Manar Elsharq Journal
For Management and Commerce Studies
ISSN: 2959-0655 (Print)
http://meijournals.com/ara/index.php/mejcms/index

AI-Optimized Sustainable Last-Mile Delivery in E-Commerce: Challenges, Solutions, and Policy Recommendations for Azerbaijan

Mohammed Binjaah[1] - Professor Aliyeva Kamala[2]
Department of Artificial Intelligence, Azerbaijan State Oil and Industry University, Baku, Azerbaijan
* Correspondence: mohammed.binjaah@asoiu.edu.az

ARTICLE INFO

Received: 20 Mar
Accepted: 23 Apr
Volume: 4
Issue: 2

Abstract

Last-mile delivery constitutes the most cost-intensive, environmentally burdensome, and operationally complex segment of e-commerce supply chains. In Azerbaijan, where e-commerce turnover has expanded by over 200 per cent since 2019 while logistics infrastructure maturity remains constrained, the sustainability challenges inherent in last-mile operations are intensifying. This paper investigates how artificial intelligence (AI) technologies can be leveraged to optimize last-mile delivery in ways that simultaneously improve operational efficiency, reduce environmental impact, and enhance service quality within Azerbaijan's e-commerce ecosystem. Integrating the Technology–Organization–Environment (TOE) framework with the dynamic capability's perspective, the study develops and empirically tests a moderated mediation model. Primary survey data from 285 logistics professionals are analyzed using Partial Least Squares Structural Equation Modelling (PLS-SEM). The results demonstrate that AI adoption significantly strengthens smart logistics capability ($\beta = 0.437$, $p < 0.001$), which in turn improves last-mile delivery performance ($\beta = 0.523$, $p < 0.001$). Capability mediates 64 per cent of AI's total effect on performance. Data quality and organizational readiness significantly moderate the respective pathway stages, with the conditional indirect effect nearly quadrupling under favorable enabling conditions compared to unfavorable ones. The paper contributes context-specific evidence from an under-studied emerging market, demonstrates the empirical validity of capability-based AI value creation in sustainable last-mile logistics, and derives five actionable policy recommendations for Azerbaijan's national digital logistics strategy. The findings underscore that technology procurement alone is insufficient; sustainable last-mile improvement requires coordinated investment in data governance, workforce analytics capabilities, and organisational transformation.

Keywords: artificial intelligence; last–mile delivery; sustainable logistics; e–commerce; smart logistics capability; Azerbaijan; PLS–SEM; emerging markets; data quality; organisational readiness; dynamic capabilities; TOE framework.

1. Introduction

The rapid proliferation of e-commerce has fundamentally reshaped the logistics landscape, elevating last-mile delivery—the final transportation segment between a distribution facility and the end consumer—from a routine operational function to a strategic focal point for competitive differentiation, environmental accountability, and customer experience management. By most industry estimates, last-mile delivery accounts for between 40 and 53 per cent of total supply chain logistics costs while representing less than a quarter of total transport distance, a disparity that reflects the inherent inefficiency of dispersing large numbers of individual parcels across heterogeneous urban and peri-urban destinations (Boysen, Fedtke, & Schwerdfeger, 2021; Mangiaracina, Perego, Seghezzi, & Tumino, 2019). Concurrently, last-mile operations are responsible for a disproportionate share of urban freight emissions, contributing to localized air pollution, greenhouse gas accumulation, noise disturbance, and traffic congestion—externalities that are increasingly subject to regulatory scrutiny and public concern (Ranieri, Digiesi, Silvestri, & Roccotelli, 2018).

The convergence of these pressures creates what may be characterized as a sustainability trilemma for last-mile logistics providers: the simultaneous imperative to reduce delivery costs (economic sustainability), decrease environmental footprint (environmental sustainability), and improve service speed and reliability (social and customer-facing sustainability). Traditional approaches to last-mile management—static routing, experience-based dispatching, and reactive exception handling—are increasingly inadequate for resolving this trilemma in the face of escalating order volumes, shrinking delivery-time expectations, and growing regulatory pressure for carbon reduction (Olsson, Hellström, & Palerås, 2019).

Artificial intelligence (AI) has emerged as a potentially transformative enabler for addressing the last-mile sustainability trilemma. AI-powered dynamic routing can reduce vehicle-kilometres travelled by 10–25 per cent compared to static alternatives; predictive demand models can improve load consolidation and reduce the number of partially loaded delivery runs; and exception-prediction algorithms can lower failed-delivery rates—each failed attempt generating a return trip, rescheduled delivery, and additional customer contact that inflates both costs and emissions (Pournader, Ghaderi, Hassanzadegan, & Fahimnia, 2021; Khedr & Sheeja Rani, 2024). Taken together, these applications promise a qualitative shift from reactive, schedule-driven last-mile operations toward adaptive, data-driven delivery execution.

However, a growing body of empirical evidence cautions against treating AI as a plug-and-play remedy. The translation of AI's analytical capabilities into sustained operational improvement depends on intermediate organizational processes—capabilities for sensing environmental changes, seizing decision opportunities, and transforming operational routines—that many logistics organizations, particularly in emerging markets, have not yet developed (Culot, Podrecca, & Nassimbeni, 2024; Teece, 2018). Moreover, the effectiveness of AI-enabled optimization is conditioned by data quality and organizational readiness, two enabling factors that are heterogeneously distributed across firms and especially constrained in economies where digital infrastructure and analytical talent remain scarce (Uren & Edwards, 2023; UNCTAD, 2024).

Azerbaijan offers a particularly instructive context for investigating these dynamics. The country's e-commerce sector has expanded sharply, with total turnover growing from 12.4 billion AZN in 2019 to 39.2 billion AZN in 2023, while cashless payment penetration rose from 28.4 to 55.6 per cent over the same period (Central Bank of Azerbaijan, 2024). Electronic retail trade turnover grew from 2.586 million AZN in 2013 to 118.076 million AZN in 2023 (CESD, 2024). Yet logistics infrastructure maturity remains constrained: Azerbaijan's Logistics Performance Index score of approximately 2.89/5.0 reveals persistent gaps in tracking and tracing, logistics competence, and infrastructure quality (World Bank, 2023). The resulting combination—rapidly growing demand for last-mile delivery services alongside limited supply-side capability—makes Azerbaijan a theoretically and practically significant site for examining whether and how AI can deliver sustainable last-mile improvements.

Against this background, the present paper addresses three interrelated research questions: (RQ1) To what extent does AI adoption improve last-mile delivery performance through the development of smart logistics capability? (RQ2) Do data quality and organisational readiness moderate the strength of this capability-mediated pathway? (RQ3) What policy recommendations can be derived from the empirical findings to support Azerbaijan's national digital logistics strategy? The paper contributes to the literature in three ways: first, by providing integrated empirical evidence from an under-studied emerging market; second, by demonstrating the applicability of a moderated mediation framework to the specific domain of sustainable last-mile delivery; and third, by bridging the persistent gap between academic AI-logistics research and actionable policy guidance.

