). Internet of things and supply chain management: a literature review. International Journal of Production Research, 57(15-16), 4719–4742. https://doi.org/10.1080/00207543.2017.1402140

Carvalho, A. M., Sampaio, P., Rebentisch, E., Carvalho, J. Á., & Saraiva, P. (2019). Operational excellence, organisational culture and agility: the missing link? Total Quality Management & Business Excellence, 30(13-14), 1495–1514. https://doi.org/10.1080/14783363.2017.1374833

Choi, T.-M., Wallace, S. W., & Wang, Y. (2018). Big Data Analytics in Operations Management. Production and Operations Management, 27(10), 1868–1883. https://doi.org/10.1111/poms.12838

Davenport, T. H., & Harris, J. G. (2007). Competing on analytics: The new science of winning. Harvard Business School Press.

Duan, Y., Edwards, J. S., & Dwivedi, Y. K. (2019). Artificial intelligence for decision making in the era of Big Data – evolution, challenges and research agenda. International Journal of Information Management, 48, 63–71. https://doi.org/10.1016/j.ijinfomgt.2019.01.021

Dubey, R., Bryde, D. J., Dwivedi, Y. K., Graham, G., & Foropon, C. (2022). Impact of artificial intelligence-driven big data analytics culture on agility and resilience in humanitarian supply chain: A practice-based view. International Journal of Production Economics, 250, 108618. https://doi.org/10.1016/j.ijpe.2022.108618

Dubey, R., Gunasekaran, A., Childe, S. J., Blome, C., & Papadopoulos, T. (2019). Big Data and Predictive Analytics and Manufacturing Performance: Integrating Institutional Theory, Resource-Based View and Big Data Culture. British Journal of Management, 30(2), 341–361. https://doi.org/10.1111/1467-8551.12355

Dwivedi, Y. K., Hughes, L., Ismagilova, E., Aarts, G., Coombs, C., Crick, T., Duan, Y., Dwivedi, R., Edwards, J., Eirug, A., Galanos, V., Ilavarasan, P. V., Janssen, M., Jones, P., Kar, A. K., Kizgin, H., Kronemann, B., Lal, B., Lucini, B., ... Williams, M. D. (2021). Artificial Intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy. International Journal of Information Management, 57, 101994. https://doi.org/10.1016/j.ijinfomgt.2019.08.002

Enholm, I. M., Papagiannidis, E., Mikalef, P., & Krogstie, J. (2022). Artificial Intelligence and Business Value: a Literature Review. Information Systems Frontiers, 24(5), 1709–1734. https://doi.org/10.1007/s10796-021-10186-w

Franke, G., & Sarstedt, M. (2019). Heuristics versus statistics in discriminant validity testing: a comparison of four procedures. Internet Research, 29(3), 430–447. https://doi.org/10.1108/intr-12-2017-0515

Grover, P., Kar, A. K., & Dwivedi, Y. K. (2022). Understanding artificial intelligence adoption in operations management: insights from the review of academic literature and social media discussions. Annals of Operations Research, 308(1-2), 177–213. https://doi.org/10.1007/s10479-020-03683-9

Gunasekaran, A., Papadopoulos, T., Dubey, R., Wamba, S. F., Childe, S. J., Hazen, B., & Akter, S. (2017). Big data and predictive analytics for supply chain and organizational performance. Journal of Business Research, 70, 308–317. https://doi.org/10.1016/j.jbusres.2016.08.004

Gupta, M., & George, J. F. (2016). Toward the development of a big data analytics capability. Information & Management, 53(8), 1049–1064. https://doi.org/10.1016/j.im.2016.07.004

Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. European Business Review, 31(1), 2–24. https://doi.org/10.1108/ebr-11-2018-0203

Henseler, J., Ringle, C. M., & Sarstedt, M. (2016). Testing measurement invariance of composites using partial least squares. International Marketing Review, 33(3), 405–431. https://doi.org/10.1108/imr-09-2014-0304

