Advances in Consumer Research
https://acr-journal.com/
Volume-3 | Issue-10 |Sep: 2026

Original Researcher Article

The Role of Artificial Intelligence in Logistics: Implications for Marketing Performance and Financial Sustainability

Dr. Shweta Kulshrestha[1], Avdhesh Kumar Yadav[2], Yasser Ahmad Khan[3]
[1] Department of Finance, School of Business, Galgotias University, India.
ORCID: 0009-0009-7937-899X
Email: shweta.kulshrestha@galgotiasuniversity.edu.in

[2] Department of Logistics & Supply Chain Management, School of Aviation, Logistics and Tourism Management, Galgotias University, India.
ORCID: 0000-0002-2287-2753
Email: avdhesh.yadav@galgotiasuniversity.edu.in

[3] Department of Management, School of Business, Galgotias University, India.
ORCID: 0000-0001-5448-0052
Email: yasser.khan@galgotiasuniversity.edu.in

.

ABSTRACT

Logistics is no longer just a back-office function that gets goods from A to B; increasingly, it is where firms win or lose customers, and where operating costs quietly determine whether growth is sustainable. Artificial intelligence (AI) has moved into nearly every corner of this function, from demand forecasting to warehouse robotics to the chatbot that tells a customer their parcel is running late. What is less settled is how these gains actually flow through to two outcomes firms care about most: how the market perceives them, and whether the numbers hold up over time. This paper works through that question by pulling together three streams of theory, the resource-based view, dynamic capabilities theory, and the technology-organization-environment framework, into a single account of how AI-enabled logistics capability shapes marketing performance and financial sustainability, and how those two outcomes feed back into one another. Three objectives guide the paper: examining how far AI adoption in logistics shapes marketing-relevant outcomes such as customer satisfaction, service responsiveness, delivery accuracy, and brand competitiveness; assessing what AI-driven logistics practices do for financial sustainability, including cost efficiency, profitability, resource optimization, and resilience; and asking how marketing performance and financial sustainability relate to each other once AI is added to the picture, whether as a mediator, a moderator, or both. A set of theoretical propositions is developed along the way and illustrated against real, publicly available data comparing two major logistics carriers with markedly different AI-adoption timelines. A concrete design for testing the propositions directly, a matched multi-informant survey analyzed with partial least squares structural equation modeling, is also set out, followed by a discussion of what this means for theory and for practice, and a closing look at the argument's remaining limitations....

Keywords: artificial intelligence; logistics; marketing performance; financial sustainability; dynamic capabilities; supply chain management..

INTRODUCTION

Logistics used to be something firms worried about after the strategy had already been decided. That is changing. E-commerce growth, shrinking delivery windows, and increasingly tangled global supply networks have pushed logistics into full view of the customer, so that it now functions as a visible, competitive signal rather than a cost line buried in the back office. At the same time, firms are under pressure to show that they can absorb volatile demand, rising input costs, and geopolitical shocks without their finances taking permanent damage. Artificial intelligence (AI) sits at the center of how firms are trying to do both at once: it now touches demand forecasting, route and network optimization, warehouse automation, predictive maintenance, real-time shipment tracking, and the automated messages customers get about their orders (Chen, Men, Fuster, Osorio, & Juan, 2024; Walter, Ahsan, & Rahman, 2025).

The trouble is that research on this shift has grown up in silos. Operations and supply chain scholars have mostly asked what AI does for efficiency, cost, and resilience, treating logistics performance as something that happens inside the firm (Modgil, Singh, & Hannibal, 2022; Richey, Chowdhury, Davis-Sramek, Giannakis, & Dwivedi, 2023). Marketing scholars, working largely on their own track, care about satisfaction, service quality, and brand differentiation, and tend to treat logistics as a supporting act rather than a capability worth studying on its own terms. A third camp, closer to corporate finance and strategy, looks at how digital and AI investment eventually shows up in profitability, cost structure, and resilience (Bag, Gupta, & Luo, 2020; Alayed & Alateeg, 2026). Each of these literatures has something useful to say. What none of them quite does is put AI-enabled logistics capability, marketing outcomes, and financial outcomes into the same picture.

That gap matters because logistics does not respect the boundaries between operations, marketing, and finance. A late delivery is an operational failure, a dent in how the customer sees the brand, and a cost event, all in the same moment. Flip that around: an AI-driven gain in delivery accuracy can cut reverse-logistics costs, lift satisfaction, and sharpen brand competitiveness at the same time. Study these effects one at a time and it becomes easy to underrate both the upside and the downside of investing in AI logistics. There is also a subtler problem. Where researchers have managed to measure AI's effect on operational or financial outcomes, the effect is often indirect rather than direct: AI works as a resource that still has to be converted into organizational capability before it shows up in the numbers, and firms differ a great deal in how well they manage that conversion (Alayed & Alateeg, 2026).

This paper tries to close that gap with a conceptual framework that treats AI-enabled logistics, marketing performance, and financial sustainability as parts of one system, and that treats the marketing-financial relationship itself as something AI integration can strengthen or weaken depending on how deeply it has taken hold. Three objectives organize what follows: how far AI adoption in logistics shapes marketing outcomes such as customer satisfaction, service responsiveness, delivery accuracy, and brand competitiveness; what AI-driven logistics practices do to financial sustainability, particularly cost efficiency, profitability, resource optimization, and long-run resilience; and how marketing performance and financial sustainability relate to one another once AI enters as a mediator or moderator, including whether the relationship can run in both directions.

The contribution is threefold, though not in a rigid checklist sense. It pulls together strands of logistics, marketing, and financial-sustainability research that have rarely been read against each other, using established strategic-management theory as the connective tissue. It turns that synthesis into propositions that can actually be tested, whether through survey work or longitudinal designs. And it gives managers a slightly different way of thinking about AI spending in logistics: not as one decision, but as a set of choices between backend optimization and customer-facing applications, each with its own marketing and financial payoff depending on how well the organization builds the capability behind it. Section 2 reviews the relevant literature; Section 3 lays out the theory; Section 4 builds the conceptual model and its propositions; Section 5 illustrates parts of that model against real, publicly available data from two major logistics carriers; Section 6 sets out a concrete design and analysis plan for testing the propositions with primary data; Sections 7 through 10 work through the implications, limitations, and open questions for future research.