2. Literature Review and Theoretical Background

2.1 The Last-Mile Sustainability Challenge

Last-mile delivery is widely recognized as the most operationally challenging and environmentally consequential segment of e-commerce logistics. The fundamental structural difficulty lies in the disaggregation of consolidated freight flows into individual deliveries to dispersed residential destinations, which prevents the economies of scale that characterize upstream transport segments. Each delivery stop involves non-productive time—parking search, building access, customer interaction, proof-of-delivery recording—that cumulatively dominates driver hours and suppresses vehicle utilization rates. In urban environments, average vehicle utilization for parcel delivery rarely exceeds 50 per cent of volumetric capacity, and a substantial proportion of driving time is spent on low-speed maneuvering rather than productive inter-stop transit (Boysen et al., 2021; Mangiaracina et al., 2019).

The environmental burden of last-mile delivery has attracted increasing scholarly and policy attention. Urban freight vehicles contribute approximately 25 per cent of transport-related CO_2 emissions in European cities, a share that has been rising as e-commerce volumes grow (Ranieri et al., 2018). Failed deliveries—conservatively estimated at 5–12 per cent of first-attempt deliveries depending on market, product category, and delivery model—compound the environmental cost by generating return trips that effectively double the emissions intensity of those parcels. The emergence of instant-delivery and same-day fulfilment expectations further exacerbates the problem by fragmenting delivery batches and reducing consolidation opportunities (Lim, Jin, & Srai, 2018; Olsson et al., 2019).

From a triple-bottom-line perspective, sustainable last-mile delivery requires simultaneous progress across three dimensions. Economic sustainability demands that cost per delivery remains commercially viable as volume grows and service expectations escalate. Environmental sustainability requires reductions in carbon emissions per parcel, local air pollutant intensity, and traffic congestion attributable to delivery vehicles. Social sustainability encompasses considerations of driver working conditions, equitable geographic access to delivery services, and the impact of delivery operations on urban livability. The challenge confronting both practitioners and policymakers is that these dimensions frequently tension against one another: faster delivery typically increases emissions per parcel, while cost reduction through route optimization may concentrate service improvements in high-density areas at the expense of peripheral communities (Christopher, 2016; Simchi-Levi, Kaminsky, & Simchi-Levi, 2014).

Table 1. Research gaps in AI-enabled sustainable last-mile delivery

Gap identified	**Evidence**	**How this paper responds**
Direct-effect models dominate; mediating mechanisms under-tested	Culot et al. (2024): 85-study SLR finds capability mechanisms rarely tested	Tests mediation through smart logistics capability (sensing, seizing, transforming)
Boundary conditions discussed conceptually but rarely modelled formally	Hazen et al. (2014); Uren & Edwards (2023): DQ and OR	Formally tests DQ and OR as moderators within moderated mediation model

	identified but not tested as moderators	
Evidence concentrated in advanced economies	UNCTAD (2024): persistent data divides between advanced and developing economies	Provides context-specific evidence from Azerbaijan's emerging e-commerce ecosystem
Sustainability dimension of AI-logistics under-integrated	Mangiaracina et al. (2019); Ranieri et al. (2018): sustainability and AI literatures remain siloed	Integrates sustainability indicators into last-mile performance measurement

2.2 AI Applications for Sustainable Last-Mile Delivery

The application of AI to last-mile delivery spans several interconnected operational domains, each contributing distinct mechanisms through which the sustainability trilemma can be addressed.

Dynamic route optimization employs mathematical programming solvers augmented with machine learning to generate delivery sequences that minimize total distance, time, or fuel consumption while satisfying heterogeneous constraints including delivery time windows, vehicle capacity, driver hours, and customer preferences. When integrated with real-time traffic data, GPS-based driver tracking, and customer availability predictions, these systems enable continuous re-routing during execution—a capability that static routing approaches cannot provide. Empirical evaluations report vehicle-kilometre reductions of 10–25 per cent compared to experience-based routing, with proportionate reductions in fuel consumption and tailpipe emissions (Boysen et al., 2021; Winkenbach, Kleindorfer, & Spinler, 2016). Reinforcement learning approaches offer additional potential by discovering routing policies that adapt to recurring urban congestion patterns, seasonal demand shifts, and zone-specific delivery success probabilities.

Demand forecasting and load consolidation leverage gradient boosting, LSTM networks, and ensemble methods to predict order volumes at fine spatial and temporal granularity. Accurate short-term forecasts enable logistics providers to pre-position inventory, schedule labour, and consolidate parcels into fuller loads, thereby reducing the number of delivery runs required per geographic zone. Models that incorporate promotional calendars, weather data, marketplace signals, and historical seasonality patterns can improve forecast accuracy by 15–30 per cent over naïve baselines, translating into measurably higher vehicle utilization rates and fewer partially loaded trips (Khedr & Sheeja Rani, 2024; Carbonneau, Laframboise, & Bhargava, 2008).

Predictive delivery success and exception management address one of the most significant sources of waste in last-mile operations: failed delivery attempts. By modelling delivery success probability as a function of address characteristics, historical outcomes, customer behaviour, time-of-day, and weather conditions, AI systems can trigger proactive interventions—pre-delivery contact, time-window adjustment, redirection to parcel lockers or collection points—before a failure occurs. Reducing the failed delivery rate from a typical 8–10 per cent to 4–5 per cent eliminates roughly half of the associated return trips, with meaningful cost, emissions, and customer satisfaction benefits (Toorajipour et al., 2021; Baryannis, Dani, & Antoniou, 2019).

ETA prediction and proactive communication provide customers with accurate estimated delivery times, reducing the probability that recipients will be absent when the courier arrives. AI-based ETA models incorporating real-time traffic, stop-sequence progress, and historical stop-time distributions can achieve prediction accuracy within 15–20 minute windows—a substantial improvement over the 2–4 hour windows typical of traditional scheduling (Baryannis et al., 2019).

Fleet electrification and modal shift support constitute an increasingly important application domain. EV routing must account for battery range constraints, charging infrastructure locations, and energy consumption variation with load weight, terrain, and temperature. AI-enabled energy-consumption prediction and charge scheduling allow logistics providers to maximize EV utilization within operational constraints, accelerating fleet electrification and reducing the well-to-wheel carbon intensity of last-mile delivery. Similarly, AI-based demand clustering can identify zones suitable for cargo bicycle or micro-hub operations, enabling modal shifts that further reduce emissions in dense urban cores (Figliozzi, 2020).

2.3 Capability-Based AI Value Creation: Theoretical Foundations

The relationship between AI adoption and operational performance is neither automatic nor direct. A growing body of theoretical and empirical work, anchored in the dynamic capabilities framework (Teece, 2018), argues that technology creates sustained performance advantages only when it is embedded within organizational routines that enable sensing (detecting changes in the operational environment), seizing (coordinating rapid responses to those changes), and transforming (learning from operational feedback and reconfiguring routines accordingly). In the last-mile delivery context, sensing manifests as real-time detection of emerging delivery exceptions, demand surges, or route disruptions; seizing manifests as dynamic re-routing, resource reassignment, and proactive customer communication; and transforming manifests as systematic improvement of prediction models, process redesign, and governance adaptation based on accumulated operational experience.