Huang, M.-H., & Rust, R. T. (2018). Artificial Intelligence in Service. Journal of Service Research, 21(2), 155–172. https://doi.org/10.1177/1094670517752459

Huang, M.-H., & Rust, R. T. (2021). A strategic framework for artificial intelligence in marketing. Journal of the Academy of Marketing Science, 49(1), 30–50. https://doi.org/10.1007/s11747-020-00749-9

Ivanov, D., Dolgui, A., & Sokolov, B. (2019). The impact of digital technology and Industry 4.0 on the ripple effect and supply chain risk analytics. International Journal of Production Research, 57(3), 829–846. https://doi.org/10.1080/00207543.2018.1488086

Jordan, P. J., & Troth, A. C. (2020). Common method bias in applied settings: The dilemma of researching in organizations. Australian Journal of Management, 45(1), 3–14. https://doi.org/10.1177/0312896219871976

Lasi, H., Fettke, P., Kemper, H.-G., Feld, T., & Hoffmann, M. (2014). Industry 4.0. Business & Information Systems Engineering, 6(4), 239–242. https://doi.org/10.1007/s12599-014-0334-4

Lemon, K. N., & Verhoef, P. C. (2016). Understanding Customer Experience Throughout the Customer Journey. Journal of Marketing, 80(6), 69–96. https://doi.org/10.1509/jm.15.0420

Makridakis, S., Spiliotis, E., & Assimakopoulos, V. (2018). Statistical and Machine Learning forecasting methods: Concerns and ways forward. PLOS ONE, 13(3), e0194889. https://doi.org/10.1371/journal.pone.0194889

Mikalef, P., & Gupta, M. (2021). Artificial intelligence capability: Conceptualization, measurement calibration, and empirical study on its impact on organizational creativity and firm performance. Information & Management, 58(3), 103434. https://doi.org/10.1016/j.im.2021.103434

Mikalef, P., Boura, M., Lekakos, G., & Krogstie, J. (2019). Big data analytics and firm performance: Findings from a mixed-method approach. Journal of Business Research, 98, 261–276. https://doi.org/10.1016/j.jbusres.2019.01.044

Mikalef, P., Krogstie, J., Pappas, I. O., & Pavlou, P. (2020). Exploring the relationship between big data analytics capability and competitive performance: The mediating roles of dynamic and operational capabilities. Information & Management, 57(2), 103169. https://doi.org/10.1016/j.im.2019.05.004

Modgil, S., Singh, R. K., & Hannibal, C. (2022). Artificial intelligence for supply chain resilience: learning from Covid-19. The International Journal of Logistics Management, 33(4), 1246–1268. https://doi.org/10.1108/ijlm-02-2021-0094

Nguyen, T., Zhou, L., Spiegler, V., Ieromonachou, P., & Lin, Y. (2018). Big data analytics in supply chain management: A state-of-the-art literature review. Computers & Operations Research, 98, 254–264. https://doi.org/10.1016/j.cor.2017.07.004

Nitzl, C., Roldan, J. L., & Cepeda, G. (2016). Mediation analysis in partial least squares path modeling: Helping researchers discuss more sophisticated models. Industrial Management & Data Systems, 116(9), 1849–1864. https://doi.org/10.1108/imds-07-2015-0302

Otto, A. S., Szymanski, D. M., & Varadarajan, R. (2020). Customer satisfaction and firm performance: insights from over a quarter century of empirical research. Journal of the Academy of Marketing Science, 48(3), 543–564. https://doi.org/10.1007/s11747-019-00657-7

Prentice, C., Dominique Lopes, S., & Wang, X. (2020). The impact of artificial intelligence and employee service quality on customer satisfaction and loyalty. Journal of Hospitality Marketing & Management, 29(7), 739–756. https://doi.org/10.1080/19368623.2020.1722304