2. Literature Review

2.1 Artificial Intelligence in Logistics Operations

AI in logistics is not one thing but a collection of tools: machine-learning demand forecasting, predictive analytics for inventory and maintenance, computer-vision warehouse automation, robotic material handling, AI-driven route and network optimization, and natural-language tools that handle customer-facing shipment communication (Toth, Goga, & Boşcoianu, 2025; Walter et al., 2025). Walter et al.'s (2025) systematic review of AI in supply-chain demand planning found that, despite a decade and a half of growing scholarly interest, the field is still fairly young, with adoption clustered around specific use cases rather than spread evenly across the logistics value chain. Chen et al. (2024) reach a similar conclusion looking at logistics optimization more broadly: applications that try to balance cost, service, and environmental criteria together are on the rise, but they are still the exception rather than the rule next to narrower efficiency-driven use cases.

The evidence on what AI usage actually buys firms is building up, but it is uneven. Alayed and Alateeg (2026), studying logistics firms in Saudi Arabia's e-commerce sector, found that AI usage was positively linked to supply chain consistency and logistics capabilities, and that these two capabilities mediated the relationship between AI usage and overall firm performance. What stands out in their results is that AI usage explained only a modest share of the variance in those capabilities themselves; workforce skills, coordination mechanisms, and infrastructure quality all mattered too. That fits a pattern that shows up elsewhere in the literature: AI's contribution to performance tends to run through the capabilities it helps build, rather than acting as a direct technology-to-performance shortcut (Bag et al., 2020; Richey et al., 2023).

Richey et al. (2023), in a research roadmap for the field, point out that most existing empirical work has stayed close to operational efficiency and resilience, leaving the customer-facing and financial side of AI in logistics comparatively unexamined. Modgil, Singh, and Hannibal (2022) push in a related direction, showing that AI-enabled sensing and response capabilities helped supply chains hold up during the COVID-19 disruption, an outcome with obvious financial stakes even though those studies rarely put a number on them. Malhotra and Kharub (2025) document how AI adoption lifts logistics performance in e-commerce settings, which hints at service-quality effects that the literature has not yet connected explicitly to marketing outcomes. Put together, these studies make a reasonably strong case that AI drives logistics performance, unevenly and through capability-building rather than automatically, but none of them follow that performance all the way through to marketing and financial results.

2.2 Marketing Performance in the AI-Enabled Logistics Context

Marketing performance covers several overlapping ideas: customer satisfaction, service responsiveness, service quality and reliability, customer retention, and brand competitiveness relative to rivals. Logistics has always been part of the marketing mix, at least on paper, as the physical-distribution piece, but it has usually been treated as background scenery rather than a capability worth studying in its own right. That is starting to shift as AI-enabled, customer-facing logistics applications become more common. Predictive delivery-time estimates, proactive alerts when something goes wrong, personalized delivery windows, and AI-assisted customer service all put backend logistics optimization directly in front of the customer (Ponomarenko & Ponomarenko, 2023).

Ponomarenko and Ponomarenko (2023) make this connection explicit, arguing that AI-powered logistics and digital marketing are becoming complementary systems rather than separate ones: logistics data feeds marketing personalization, and marketing-driven demand signals feed back into logistics planning. Read this way, delivery accuracy and reliability, long treated as purely operational metrics, look more like service-quality attributes that belong in the marketing conversation, especially in e-commerce and omnichannel retail, where the delivery moment is often the customer's clearest interaction with a brand after the sale. Malhotra and Kharub's (2025) findings on AI-elevated logistics performance in e-commerce settings point in the same direction, even though their own analysis stops short of the marketing frame.

Even so, direct evidence tying AI-enabled logistics capability to marketing constructs like brand competitiveness is thin on the ground. Richey et al. (2023) flag this explicitly, noting that customer-facing and marketing-relevant outcomes of AI in logistics remain understudied next to the operational and resilience side. That is the gap the first objective of this paper is aimed at: working out, on theoretical grounds, why AI-enabled logistics capability should shape marketing performance, and under what conditions that relationship should be strongest.

2.3 Financial Sustainability and AI-Driven Logistics

Financial sustainability, as the term is used here, means more than next quarter's profit margin. It covers cost efficiency, resource optimization, and a firm's ability to absorb demand, supply, and cost shocks without lasting damage to its finances. That framing pushes logistics-related AI investment toward a resilience-oriented reading of firm performance rather than a purely accounting one. Bag et al. (2020) find that logistics 4.0-enabled dynamic capabilities, not technology adoption on its own, are the more immediate driver of performance gains, a pattern that echoes the capability-mediation result Alayed and Alateeg (2026) later report specifically for AI usage.

Some of this is fairly concrete. AI applications in reverse logistics have been shown to cut costs and improve resource recovery, which is one clear mechanism by which AI-driven logistics can raise cost efficiency and resource optimization together (Alkalha, Ali, & Jum'a, 2025). Chen et al. (2024) find something similar: AI-enabled logistics optimization is increasingly built around sustainability criteria alongside cost and service, suggesting that efficiency and long-term resource stewardship are becoming linked goals rather than trade-offs. But the broader literature on AI adoption and financial performance is cautious about assuming a quick or automatic payoff. Value tends to depend on complementary investment, in workforce AI literacy, data infrastructure, and process redesign, and is probably better understood as a long-term strategic bet than a short-term efficiency win (Alayed & Alateeg, 2026).

That distinction matters for the paper's second objective. Rather than treating AI-driven logistics as a direct lever on profitability, the financial-sustainability literature points to something more conditional: AI moves cost efficiency and resource optimization fairly directly, while its effect on profitability and long-term resilience is more likely mediated by the capabilities it helps build, and shaped by how much firms invest in the complementary resources needed to turn AI capability into financial results.

3. Theoretical Foundations

Pulling the literature above into one framework requires borrowing from three theoretical traditions that, taken together, cover different parts of the problem: the resource-based view explains why AI might be a source of advantage in the first place, dynamic capabilities theory explains how that advantage gets built and kept up to date, and the technology-organization-environment framework explains why the same AI investment plays out so differently across firms.

3.1 The Resource-Based View

The resource-based view (RBV) argues that sustained competitive advantage comes from resources that are valuable, rare, hard to imitate, and hard to substitute (Barney, 1991). Under this framing, AI counts as a strategic resource only when it is embedded in a firm's own data, processes, and routines in ways rivals cannot easily copy; a generic, off-the-shelf AI tool does not really qualify. Alayed and Alateeg (2026) apply exactly this logic to logistics, treating AI usage as an organizational resource that firms convert into supply chain consistency and logistics capabilities. That gives the RBV a useful role here: it is the reason AI-enabled logistics can be read as more than a cost-cutting tool, potentially a source of differentiated marketing and financial outcomes, but only where the resource is genuinely difficult for competitors to reproduce.