Culot et al. (2024), in a systematic review of 85 empirical studies on AI in supply chain management, find that performance benefits are most consistently observed when AI is embedded within end-to-end operational processes and supported by cross-functional coordination, rather than deployed as isolated point solutions. Mikalef and Gupta (2021) demonstrate empirically that AI capability—configured as a composite of technological, human, and organizational resources—drives firm performance through orchestration rather than mere resource possession. Dubey et al. (2020) provide complementary evidence that BDA-AI capability improves operational performance contingent on strategic orientation and environmental dynamism. Fosso Wamba et al. (2017) show that dynamic capabilities mediate the analytics-to-performance relationship. This study builds on these foundations by proposing smart logistics capability—defined as the integrated development of sensing, seizing, and transforming routines in last-mile delivery—as the mediating mechanism through which AI adoption translates into sustainable performance improvement.

2.4 Enabling Conditions: Data Quality and Organizational Readiness

Two enabling conditions are theorized to moderate the strength of the AI-capability-performance pathway. Data quality—defined following Wang and Strong (1996) as the accuracy, completeness, timeliness, and consistency of operational data—moderates the AI adoption–capability link because AI models are fundamentally constrained by the data on which they are trained and operationally deployed. In last-mile delivery, critical data streams include address databases and geocoding records, real-time vehicle and courier tracking, customer availability histories, delivery outcome records, and traffic and weather feeds. When these data are fragmented across disconnected systems, delayed in transmission, or contaminated by inaccuracies, AI outputs become unreliable, user trust erodes, and the translation of AI tools into operational capability is impaired (Hazen et al., 2014; Sculley et al., 2015; Amershi et al., 2019).

Organizational readiness—encompassing technology infrastructure, analytical workforce skills, governance mechanisms, leadership commitment, and cross-functional coordination capacity—moderates the capability–performance link. Even when an organization has developed substantial sensing, seizing, and transforming capabilities, performance improvement depends on the organizational structures that enable AI-informed decisions to be executed consistently at operational scale. Readiness is particularly heterogeneous in emerging markets, where talent scarcity, limited cloud adoption, dependence on third-party vendor solutions, and institutional constraints on data sharing can impede the operationalization of analytical capabilities (Uren & Edwards, 2023; Jöhnk et al., 2021; EBRD, 2024).

3. Hypotheses Development

Drawing on the theoretical foundations established above, the study proposes six hypotheses that collectively specify a moderated mediation model linking AI adoption to sustainable last-mile delivery performance through smart logistics capability, conditioned by data quality and organizational readiness.

AI technologies provide the informational and analytical substrate upon which sensing, seizing, and transforming routines are constructed. Predictive models generate the intelligence that feeds sensing; optimization algorithms produce the recommendations that enable seizing; and feedback-driven learning systems provide the mechanism for transforming. Without AI adoption, the development of these routines is constrained to what manual analysis and traditional decision-support tools can produce—a level increasingly insufficient for the volume and velocity of modern e-commerce logistics. Accordingly:

H1: AI adoption has a positive effect on smart logistics capability in last-mile delivery.

Smart logistics capability enables organizations to translate analytical intelligence into coordinated operational action. Sensing capability improves delivery visibility and exception detection; seizing capability enables adaptive routing, dispatching, and customer communication; and transforming capability drives continuous process improvement and model refinement. These mechanisms directly influence the efficiency (cost reduction through optimization), effectiveness (service reliability through exception management), and sustainability (emissions reduction through vehicle-kilometre minimisation) dimensions of last-mile performance. Accordingly:

H2: Smart logistics capability has a positive effect on last-mile delivery performance, including sustainability outcomes.

The capability-mediation argument implies that AI's performance effect operates primarily through an indirect pathway—adoption → capability → performance—rather than through direct technology-to-performance substitution. While a residual direct effect may exist (e.g., through basic automation), the dominant mechanism is capability development. Accordingly:

H3: Smart logistics capability mediates the relationship between AI adoption and last-mile delivery performance.

The effectiveness of AI in building capability depends on the quality of the data available for model training and operational inference. High-quality data enables reliable predictions and trustworthy recommendations; low-quality data produces unstable outputs that undermine user confidence and impede capability development. Accordingly:

H4: Data quality positively moderates the AI adoption–smart logistics capability relationship.

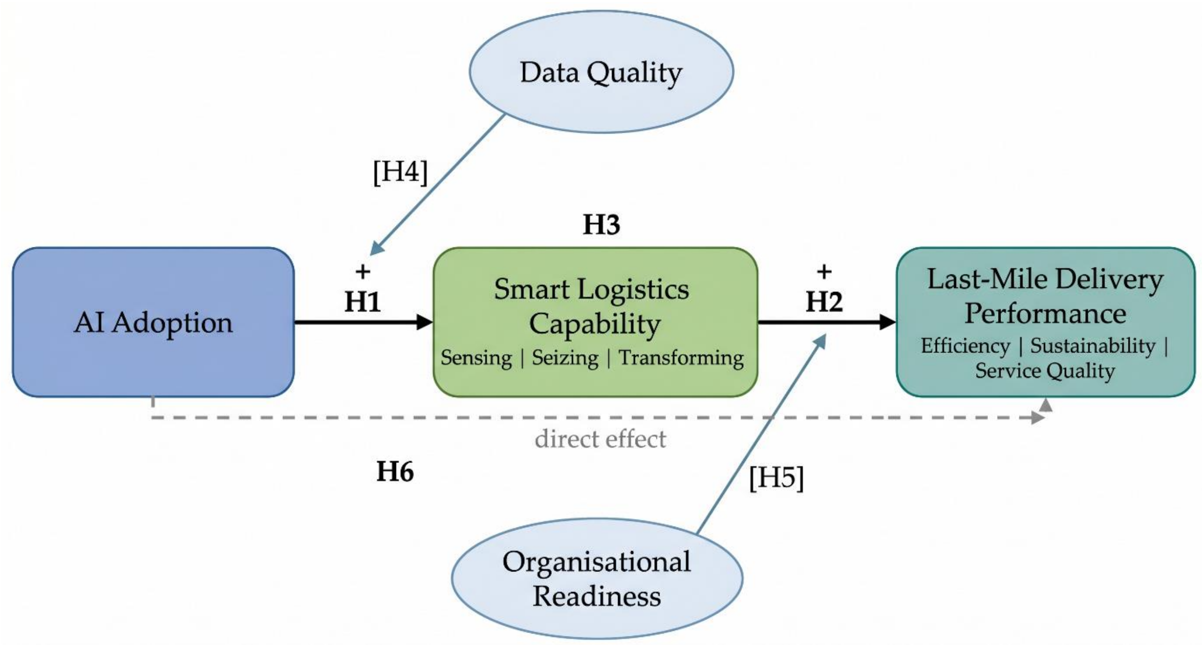
The conversion of capability into performance depends on organizational conditions that enable consistent execution of AI-informed decisions. High readiness—encompassing skills, governance, infrastructure, and leadership—amplifies the performance returns to capability; low readiness constrains this conversion. Accordingly:

H5: Organizational readiness positively moderates the smart logistics capability–performance relationship.