Ringle, C. M., & Sarstedt, M. (2016). Gain more insight from your PLS-SEM results: The importance-performance map analysis. Industrial Management & Data Systems, 116(9), 1865–1886. https://doi.org/10.1108/imds-10-2015-0449

Sarstedt, M., Hair, J. F., Cheah, J.-H., Becker, J.-M., & Ringle, C. M. (2019). How to Specify, Estimate, and Validate Higher-Order Constructs in PLS-SEM. Australasian Marketing Journal, 27(3), 197–211. https://doi.org/10.1016/j.ausmj.2019.05.003

Schilke, O., Hu, S., & Helfat, C. E. (2018). Quo Vadis, Dynamic Capabilities? A Content-Analytic Review of the Current State of Knowledge and Recommendations for Future Research. Academy of Management Annals, 12(1), 390–439. https://doi.org/10.5465/annals.2016.0014

Seyedan, M., & Mafakheri, F. (2020). Predictive big data analytics for supply chain demand forecasting: methods, applications, and research opportunities. Journal of Big Data, 7(1), 53. https://doi.org/10.1186/s40537-020-00329-2

Shmueli, G., Sarstedt, M., Hair, J. F., Cheah, J.-H., Ting, H., Vaithilingam, S., & Ringle, C. M. (2019). Predictive model assessment in PLS-SEM: guidelines for using PLSpredict. European Journal of Marketing, 53(11), 2322–2347. https://doi.org/10.1108/ejm-02-2019-0189

Srinivasan, R., & Swink, M. (2018). An Investigation of Visibility and Flexibility as Complements to Supply Chain Analytics: An Organizational Information Processing Theory Perspective. Production and Operations Management, 27(10), 1849–1867. https://doi.org/10.1111/poms.12746

Toorajipour, R., Sohrabpour, V., Nazarpour, A., Oghazi, P., & Fischl, M. (2021). Artificial intelligence in supply chain management: A systematic literature review. Journal of Business Research, 122, 502–517. https://doi.org/10.1016/j.jbusres.2020.09.009

Vakulenko, Y., Shams, P., Hellström, D., & Hjort, K. (2019). Service innovation in e-commerce last mile delivery: Mapping the e-customer journey. Journal of Business Research, 101, 461–468. https://doi.org/10.1016/j.jbusres.2019.01.016

Verhoef, P. C., Broekhuizen, T., Bart, Y., Bhattacharya, A., Qi Dong, J., Fabian, N., & Haenlein, M. (2021). Digital transformation: A multidisciplinary reflection and research agenda. Journal of Business Research, 122, 889–901. https://doi.org/10.1016/j.jbusres.2019.09.022

Vial, G. (2019). Understanding digital transformation: A review and a research agenda. The Journal of Strategic Information Systems, 28(2), 118–144. https://doi.org/10.1016/j.jsis.2019.01.003

Wamba, S. F., Dubey, R., Gunasekaran, A., & Akter, S. (2020). The performance effects of big data analytics and supply chain ambidexterity: The moderating effect of environmental dynamism. International Journal of Production Economics, 222, 107498. https://doi.org/10.1016/j.ijpe.2019.09.019

Wamba, S. F., Gunasekaran, A., Akter, S., Ren, S. J.-F., Dubey, R., & Childe, S. J. (2017). Big data analytics and firm performance: Effects of dynamic capabilities. Journal of Business Research, 70, 356–365. https://doi.org/10.1016/j.jbusres.2016.08.009

Wang, G., Gunasekaran, A., Ngai, E. W. T., & Papadopoulos, T. (2016). Big data analytics in logistics and supply chain management: Certain investigations for research and applications. International Journal of Production Economics, 176, 98–110. https://doi.org/10.1016/j.ijpe.2016.03.014

Winkelhaus, S., & Grosse, E. H. (2020). Logistics 4.0: a systematic review towards a new logistics system. International Journal of Production Research, 58(1), 18–43. https://doi.org/10.1080/00207543.2019.1612964