3.2 Dynamic Capabilities Theory

Dynamic capabilities theory builds on the RBV by asking how firms sense opportunities and threats, seize them through timely resource deployment, and reconfigure what they have as the environment shifts (Teece, Pisano, & Shuen, 1997). Applied to logistics, the point is that the value is not in the AI technology as such but in a firm's ability to use it: to sense demand shifts and disruptions, to seize openings through fast route or network changes, and to keep reconfiguring logistics processes as conditions move (Toth et al., 2025; Bag et al., 2020). This lens does particularly useful work for financial resilience, since it is concerned with a firm's capacity to adapt under stress rather than just its efficiency when nothing is going wrong, which lines up with evidence that AI-enabled sensing and response capabilities helped supply chains hold together during the COVID-19 disruption (Modgil et al., 2022).

3.3 The Technology–Organization–Environment Framework

The technology-organization-environment (TOE) framework treats technology adoption and value realization as a function of three things at once: the technology's own characteristics, the organization's internal readiness (its structure, resources, culture), and the external environment it operates in (industry structure, competitive pressure, regulation) (Tornatzky & Fleischer, 1990). Alrsheedi and Iskandar (2025) apply the framework to AI adoption in emerging-market financial settings, and their work helps explain why identical technology produces different outcomes in different firms. For this paper, TOE supplies the missing piece: a reason AI-enabled logistics capability would not translate the same way into marketing or financial outcomes everywhere. Firms with more organizational readiness, skilled staff, integrated data systems, and more favorable environmental conditions, customers who reward service differentiation, competitors who punish inefficiency, should get more out of a given level of AI investment than firms without those advantages.

Put the three together and AI-enabled logistics looks like a strategic resource (RBV) that firms turn into operational capability through an ongoing, adaptive process (dynamic capabilities), with how fast and how well that happens shaped by organizational and environmental contingencies (TOE). That combined view is what underlies the conceptual model developed next.

4. Conceptual Framework and Propositions

With the theory in place, this section builds a conceptual model connecting AI-enabled logistics capability to marketing performance and financial sustainability, and looks at how those two outcomes relate to each other. Figure 1 lays out the model as a whole; the discussion below works through the paper's three objectives in turn, and Table 1 later maps each proposition to its theoretical basis.

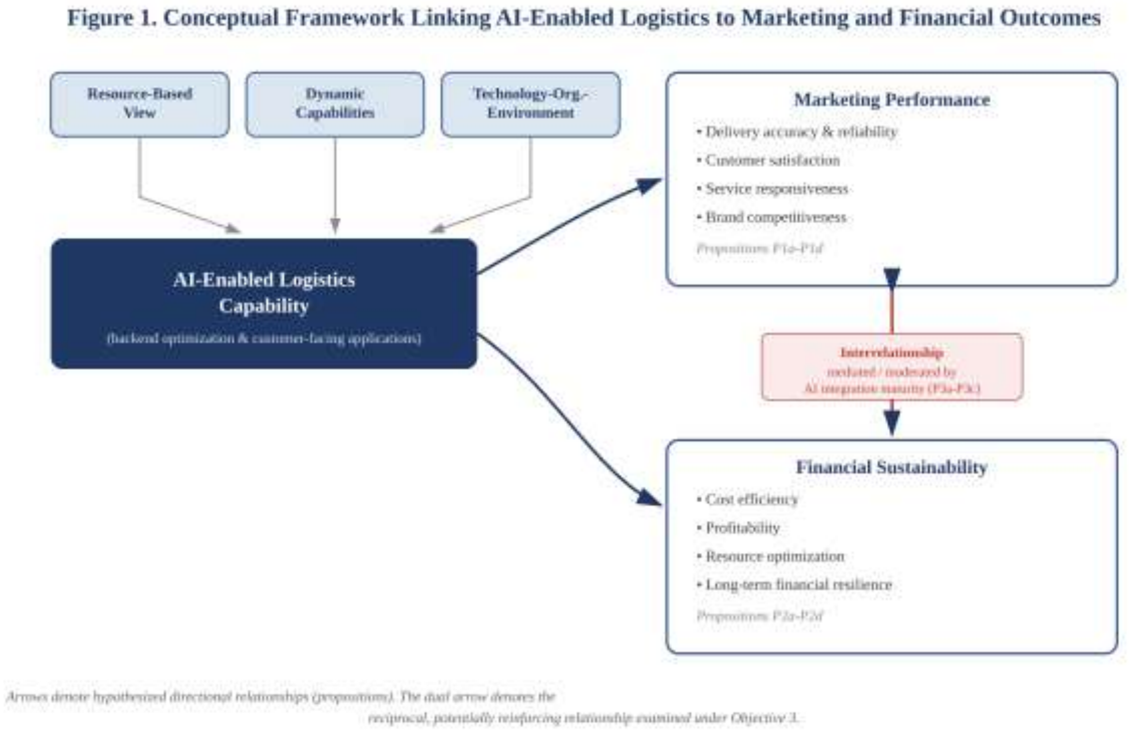

Figure 1. Conceptual framework linking AI-enabled logistics capability to marketing performance and financial sustainability, grounded in the resource-based view, dynamic capabilities theory, and the technology-organization-environment framework.

4.1 Objective 1: AI Adoption in Logistics and Marketing Performance

How far does AI adoption in logistics actually shape marketing outcomes? Following the RBV and dynamic capabilities logic set out above, AI-enabled logistics capability makes the order-to-delivery cycle more visible, more predictable, and more responsive. Those gains do not stay behind the scenes. Customers notice them directly, through delivery accuracy, timeliness, and how well they are kept informed about their shipment. More accurate estimated-time-of-arrival predictions, combined with AI-assisted handling of delivery exceptions, cut down on how often and how badly things go wrong for the customer, while personalization lets firms match delivery options to what individual customers actually want (Ponomarenko & Ponomarenko, 2023; Malhotra & Kharub, 2025).

Four propositions follow from this. AI-enabled predictive and real-time logistics capabilities should be positively associated with delivery accuracy and reliability (P1a). That improved accuracy and reliability, together with proactive AI-enabled communication, should be positively associated with customer satisfaction (P1b). AI-enabled logistics capability should also be positively associated with service responsiveness, meaning how quickly and effectively firms catch and resolve delivery problems and customer questions (P1c). And the combined effect of better accuracy, satisfaction, and responsiveness should show up as a positive association between AI-enabled logistics capability and brand competitiveness (P1d), especially in sectors like e-commerce and omnichannel retail where logistics performance sits in plain view of the customer. Following the TOE framework's contingency logic, this last relationship should be strongest where AI has been built into customer-facing systems, tracking interfaces, communication channels, and weaker where it stays confined to backend optimization the customer never sees.