Integrating the mediation and moderation arguments, the full indirect pathway from AI adoption to performance is expected to be conditional on both data quality and organizational readiness operating simultaneously. Accordingly:

H6: The indirect effect of AI adoption on performance through smart logistics capability is conditional on data quality and organizational readiness (moderated mediation).

Figure 1. Conceptual model: AI-optimized sustainable last-mile delivery.



4. Methodology

4.1 Research Design

A cross-sectional explanatory survey design was employed to test the hypothesized moderated mediation model. Data were collected between March and May 2025 from professionals working in e-commerce logistics organizations in Azerbaijan, targeting respondents with direct operational exposure to last-mile delivery processes and familiarity with AI-related tools or analytics applications. The cross-sectional design is standard in technology adoption and supply chain capability research, though it requires explicit attention to common-method bias and the limitations of cross-sectional data for causal inference. These concerns were addressed through procedural design features (construct separation in the questionnaire, respondent anonymity, varied scale anchors) and statistical diagnostics detailed below.

4.2 Sample and Data Collection

A purposive sampling strategy was adopted. Inclusion criteria required respondents to: (a) work in an organization with active e-commerce logistics operations (including platforms, retailers, 3PLs, courier services, and fulfilment providers); (b) possess at least six months of professional experience in a logistics, analytics, IT, or operational management role; and (c) have awareness of the organization's use of analytics or automation tools relevant to logistics. A total of 350 questionnaires were distributed through organizational contact persons, professional networks, and industry associations, using a mixed-mode approach combining an online survey platform and paper-based instruments for field staff with limited digital access. Follow-up reminders were issued at one and two weeks after initial distribution. Of 292 returned questionnaires, 285 met eligibility and completeness criteria, yielding an 81.4 per cent usable response rate.

Table 2. Respondent profile (N = 285)

Characteristic	**Categories**	**Distribution**
Role type	Managerial / Technical	54.0% / 46.0%
Organization type	3PL / E-commerce platform / Courier / Other	31.2% / 28.4% / 22.8% / 17.6%
Experience	6–24 months / 2–5 years / >5 years	18.6% / 43.5% / 37.9%
Organization size	<50 / 50–249 / 250+ employees	29.8% / 41.4% / 28.8%
AI adoption stage	Exploring / Piloting / Scaling / Embedded	22.5% / 34.7% / 27.0% / 15.8%

4.3 Measurement

All constructs were measured using multi-item scales adapted from validated instruments. AI adoption (6 items) was adapted from Davenport and Ronanki (2018) and Wamba-Taguimdje et al. (2020), capturing the breadth and depth of AI tool implementation in last-mile delivery processes. Data quality (5 items) drew on Wang and Strong (1996) and Batini and Scannapieco (2016), assessing accuracy, completeness, timeliness, and consistency of operational logistics data. Organizational readiness (6 items) was adapted from Weiner (2009) and Uren and Edwards (2023), spanning technology infrastructure, analytical skills, governance, and leadership dimensions. Smart logistics capability was specified as a formative second-order construct with three reflective first-order dimensions: sensing (4 items), seizing (3 items), and transforming (3 items), drawing on Teece (2018) and Hofmann and Rüsch (2017). Logistics performance (6 items) was adapted from Mentzer et al. (2001) and extended to incorporate sustainability indicators including delivery vehicle-kilometres per order, failed delivery rate, and consolidation effectiveness. All items used 7-point Likert scales. The survey was translated into Azerbaijani using a forward-backward procedure reviewed by two bilingual domain experts. A pilot test (n = 25) confirmed item clarity and acceptable completion time.

4.4 Analytical Approach

Partial Least Squares Structural Equation Modelling (PLS-SEM) was conducted using SmartPLS 4 (Ringle, Wende, & Becker, 2024), following the two-stage measurement-thenstructural protocol of Hair et al. (2022). Bootstrapping with 5,000 resamples was used throughout. Common method bias was assessed through three complementary diagnostics: Harman's single-factor test (no factor exceeded 35% of total variance), full-collinearity VIF assessment (all values below 3.3, per Kock, 2015), and a theoretically unrelated marker variable approach. All diagnostics indicated that common method bias is unlikely to substantially influence the findings. Nonresponse bias was evaluated by comparing early and late respondent quartiles on all construct indicators; no significant differences were found (Armstrong & Overton, 1977). Control variables included organisation size (log-transformed), respondent experience, and AI adoption stage.

5. Results

5.1 Measurement Model Evaluation

All reflective indicator loadings exceeded the 0.70 threshold (range: 0.724–0.912). Internal consistency was confirmed through Cronbach's α (all > 0.82), composite reliability (all > 0.88), and rho_A (all > 0.83). Convergent validity was established through AVE exceeding 0.50 for all reflective constructs (range: 0.617–0.727). Discriminant validity was confirmed through the HTMT criterion, with all inter-construct ratios below the 0.85 threshold. For the formative second-order SLC construct, VIF values for sensing (1.724), seizing (1.893), and transforming (1.651) were below the 3.3 threshold, and all dimension weights were statistically significant ($p < 0.001$).

Table 3. Measurement model: reliability and validity

Construct	Loading range	α	CR	rho_A	AVE
AI Adoption	0.758–0.891	0.893	0.919	0.897	0.657
Data Quality	0.785–0.912	0.907	0.930	0.911	0.727
Org. Readiness	0.724–0.868	0.875	0.905	0.881	0.617
SLC—Sensing	0.809–0.889	0.861	0.906	0.866	0.708
SLC—Seizing	0.773–0.876	0.842	0.894	0.849	0.680
SLC—Transforming	0.752–0.861	0.823	0.883	0.830	0.654
Logistics Performance	0.741–0.895	0.901	0.923	0.905	0.668

Note. α = Cronbach's alpha; CR = composite reliability; AVE = average variance extracted.

Table 4. Discriminant validity: HTMT matrix

	AIA	DQ	OR	SLC
DQ	0.614			
OR	0.571	0.683		
SLC	0.742	0.691	0.658	
LP	0.583	0.627	0.715	0.813

Note. All values < 0.85, confirming discriminant validity.