4.2 Objective 2: AI-Driven Logistics and Financial Sustainability

The second objective turns to what AI-driven logistics practices do for financial sustainability: cost efficiency, profitability, resource optimization, and long-term resilience. The literature reviewed earlier suggests this is not a uniform relationship. Some dimensions respond fairly directly to AI adoption; others depend much more on the capabilities that adoption helps build. Cost efficiency and resource optimization, fewer empty miles, better fleet utilization, more accurate inventory positioning, tend to follow relatively directly from AI-enabled forecasting and optimization, as seen in reverse-logistics settings where AI adoption cut costs and improved resource recovery (Alkalha et al., 2025).

Profitability and long-term resilience look different. Evidence from Saudi Arabian logistics firms suggests that AI usage's effect on overall firm performance runs largely through supply chain consistency and logistics capabilities rather than acting directly (Alayed & Alateeg, 2026), and broader work on AI-enabled dynamic capabilities suggests that resilience benefits show up mainly when the environment is turbulent, when a firm's ability to sense and respond to shocks actually gets tested financially (Modgil et al., 2022). Four propositions follow. AI adoption in logistics should be positively associated with cost efficiency (P2a) and with resource optimization, covering inventory turnover, asset utilization, and fleet efficiency (P2b). The link between AI adoption and profitability should run mainly through logistics capability development rather than operate as a direct effect (P2c). And AI-enabled dynamic capabilities, sensing and reconfiguration in particular, should strengthen financial resilience, an effect that should be more visible under environmental turbulence or supply chain disruption than under stable conditions (P2d).

4.3 Objective 3: The Interrelationship between Marketing Performance and Financial Sustainability under AI Integration

The third objective is about how marketing performance and financial sustainability relate to each other once AI is in the picture. Two logics seem plausible, and this paper's position is that they probably coexist rather than compete. One runs from marketing to finance, in the spirit of the classic service-profit-chain argument: better customer satisfaction, service responsiveness, and brand competitiveness raise retention and willingness to pay, which feeds revenue growth and eventually profitability. The other runs the other way: firms with stronger financial sustainability, more cost efficiency, better resource optimization, more resilience, have the financial room to keep investing in AI-enabled, customer-facing logistics systems, which then strengthens marketing performance further down the line.

AI integration, in this account, plays two roles at once, mediator and moderator. As a mediator, AI-enabled logistics capability is the channel that turns financial resources into marketing capability, through reinvestment in customer-facing AI, and turns marketing gains into financial outcomes, through the operational capabilities that drive customer satisfaction and cost efficiency together. As a moderator, how mature and how customer-facing a firm's AI integration is determines how tightly marketing and financial outcomes move together. Firms with deep, customer-facing AI should show a closer coupling between the two than firms whose AI adoption stays shallow or backend-only, where operational gains may never become visible enough to customers to pay off in marketing terms, and where marketing initiatives may outrun the logistics infrastructure needed to back them up.

Three propositions follow. Marketing performance should be positively associated with financial sustainability, and profitability in particular, through retention and revenue effects (P3a). That marketing-financial relationship should be stronger among firms with mature, customer-facing AI-enabled logistics than among firms whose AI adoption stops at the backend (P3b). And financial sustainability should positively influence how deeply firms invest in AI going forward, which opens the door to a reinforcing loop where financial resources, AI capability depth, and marketing performance build on one another over time (P3c). The same loop can run backward, though: where early AI investment fails to build real capability, financial and marketing outcomes can drag each other down instead. That possibility matters. It means the marketing-financial relationship under AI integration should not be treated as automatically positive or self-sustaining; it depends on whether the AI investment actually converts into the operational capabilities discussed in Sections 4.1 and 4.2.

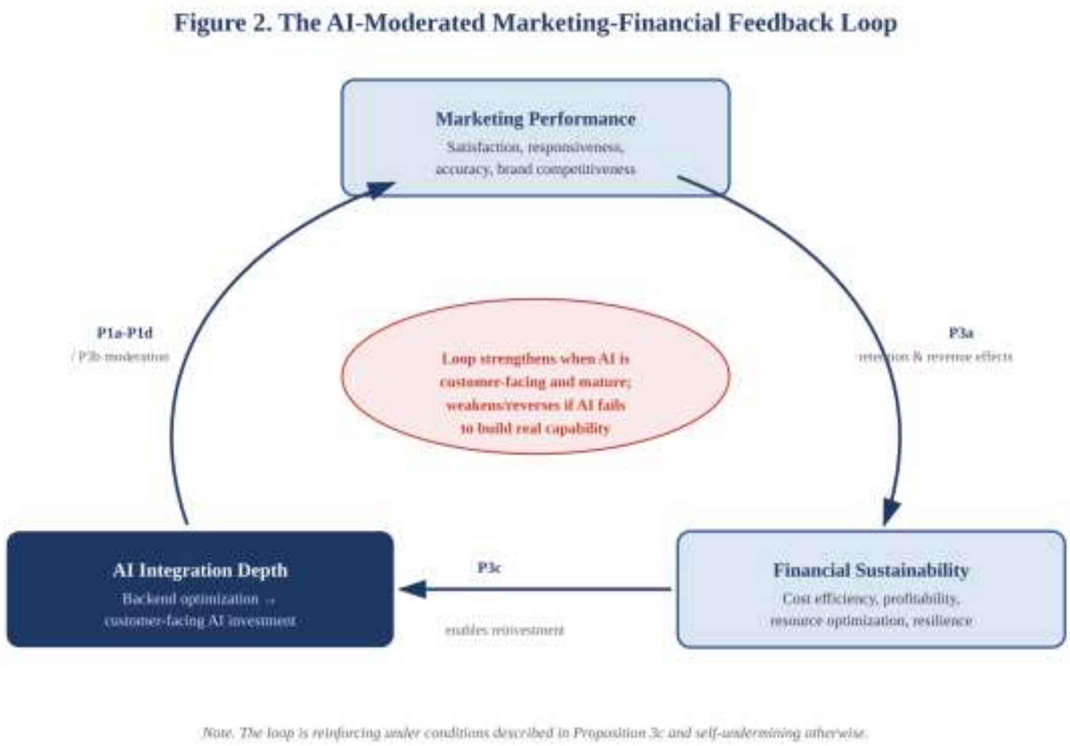

Figure 2. The AI-moderated marketing-financial feedback loop. Financial sustainability enables deeper AI investment (P3c), which strengthens marketing performance (P1a-P1d; P3b moderation), which in turn supports financial sustainability through retention and revenue effects (P3a).

Table 1 pulls all of this together, organized by objective, as a reference point for the empirical testing that would need to follow.

Proposition	Relationship	Theoretical Basis
P1a	AI-enabled logistics capability → delivery accuracy and reliability	RBV; dynamic capabilities (sensing/seizing)
P1b	Delivery accuracy and proactive communication → customer satisfaction	Service quality / marketing performance logic
P1c	AI-enabled logistics capability → service responsiveness	Dynamic capabilities (reconfiguration)
P1d	Cumulative service gains → brand competitiveness	RBV (differentiation); TOE (customer-facing boundary condition)
P2a	AI adoption → cost efficiency	RBV; operations/logistics literature
P2b	AI adoption → resource optimization	RBV; dynamic capabilities

Proposition	Relationship	Theoretical Basis
P2c	AI adoption → profitability, mediated by logistics capability	Capability-mediation logic (RBV/DC)
P2d	AI-enabled dynamic capabilities → financial resilience under turbulence	Dynamic capabilities theory
P3a	Marketing performance → financial sustainability (profitability)	Service-profit-chain logic
P3b	Marketing–financial link strengthened by mature, customer-facing AI	TOE (moderation); RBV
P3c	Financial sustainability → deeper AI investment (potential reinforcing loop)	Dynamic capabilities; TOE (organizational readiness)

5. Data Analysis

The propositions above are conceptual and have not been tested with primary data collected for this study. As a bridge toward that testing, and to ground the argument in something more concrete than theory alone, this section compares four major logistics and delivery operators, UPS, FedEx, Amazon, and the U.S. Postal Service, using real, publicly available figures: customer satisfaction scores from the American Customer Satisfaction Index (ACSI), financial margin and revenue from company filings and financial results, and documented milestones in each firm's AI adoption. UPS and FedEx anchor the comparison with a full 2012-2024 span; Amazon and USPS are added for 2023-2025, the years for which comparable ACSI shipping-category data exist for them, extending the comparison to a fully AI-native private operator (Amazon) and a large public operator with comparatively limited AI-specific investment (USPS).

The four carriers make a useful contrast because their AI timelines and organizational structures differ sharply. UPS began piloting its AI-driven routing system, ORION, in 2012 and had it fully deployed nationwide by 2016 (Weise, 2019; Nextbillion.ai, 2026). FedEx's enterprise AI investment scaled much later, gathering pace mainly after the 2020 launch of its FedEx Dataworks data platform and accelerating further through robotics and network initiatives in 2024 to 2026 (Supply Chain Dive, 2026). Amazon has invested in warehouse robotics and automation since acquiring Kiva Systems in 2012 and is widely regarded as the most AI-intensive operator among the four (Amazon.com, 2025, 2026). USPS, by contrast, is a public entity with a universal-service mandate, statutory pricing constraints, and, per its own financial disclosures, an automation agenda focused mainly on network consolidation rather than the AI-specific systems distinguishing the three private carriers (USPS, 2024).

This is not a test of the model in Section 4, and the four carriers are not on equal footing as comparators. ACSI's shipping-category score is, at best, a rough proxy for the customer-satisfaction dimension of marketing performance. Operating margin is one narrow slice of financial sustainability, not resource optimization or resilience, and it is not measured the same way across all four organizations: Amazon does not break out logistics-only financials, so its figures reflect its North America retail segment as a whole (product sales and advertising included, not logistics alone), and USPS's headline GAAP net loss includes large non-cash pension and workers'-compensation items that have no equivalent in UPS's or FedEx's operating-margin figures. AI adoption throughout is inferred from documented company milestones, not measured directly at the firm level. With this small and structurally uneven sample, no statistical test would ordinarily be meaningful; Section 5.1 reports formal regressions anyway, precisely to show what such a small, heterogeneous sample does and does not support

.

Company	Year	ACSI Score	Revenue	Margin	AI/Automation Context
UPS	2012	81	$54.13B	13.8%	ORION piloted at 6 sites; UPS

Company	Year	ACSI Score	Revenue	Margin	AI/Automation Context
					credits route technology with cutting 85M miles in 2011
UPS	2013	84	$55.44B	13.5%	ORION scaled to roughly 10,000 delivery routes
UPS	2022	78	$100.34B	13.43%	ORION at full national deployment since 2016; "Dynamic ORION" real-time upgrade rolling out
UPS	2024	77	$91.07B	8.88%	Dynamic ORION covering ~97% of the ORION-enabled fleet
FedEx	2012	82	$42.68B	7.5%	Pre-enterprise-AI period
FedEx	2013	85	$44.29B	5.8%	Pre-enterprise-AI period
FedEx	2022	76	$93.51B	6.68%	Early data-platform investment (FedEx Dataworks launched 2020)
FedEx	2024	80	$87.69B	6.34%	Scaling AI/robotics (Network 2.0, RFID sensors, robotic trailer unloading trials)
Amazon	2024	81	$387.5B*	6.45%*	Robotics-intensive fulfillment since the 2012 Kiva Systems acquisition; among the most AI-invested logistics operators in the industry

Company	Year	ACSI Score	Revenue	Margin	AI/Automation Context
Amazon	2025	80	$426.4B*	6.94%*	Continued robotics/AI scaling; agentic-AI customer-service tools expanding
USPS	2023	71	$78.2B	-8.31%†	Automation focused on network consolidation under the Delivering for America plan; limited AI-specific deployment vs. the three private carriers
USPS	2024	72	$79.5B	-11.95%†	Continued network-modernization investment; net loss driven ~80% by non-cash pension/workers'-compensation items (USPS, 2024)

*Amazon figures are North America segment revenue and operating margin (retail and logistics combined; Amazon does not disclose logistics-only financials) and are not directly comparable to UPS's and FedEx's logistics-specific operating margin. †USPS figures are GAAP net margin (net loss / operating revenue), not operating margin, and reflect a public entity with statutory pricing constraints and large non-cash pension obligations; not commercially comparable to the other three carriers.