5.2 Structural Model

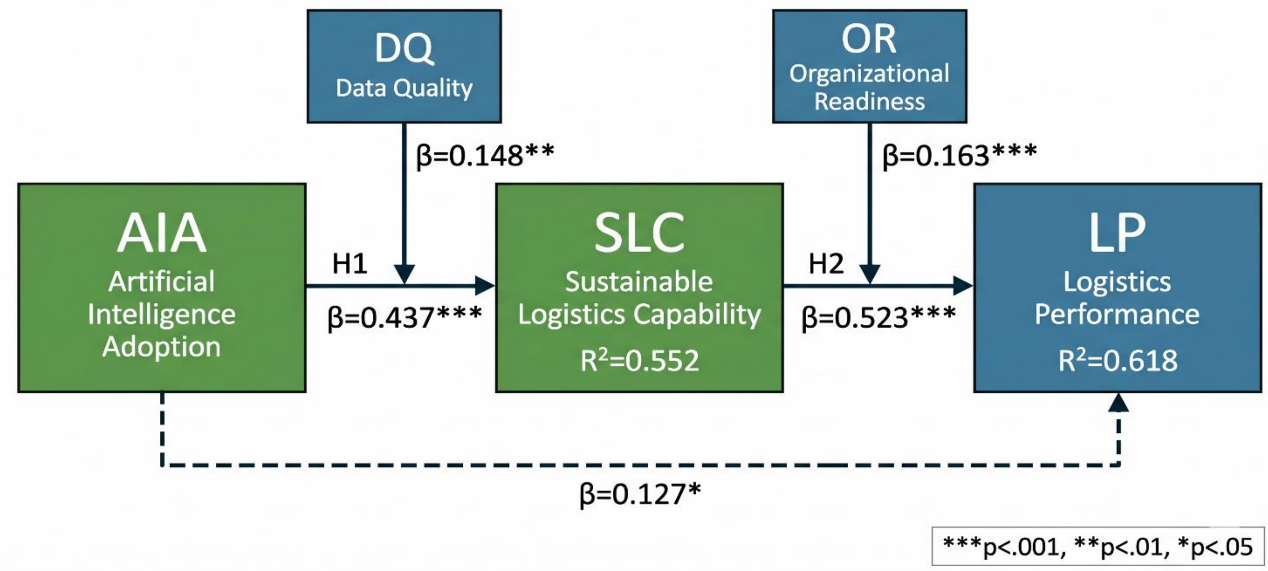
The structural model explains 55.2 per cent of the variance in SLC ($R^2 = 0.552$) and 61.8 per cent in LP ($R^2 = 0.618$). Stone-Geisser Q^2 values (SLC: 0.389; LP: 0.421) confirm satisfactory predictive relevance. PLSpredict analysis indicates medium-to-high out-of-sample predictive power, with five of six LP indicators achieving lower RMSE under PLS than under a naïve linear benchmark. SRMR is 0.058, below the 0.08 threshold.

Table 5. Structural model results: path coefficients and hypothesis testing

H	Path	β	t	p	f²	Decision
H1	AIA → SLC	0.437	7.824	<.001	0.251	Supported
H2	SLC → LP	0.523	9.156	<.001	0.342	Supported
—	AIA → LP (direct)	0.127	2.341	.019	0.021	Significant (small)
H4	AIA × DQ → SLC	0.148	3.127	.002	0.032	Supported
H5	SLC × OR → LP	0.163	3.458	<.001	0.038	Supported

Note. 5,000 bootstrap resamples. Controls: organisation size, experience, AI adoption stage.

Figure 2. Structural model with empirical results.



5.3 Mediation and Conditional Effects

The bootstrapped indirect effect of AI adoption on performance through smart logistics capability is 0.228 (95% CI: [0.167, 0.294]), confirming statistically significant mediation (H3 supported). The indirect effect accounts for 64 per cent of the total effect (0.355), indicating that capability development constitutes the principal channel through which AI creates operational value in last-mile delivery. The complementary partial mediation pattern—with a residual direct effect of 0.127—suggests that a modest portion of AI's performance contribution operates independently of capability development, plausibly through basic automation mechanisms that require minimal organizational reconfiguration.

Simple slopes analysis reveals that at high data quality (+1 SD), the AIA→SLC effect is 0.585, compared to 0.289 at low data quality (−1 SD)—approximately a two-fold difference. Similarly, at high organizational readiness, the SLC→LP effect is 0.686, versus 0.360 at low readiness. The index of moderated mediation is 0.024 (95% CI: [0.008, 0.047]), confirming that the indirect pathway is conditional on both moderators operating simultaneously (H6 supported). At simultaneously high DQ and OR, the conditional indirect effect reaches 0.401; at simultaneously low levels, it falls to 0.104—a nearly four-fold difference with substantial practical implications.

Table 6. Conditional indirect effects of AI adoption on performance

Moderator condition	Indirect effect	95% CI LL	95% CI UL
High DQ + High OR	0.401	0.298	0.516
High DQ + Low OR	0.211	0.138	0.290
Low DQ + High OR	0.198	0.124	0.281
Low DQ + Low OR	0.104	0.042	0.178
Index of moderated mediation	0.024	0.008	0.047

Figure 3. Conditional indirect effects across moderator conditions.