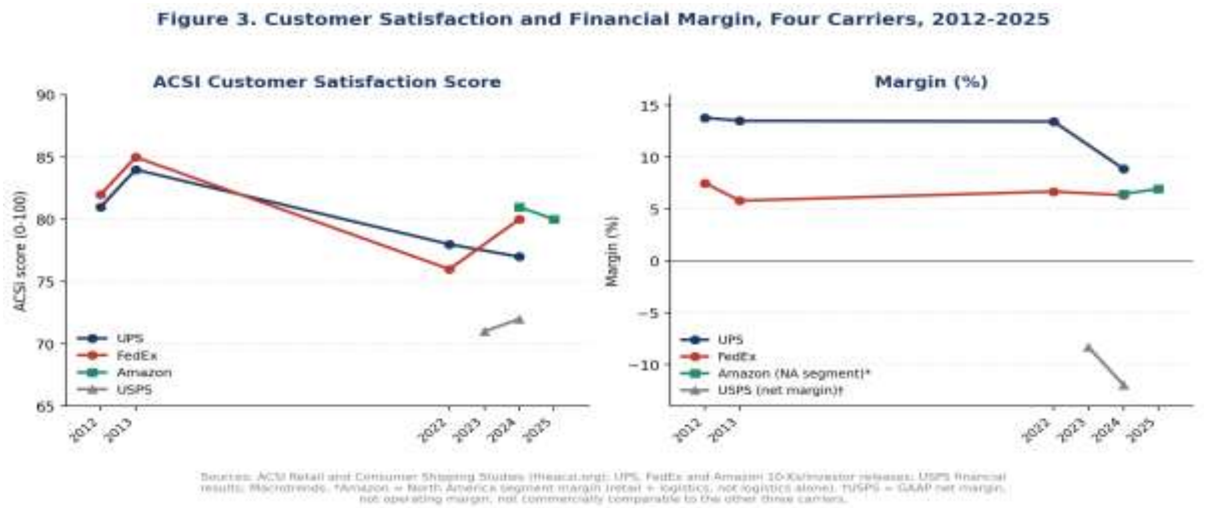

Figure 3. ACSI customer satisfaction and financial margin for four carriers, UPS, FedEx, Amazon, and USPS, 2012-2025. Sources: American Customer Satisfaction Index Retail and Consumer Shipping Studies; UPS, FedEx, and Amazon company filings and investor releases; USPS financial results; Macrotrends. See table note for Amazon and USPS metric definitions.

Table 2 lays out all twelve data points, the original eight for UPS and FedEx across 2012-2024, plus four more recent points for Amazon and USPS; Figure 3 plots all four series over time. Focusing first on UPS and FedEx, whose full 2012-2024 span allows within-firm comparison: across their pooled eight observations, customer satisfaction and operating margin show essentially no linear association (Pearson r = 0.04), which on its own would seem to undercut Proposition 3a. But that pooled figure hides a real difference between the two firms. Looked at within each company's own history, UPS's satisfaction score and operating margin move together fairly closely (r = 0.64 across its four points), while FedEx's move weakly in opposite directions (r = -0.31). Given four data points per firm, neither coefficient should be read as statistically reliable; both are reported here as description, not inference.

That said, the pattern is at least suggestive in light of the paper's argument. UPS is the firm whose AI-enabled routing capability was most mature across this window, fully scaled nationally since 2016, and it is also the firm where satisfaction and margin track each other most closely. FedEx's AI investment was comparatively immature for most of this period and only began scaling in earnest after 2020, and it is the firm where the two series move less coherently. Read cautiously, that is broadly consistent with the paper's central claim that AI's payoff depends on how far capability-building has actually progressed rather than on the fact of AI investment alone, which is the logic behind Propositions 2c and 3b. It is equally consistent, however, with any number of other explanations. Both firms' 2022 to 2024 figures sit inside a period of unusually sharp cost inflation, fuel-price swings, and post-pandemic volume normalization that hit the whole parcel sector at once (TIKR.com, 2026), and UPS's own margin decline over the same window coincided with a deliberate, disclosed pullback from lower-margin Amazon volume rather than with anything AI-related. None of that can be disentangled with two firms and four years each. Adding Amazon and USPS to the picture, as the next subsection does formally, does not resolve this ambiguity; if anything, it sharpens the caution, because those two additions differ from UPS and FedEx, and from each other, on dimensions far more consequential than AI adoption alone.

The honest reading, then, is that this comparison does not confirm the propositions in Section 4; it illustrates that the kind of pattern those propositions predict is at least visible in real carrier-level data, alongside plenty of other forces that a small, descriptive comparison cannot rule out. Section 6 sets out what a proper empirical test, with firm-level constructs, a larger sample, and controls for these confounds, would need to look like.

5.1 Formal Regression Results

The correlations above can be formalized as regressions, reported here for completeness and because a regression specification surfaces something an informal correlation does not. Table 3 presents two ordinary least squares models with margin (operating margin for UPS and FedEx, the proxy and net-margin measures noted above for Amazon and USPS) as the dependent variable and all twelve firm-year observations in Table 2 as the sample. Model 1 pools all four carriers and regresses margin on the ACSI score alone, with no adjustment for which carrier is which. Model 2 adds firm fixed effects (dummy variables for UPS, FedEx, and USPS, with Amazon as the reference category), asking whether ACSI still predicts margin once each carrier's structural baseline is accounted for.

Predictor	Model 1: Pooled	Model 2: Firm Fixed Effects	Notes
Constant	-102.27 (SE 31.23), p = .008	-3.97 (SE 17.26), p = .82	Pooled constant is precisely estimated; FE constant is not
ACSI score	1.369 (SE 0.395), p = .006	0.133 (SE 0.214), p = .55	Significant when pooled; not distinguishable from zero once firm is controlled for
UPS dummy	—	5.77 (SE 1.59), p = .008	Precisely estimated relative to Amazon (reference)

Predictor	Model 1: Pooled	Model 2: Firm Fixed Effects	Notes
FedEx dummy	—	-0.15 (SE 1.59), p = .93	Not distinguishable from Amazon
USPS dummy	—	-15.63 (SE 2.66), p = .0006	Large, precisely estimated: USPS runs far below the other three regardless of ACSI
R^2 / Adj. R^2	0.545 / 0.500	0.967 / 0.948	Model 2's fit is driven almost entirely by firm identity, not by ACSI
N	12	12	Firm-year observations, 2012–2025 (Table 2)

Table 3. OLS regression of margin on ACSI customer satisfaction score, pooled and firm-fixed-effects specifications, four carriers. Coefficients computed directly from the twelve observations in Table 2; standard errors and p-values are reported for completeness, not as reliable evidence of statistical significance given n = 12 and a structurally heterogeneous sample.

Table 3 is worth reading carefully because the two models tell opposite stories, and the reason why is the finding. In the pooled model, ACSI looks like a strong, statistically significant predictor of margin (coefficient = 1.37, p = .006, R^2 = 0.55). Taken at face value, that would seem to support Proposition 3a directly. But this result is almost entirely an artifact of USPS sitting at one extreme on both variables at once: the lowest ACSI scores in the sample and by far the most negative margins, for reasons, statutory pricing constraints, a universal-service mandate, and non-cash pension obligations, that have nothing to do with customer satisfaction. Once firm fixed effects are added in Model 2, the ACSI coefficient collapses to statistical insignificance (p = .55) and nearly all of the explanatory power shifts to the firm dummies themselves, particularly USPS's large negative coefficient (p = .0006 relative to Amazon).

This is a textbook illustration of why a naive pooled correlation across structurally different organizations can be misleading: it is not that satisfied customers cause better margins, or the reverse, but that the kind of organization a carrier is, public or private, commercial or statutory, mature-AI or early-AI, drives both variables together without either causing the other. A properly specified analysis has to separate that between-firm variation from any genuine within-firm relationship, which is exactly what Model 2 does, and exactly what a twelve-observation, four-firm sample is too small to do with any statistical confidence (five degrees of freedom remain in Model 2). The honest conclusion is not that Proposition 3a is confirmed by Model 1, nor cleanly rejected by Model 2, but that this sample cannot adjudicate the question at all, which is precisely why Section 6's primary-data design exists.

6. Proposed Empirical Validation: Design and Analysis Plan

Sections 4 and 5 make the conceptual case and illustrate it against carrier-level secondary data. Neither tests the propositions directly. This section sets out how they could be tested with primary data, so that the design is ready to field rather than left as a general call for "future research."

6.1 Research Design and Sampling

A single-informant design, where one respondent per firm reports on both the logistics/AI side and the marketing or financial outcomes, would be vulnerable to common-method bias and to respondents reporting on outcomes they do not directly observe. A matched multi-informant design is preferable: within each participating firm, one respondent from logistics or supply chain operations (reporting on AI usage, logistics capability, cost efficiency, and resource optimization) and a second respondent from marketing, customer service, or finance (reporting on customer satisfaction, service responsiveness, brand competitiveness, profitability, and resilience). Firm-level scores would be formed by pairing or averaging matched responses, which is standard practice in dyadic organizational survey research.

Target population: logistics-intensive firms operating in e-commerce, retail distribution, third-party logistics, or manufacturing with substantial distribution operations. Realistic sampling frames for a team based at a business school with logistics and supply chain faculty include: alumni and corporate-relations networks, industry bodies such as the Confederation of Indian Industry's logistics committee, the Indian Institute of Materials Management, or ISCEA India, and direct outreach through LinkedIn to logistics, operations, and marketing managers at mid-size and large firms. A convenience or purposive sample drawn through these channels, explicitly disclosed as such, is a defensible and common approach in this literature; Alayed and Alateeg (2026), the paper's core empirical anchor, used a comparable convenience-sampling design with 275 respondents.

Sample size: PLS-SEM with the number of constructs and paths implied by Figure 1 (roughly eight to ten latent constructs, several with formative or multi-item reflective indicators) typically requires a minimum of 100 to 150 valid responses for stable estimates, with 200 to 300 preferable for adequate power on the mediation and moderation tests in Propositions 2c, 3a, and 3b. A minimum target of 200 matched firm-level pairs (400 individual responses) is a reasonable planning figure, with a pilot of 25 to 30 responses run first to check item clarity and reliability before full fielding. Ethics approval from the authors' institutional review process would need to precede any fielding, and the pilot stage is also the point at which approval, informed consent language, and data-handling procedures should be finalized.

6.2 Measurement

Table 4 lists the constructs implied by the conceptual model, each measured with multiple Likert-type items (five- or seven-point agreement scales are both defensible; seven-point scales are used more often in recent PLS-SEM logistics research and are recommended here for consistency with that literature). Items would be newly developed for this study, grounded in the construct definitions used in the cited literature (e.g., AI usage following Alayed & Alateeg, 2026; logistics capability following Bag et al., 2020; marketing performance dimensions following Ponomarenko & Ponomarenko, 2023), rather than copied verbatim from any single published instrument. A full candidate item pool is provided as a companion survey instrument, alongside screening questions to confirm respondent role and firm eligibility, and demographic items (firm size, industry, respondent tenure) for use as control variables.

6.3 Planned Analytical Approach

Partial least squares structural equation modeling (PLS-SEM) fits this design well: the model combines formative and reflective constructs, includes mediation and moderation paths, and the realistic sample size sits below what covariance-based SEM typically requires. The analysis would proceed in two stages. The measurement model would first be assessed for internal consistency reliability (Cronbach's alpha and composite reliability above 0.70), convergent validity (average variance extracted above 0.50), and discriminant validity (the heterotrait-monotrait ratio below 0.85 or the Fornell-Larcker criterion), dropping or revising items that fail these thresholds before proceeding.

The structural model would then be estimated using bootstrapping (5,000 resamples is standard) to obtain path coefficients and significance levels for each proposition in Table 1: direct paths for P1a to P1d and P2a to P2d, a mediation test for P2c (AI adoption to profitability via logistics capability, using the bootstrapped indirect-effect approach), and a moderation test for P3b (interaction between AI integration maturity, split into a customer-facing versus backend-only subgroup, and the marketing-to-financial path), estimated either through a product-indicator interaction term or a multi-group PLS-SEM comparison across the two subgroups. Common method bias would be checked using Harman's single-factor test and a full collinearity assessment (variance inflation factors below 3.3), given that some constructs are measured from the same respondent within each matched pair. Software: SmartPLS 4 or the R package seminr, both standard for this type of model in the logistics and supply chain literature this paper draws on.

This plan is deliberately conservative in what it claims. It sets out how the propositions could be tested, not a guarantee of what the results would show; sign and significance of every path remain open empirical questions until the data exist.