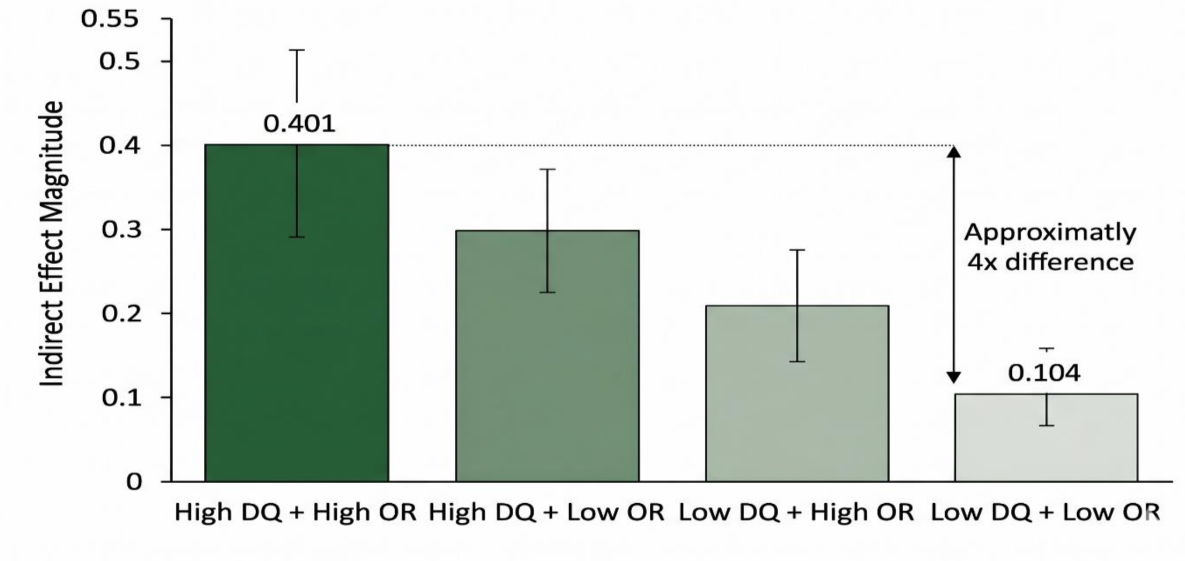


Figure 4.
Interaction plot: data quality as moderator of AI adoption → SLC

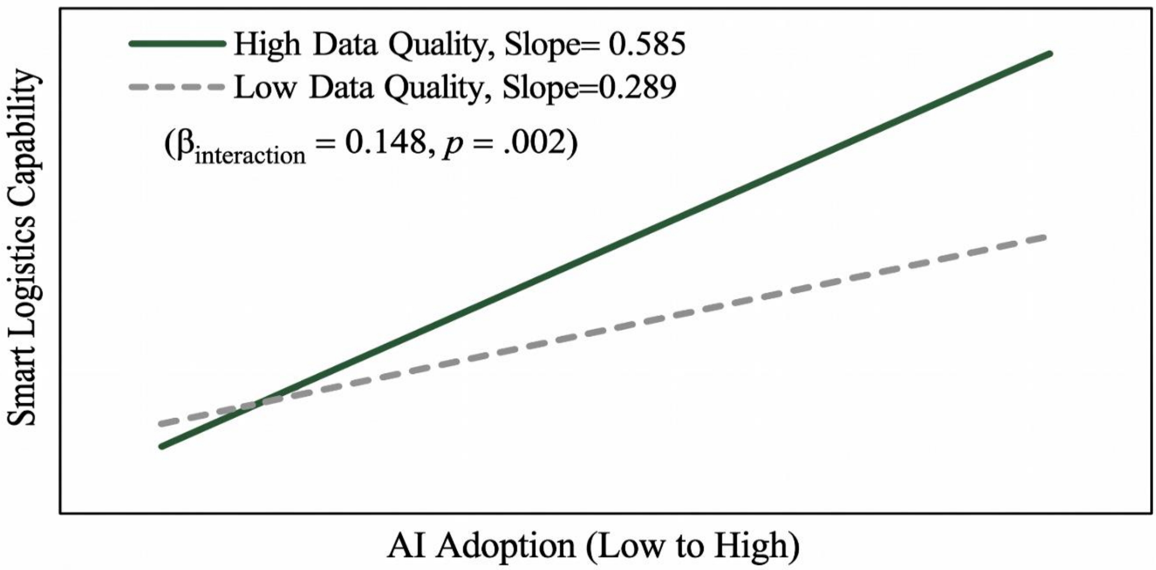
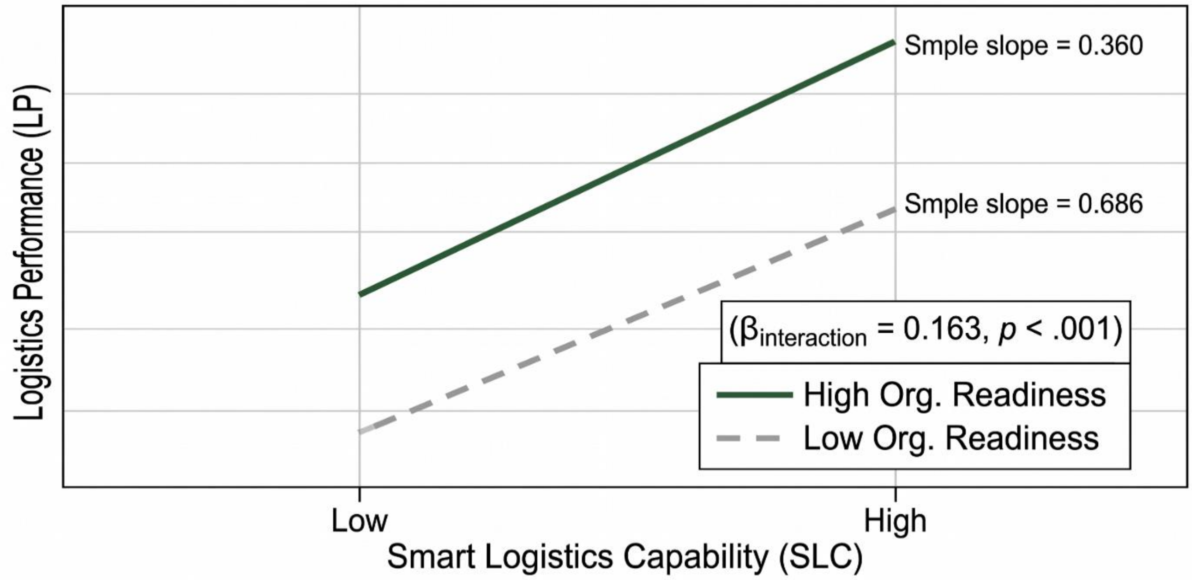


Figure 5.
Interaction plot: organisational readiness as moderator of SLC → LP.



6. Discussion and Policy Recommendations

6.1 Theoretical Contributions

The findings contribute to the digital transformation and sustainable logistics literatures in four principal ways. First, the confirmation that smart logistics capability mediates 64 per cent of AI's total effect on last-mile delivery performance provides domain-specific empirical support for the dynamic capabilities argument that has been theorized broadly but tested insufficiently in operational logistics. This result addresses directly the call by Culot et al. (2024) for research examining mediating mechanisms in AI-SCM relationships. The effect magnitude is broadly consistent with—though somewhat stronger than—comparable estimates from adjacent domains: Dubey et al. (2020) report $\beta = 0.38$ for BDA-AI capability and operational performance in Indian manufacturing, while Mikalef and Gupta (2021) report $\beta = 0.31$ for AI capability and firm performance in Norway. The somewhat larger effect observed here may reflect the particular suitability of last-mile delivery for AI-driven optimization, given its inherent demand volatility, geographic complexity, and data-rich operational environment.

Second, the significant moderation effects transform conceptual observations—long present in the readiness and information quality literatures—into quantified evidence with actionable implications. The finding that data quality approximately doubles the capability-building effectiveness of AI adoption (simple slope ratio: $0.585/0.289 \approx 2.02$) provides a concrete basis for investment prioritization. Third, the Azerbaijan context diversifies the geographical evidence base beyond the advanced economies (China, India, US, Western Europe) in which the vast majority of AI-logistics research has been conducted, revealing that boundary conditions are particularly salient in SME-dominated, infrastructure-constrained settings. Fourth, the integration of sustainability indicators within the performance construct extends the applicability of capability-based AI frameworks to the emerging field of sustainable last-mile delivery.

6.2 Sustainability Implications

The results carry specific implications for the environmental sustainability of last-mile delivery in Azerbaijan and comparable emerging markets. AI-enabled route optimization, demand-driven consolidation, and exception prediction collectively reduce vehicle-kilometres, improve first-attempt delivery success rates, and enable higher load utilization—mechanisms that directly decrease the carbon intensity and cost of last-mile operations. However, the moderation findings introduce an essential qualification: these sustainability benefits are conditional on data quality and organizational readiness. An organization that deploys AI routing software but operates with inaccurate address databases, incomplete delivery-outcome records, and fragmented carrier data will capture substantially less environmental benefit than one that has invested in data governance alongside AI tools.

This conditionality has implications for how sustainability targets are formulated and monitored. Policy instruments that mandate emissions reductions from logistics operations—whether through carbon pricing, reporting requirements, or green procurement criteria—should be accompanied by investments in the data infrastructure and organizational capabilities that enable AI-driven optimization to deliver on its environmental promise. Technology mandates without capability support risk producing compliance costs without commensurate environmental gains—a waste of both financial and regulatory capital. The moderated mediation finding—that the indirect sustainability effect quadruples under favorable enabling conditions—quantifies the magnitude of this risk and the potential return on enabling investments.

6.3 Policy Recommendations for Azerbaijan

Drawing on the empirical findings and their contextual interpretation, five policy recommendations are offered for Azerbaijan's national digital logistics strategy. Each recommendation is linked to a specific empirical finding and assigned an implementation priority.

Recommendation 1: National logistics data exchange standard. The moderating role of data quality (H4: $\beta = 0.148$, $p = .002$) provides empirical justification for ecosystem-level data standardization. The Ministry of Digital Development and Transport's announced digital logistics platform (2025) should prioritise standardized address formats, shipment identifiers, and delivery event-reporting protocols, with international interoperability for trans-Caspian trade corridors designed from the outset.

Recommendation 2: Hybrid analytics-logistics workforce development. The moderating role of organizational readiness (H5: $\beta = 0.163$, $p < .001$) underscores the need for professionals who bridge logistics domain expertise and data analytics skills. Public-private training initiatives, university curriculum reforms integrating logistics operations with data science, and apprenticeship programs should be prioritized.

Recommendation 3: AI-logistics regulatory sandbox. A structured sandbox environment would allow logistics firms—particularly SMEs—to experiment with AI applications under monitored governance, reducing perceived investment risk while enabling regulators to develop evidence-based frameworks for algorithmic accountability and data-sharing protocols.

Recommendation 4: Green AI-delivery incentive alignment. Tax incentives, green procurement criteria, and carbon reporting requirements should be designed to reward firms combining AI optimization with sustainable delivery practices: EV fleet adoption, parcel locker deployment, cargo bicycle operations, and demand-driven consolidation strategies.

Recommendation 5: Shared AI infrastructure for SMEs. The threshold-effect evidence—SMEs with limited data volumes struggle to achieve stable AI model learning—justifies shared-services models: industry-consortium AI platforms, cloud-based analytics tailored to logistics, or government-subsidized analytical support centres that democratize AI access.

Table 7. Policy recommendations: evidence base and implementation roadmap

Recommendation	Empirical basis	Lead actors	Timeline
Data exchange standard	DQ moderates AI→SLC (β=0.148**); fragmentation constrains data quality	Ministry; WEF C4IR	1–2 years

Hybrid workforce	OR moderates SLC→LP (β=0.163***); skills scarcity constrains readiness	Universities; industry	2–4 years
Regulatory sandbox	Regulatory uncertainty inhibits investment; SMEs need risk-reduced environments	Government; C4IR	1–2 years
Green delivery incentives	AI optimization enables sustainability gains; incentives align private/social returns	Government; platforms	2–3 years
SME shared AI	Threshold effects limit SME AI value; shared services lower barriers	Industry consortia	2–4 years

6.4 Limitations

Several limitations should be acknowledged. First, the cross-sectional design constrains causal inference; longitudinal designs tracking organizations through AI adoption, capability development, and performance change would provide stronger evidence. Second, single-informant perceptual measures, while standard, would benefit from triangulation with objective operational data (vehicle-kilometres per order, CO_2 emissions per delivery, failed-delivery rates from TMS systems). Third, purposive sampling limits strict statistical generalizability beyond Azerbaijan's e-commerce logistics sector. Fourth, the performance construct, while extended to include sustainability indicators, relies on perceptual rather than metered environmental metrics. Fifth, the model does not disaggregate AI applications by type; future research could examine whether routing optimization, demand forecasting, and exception prediction exhibit different sensitivity profiles to data quality and readiness conditions.

7. Conclusion

This paper has investigated how AI technologies can optimize last-mile delivery for e-commerce in Azerbaijan to simultaneously advance efficiency, service quality, and environmental sustainability. The empirical analysis, grounded in primary data from 285 logistics professionals and conducted within a PLS-SEM moderated mediation framework, yields three principal findings with implications for theory, practice, and policy.

First, AI adoption improves last-mile delivery performance primarily through the development of smart logistics capability—the organization's integrated capacity for sensing, seizing, and transforming delivery operations—rather than through technology deployment alone. This capability pathway accounts for 64 per cent of AI’s total performance effect, confirming the dynamic capabilities argument in a domain where it has been theorized but insufficiently tested.

Second, data quality and organizational readiness function as critical enablers that condition the strength of this capability-mediated pathway. When both conditions are simultaneously favorable, the indirect effect of AI on performance nearly quadruples; when both are unfavorable, the returns to AI investment are severely attenuated. This conditionality means that the sustainability benefits of AI-optimized delivery—reduced vehicle-kilometres, lower emissions, improved consolidation—are achievable but contingent on complementary investments in data governance and organizational capability.

Third, the five policy recommendations derived from the findings—national data exchange standards, hybrid workforce development, regulatory sandboxes, green delivery incentives, and shared AI infrastructure for SMEs—provide an evidence-based roadmap for Azerbaijan’s digital logistics strategy. These recommendations address the ecosystem-level enabling conditions that individual firms cannot resolve independently, creating the institutional foundation for a last-mile delivery system that is not merely technologically sophisticated but organizationally capable and environmentally sustainable.

For Azerbaijan’s rapidly growing e-commerce sector—and for comparable emerging markets confronting similar demand-supply imbalances—the overarching message of this research is that sustainable last-mile improvement requires a coordinated, multi-level approach. Technology procurement is necessary but insufficient. Data governance, workforce development, organizational transformation, and supportive policy frameworks must advance in parallel if AI is to fulfil its considerable promise for making last-mile delivery not only faster and cheaper, but genuinely more sustainable.

References

Amershi, S., Begel, A., Bird, C., DeLine, R., Gall, H., Kamar, E., Nagappan, N., & Nushi, B. (2019). Software engineering for machine learning: A case study. In Proceedings of ICSE-SEIP 2019 (pp. 291–300). IEEE/ACM. https://doi.org/10.1109/ICSE-SEIP.2019.00042

Armstrong, J. S., & Overton, T. S. (1977). Estimating nonresponse bias in mail surveys. Journal of Marketing Research, 14(3), 396–402. https://doi.org/10.1177/002224377701400320

Baryannis, G., Dani, S., & Antoniou, G. (2019). Predictive analytics and artificial intelligence in supply chain management. Computers & Industrial Engineering, 137, 106024. https://doi.org/10.1016/j.cie.2019.106024

Batini, C., & Scannapieco, M. (2016). Data and information quality: Dimensions, principles and techniques. Springer. https://doi.org/10.1007/978-3-319-24106-7

Boysen, N., Fedtke, S., & Schwerdfeger, S. (2021). Last-mile delivery concepts: A survey from an operational research perspective. OR Spectrum, 43, 1–58. https://doi.org/10.1007/s00291-020-00607-8

Carbonneau, R., Laframboise, K., & Bhargava, R. (2008). Application of machine learning techniques for supply chain demand forecasting. European Journal of Operational Research, 184(3), 1140–1154. https://doi.org/10.1016/j.ejor.2006.12.004

Central Bank of the Republic of Azerbaijan. (2024). Digital payments report 2023. https://www.cbar.az/page-47/digital-payments

Centre for Economic and Social Development (CESD). (2024). Targeting e-commerce in Azerbaijan from the perspective of resource curse (Policy paper).

Christopher, M. (2016). Logistics & supply chain management (5th ed.). Pearson.

Culot, G., Podrecca, M., & Nassimbeni, G. (2024). Artificial intelligence in supply chain management: A systematic literature review of empirical studies. Computers in Industry, 162, 104132. https://doi.org/10.1016/j.compind.2024.104132

Davenport, T. H., & Ronanki, R. (2018). Artificial intelligence for the real world. Harvard Business Review, 96(1), 108–116.

Dubey, R., Gunasekaran, A., Childe, S. J., Bryde, D. J., Giannakis, M., Foropon, C., Roubaud, D., & Hazen, B. T. (2020). Big data analytics and artificial intelligence pathway to operational performance. International Journal of Production Economics, 226, 107599. https://doi.org/10.1016/j.ijpe.2019.107599

European Bank for Reconstruction and Development (EBRD). (2024). Azerbaijan diagnostic 2024 (Country diagnostic report).

Figliozzi, M. A. (2020). Carbon emissions reductions in last mile and grocery deliveries utilizing air and ground autonomous vehicles. Transportation Research Part D: Transport and Environment, 85, 102443. https://doi.org/10.1016/j.trd.2020.102443

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

Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2022). A primer on partial least squares structural equation modeling (PLS-SEM) (3rd ed.). Sage.

Hazen, B. T., Boone, C. A., Ezell, J. D., & Jones-Farmer, L. A. (2014). Data quality for data science, predictive analytics, and big data in supply chain management. International Journal of Production Economics, 154, 72–80. https://doi.org/10.1016/j.ijpe.2014.04.018

Hofmann, E., & Rüsch, M. (2017). Industry 4.0 and the current status as well as future prospects on logistics. Computers in Industry, 89, 23–34. https://doi.org/10.1016/j.compind.2017.04.002

Ivanov, D., & Dolgui, A. (2020). A digital supply chain twin for managing the disruption risks and resilience. Production Planning & Control, 32(9), 775–788. https://doi.org/10.1080/09537287.2020.1768450

Jöhnk, J., Weißert, M., & Wyrtki, K. (2021). Ready or not, AI comes—An interview study of organizational AI readiness factors. Business & Information Systems Engineering, 63, 5–20. https://doi.org/10.1007/s12599-020-00676-7

Khedr, A. M., & Sheeja Rani, S. (2024). Enhancing supply chain management with deep learning and machine learning techniques: A review. Journal of Open Innovation: Technology, Market, and Complexity, 10(4), 100379. https://doi.org/10.1016/j.joitmc.2024.100379

Kock, N. (2015). Common method bias in PLS-SEM: A full collinearity assessment approach. International Journal of e-Collaboration, 11(4), 1–10. https://doi.org/10.4018/ijec.2015100101

Lim, S. F. W. T., Jin, X., & Srai, J. S. (2018). Consumer-driven e-commerce: A literature review, design framework, and research agenda on last-mile logistics models. International Journal of Physical Distribution & Logistics Management, 48(3), 308–332. https://doi.org/10.1108/IJPDLM-02-2017-0081

Mangiaracina, R., Perego, A., Seghezzi, A., & Tumino, A. (2019). Innovative solutions to increase last-mile delivery efficiency in B2C e-commerce: A literature review. International Journal of Physical Distribution & Logistics Management, 49(9), 901–920. https://doi.org/10.1108/IJPDLM-02-2019-0048

Mentzer, J. T., Flint, D. J., & Hult, G. T. M. (2001). Logistics service quality as a segment-customized process. Journal of Marketing, 65(4), 82–104. https://doi.org/10.1509/jmkg.65.4.82.18390

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

Ministry of Digital Development and Transport of Azerbaijan. (2025). Azerbaijan to launch digital logistics platform (News release).

Olsson, J., Hellström, D., & Palerås, H. (2019). Consumer expectations on delivery and returns in the omni-channel context. International Journal of Retail & Distribution Management, 47(4), 384–403. https://doi.org/10.1108/IJRDM-09-2018-0204

Pournader, M., Ghaderi, H., Hassanzadegan, A., & Fahimnia, B. (2021). Artificial intelligence applications in supply chain management. International Journal of Production Economics, 241, 108250. https://doi.org/10.1016/j.ijpe.2021.108250

Ranieri, L., Digiesi, S., Silvestri, B., & Roccotelli, M. (2018). A review of last mile logistics innovations in an externalities cost reduction vision. Sustainability, 10(3), 782. https://doi.org/10.3390/su10030782

Ringle, C. M., Wende, S., & Becker, J.-M. (2024). SmartPLS 4. SmartPLS GmbH.

Sculley, D., Holt, G., Golovin, D., et al. (2015). Hidden technical debt in machine learning systems. In Advances in Neural Information Processing Systems (Vol. 28).

Simchi-Levi, D., Kaminsky, P., & Simchi-Levi, E. (2014). Designing and managing the supply chain (3rd ed.). McGraw-Hill.

Teece, D. J. (2018). Business models and dynamic capabilities. Long Range Planning, 51(1), 40–49. https://doi.org/10.1016/j.lrp.2017.06.007

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

Tornatzky, L. G., & Fleischer, M. (1990). The processes of technological innovation. Lexington Books.

UNCTAD. (2024). Digital economy report 2024: Shaping an environmentally sustainable and inclusive digital future. United Nations.

Uren, V., & Edwards, J. S. (2023). Technology readiness and the organizational journey towards AI adoption. International Journal of Information Management, 68, 102588. https://doi.org/10.1016/j.ijinfomgt.2022.102608

Wamba-Taguimdje, S.-L., Fosso Wamba, S., Kala Kamdjoug, J. R., & Tchatchouang Wanko, C. E. (2020). Influence of artificial intelligence (AI) on firm performance. Business Process Management Journal, 26(7), 1893–1924. https://doi.org/10.1108/BPMJ-10-2019-0411

Wang, R. Y., & Strong, D. M. (1996). Beyond accuracy: What data quality means to data consumers. Journal of Management Information Systems, 12(4), 5–33. https://doi.org/10.1080/07421222.1996.11518099

Weiner, B. J. (2009). A theory of organizational readiness for change. Implementation Science, 4, 67. https://doi.org/10.1186/1748-5908-4-67

Winkenbach, M., Kleindorfer, P. R., & Spinler, S. (2016). Enabling urban logistics services at La Poste through multi-echelon location-routing. Transportation Science, 50(2), 520–540. https://doi.org/10.1287/trsc.2015.0624

World Bank. (2023). Connecting to Compete 2023: Trade logistics in an uncertain global economy—The Logistics Performance Index.

World Economic Forum. (2024). IDEA: Investing in the digital economy of Azerbaijan—Policy roadmap for digital transformation.