Construct	Definition (as used here)	Respondent	Grounded in
AI Usage in Logistics	Extent of AI use across forecasting, routing, warehouse, and customer-communication tasks	Logistics/Ops	Alayed & Alateeg (2026); Walter et al. (2025)
Logistics Capability	Supply chain consistency, responsiveness, and reconfiguration ability	Logistics/Ops	Bag et al. (2020); Alayed &

Construct	Definition (as used here)	Respondent	Grounded in
			Alateeg (2026)
Delivery Accuracy & Reliability	On-time, complete, and error-free order fulfillment	Logistics/Ops	Malhotra & Kharub (2025)
Cost Efficiency	Perceived reduction in logistics operating costs	Logistics/Ops	Alkalha et al. (2025)
Resource Optimization	Inventory turnover, asset utilization, fleet efficiency	Logistics/Ops	Chen et al. (2024)
Customer Satisfaction	Overall satisfaction with delivery experience	Marketing/CS	Ponomarenko & Ponomarenko (2023)
Service Responsiveness	Speed and quality of exception handling and communication	Marketing/CS	Ponomarenko & Ponomarenko (2023)
Brand Competitiveness	Perceived differentiation vs. competitors on delivery experience	Marketing/CS	Richey et al. (2023)
Profitability	Perceived margin and revenue performance trend	Finance/Mgmt	Bag et al. (2020)
Financial Resilience	Perceived capacity to absorb demand/cost shocks	Finance/Mgmt	Modgil et al. (2022)

The full item pool referenced in Table 4, including all measurement items, screening questions, response scales, and consent language, is provided in a companion survey instrument ready for pilot testing once ethics approval is secured.

7. Discussion

A few themes cut across the propositions developed above. AI's contribution to marketing and financial outcomes in logistics is not automatic, and it depends on capability-building rather than the technology itself. That lines up with the finding that AI usage explains only a modest share of variance in logistics capabilities (Alayed & Alateeg, 2026): AI looks like a necessary but not sufficient condition for better marketing and financial performance. Firms that bolt on AI without investing in workforce skills, data infrastructure, and process redesign are unlikely to see the full benefits the propositions above describe.

Logistics also works as a bridge between operational excellence and market-facing outcomes, but only when the AI behind it is something customers can actually notice. Backend optimization, route planning, warehouse robotics, predictive maintenance, generates cost and efficiency gains that support financial sustainability fairly directly, but whether that pays off in marketing terms depends on whether it turns into faster, more reliable, better-communicated deliveries that customers experience (Ponomarenko & Ponomarenko, 2023). This backend-versus-customer-facing distinction keeps showing up across the propositions in Section 4, and it is a fairly practical lens for firms trying to decide where to put their next AI dollar.

There is a third point worth drawing out: the relationship between marketing performance and financial sustainability probably runs both ways, reinforcing or undermining itself depending on how things go, rather than flowing in one direction only. That cuts against a habit in both the marketing and finance literatures of treating one domain as feeding the other rather than as two outcomes tied together through the same AI-enabled logistics infrastructure. What that means for how firms sequence and evaluate AI investment is picked up next.

8. Theoretical and Managerial Implications

8.1 Theoretical Implications

Three contributions to theory come out of this. The paper extends the resource-based view and dynamic capabilities theory into a joint marketing-finance space that logistics and supply chain research has mostly kept separate. It treats AI-enabled logistics capability as a resource that spans boundaries, linking internally oriented operational processes to two externally facing outcomes, marketing and financial sustainability, that are usually studied apart from each other. And it frames the marketing-financial relationship as a feedback loop shaped by how mature and how customer-facing a firm's AI integration is, which is a more dynamic picture than the static, one-directional models that tend to dominate work on marketing performance or technology-performance links.

8.2 Managerial Implications

For logistics and marketing managers, a few practical points follow. Firms after a marketing payoff from AI investment should put customer-facing applications first, predictive delivery communication, personalized delivery options, responsive handling of exceptions, rather than assuming backend efficiency gains will somehow translate into better customer perception on their own. Firms after a financial payoff should expect to be patient: cost-efficiency and resource-optimization gains usually show up before profitability does, and profitability depends on actually converting AI capability into operating routines rather than just buying the technology. Because both kinds of payoff depend on complementary investment, it probably makes more sense to treat AI adoption in logistics as a capability-building program, workforce training, data infrastructure, coordination across logistics, marketing, and finance, than as a single technology purchase.

In emerging-market or resource-constrained settings, the TOE logic behind this framework suggests that policy support and industry-level investment in AI literacy, digital infrastructure, and skills can make a real difference in whether AI investment ever turns into marketing or financial gains, a point that echoes the policy implications drawn from country-specific logistics research (Alayed & Alateeg, 2026).

9. Limitations and Future Research Directions

Being a conceptual paper, what is offered here are theoretically grounded propositions, not tested findings, and that limitation should shape what comes next. The four-carrier comparison in Section 5 was deliberately kept modest and honestly framed as descriptive; a real test of the propositions in Section 4 needs firm-level primary data, not carrier-level proxies drawn from four structurally dissimilar organizations. Section 6 sets out a concrete design for that test, a matched multi-informant survey analyzed with PLS-SEM, which would also allow the backend-versus-customer-facing distinction developed here to be tested directly instead of inferred from company disclosures. That design is the obvious next step; nothing in this paper substitutes for actually fielding it.

The feedback-loop argument in Section 4.3 is inherently a claim about change over time, and it would be better tested with longitudinal or panel data that can actually capture reinforcing or self-undermining cycles, rather than the cross-sectional designs that dominate the existing AI-logistics literature (Alayed & Alateeg, 2026). It would also help to know how firm size, industry sector (e-commerce versus manufacturing or industrial logistics), and region moderate these propositions, given some evidence that AI's financial payoff in emerging markets can be slower or more conditional than in more resource-rich settings. Finally, measuring financial sustainability as a multidimensional construct, spanning cost efficiency, profitability, resource optimization, and resilience, is not a trivial methodological problem, and neither is building reliable, comparable measures of brand competitiveness that can be traced specifically to logistics performance rather than marketing activity more broadly.

10. Conclusion

This paper set out a conceptual framework connecting AI-enabled logistics to marketing performance and financial sustainability, built on the resource-based view, dynamic capabilities theory, and the technology-organization-environment framework. The core argument is that AI works as a strategic resource whose marketing and financial payoffs are neither guaranteed nor uniform: they depend on whether AI capability gets converted into operating routines, on whether the AI in question is customer-facing or stays backend, and on organizational and environmental conditions that differ from firm to firm. Working through the paper's three objectives, the analysis suggests that AI-enabled logistics capability shapes delivery accuracy, customer satisfaction, service responsiveness, and brand competitiveness; that its effect on cost efficiency and resource optimization is fairly direct while its effect on profitability and resilience runs more through capability development; and that marketing performance and financial sustainability are best read as outcomes that feed each other, more strongly as AI integration matures, and potentially in reverse when AI investment does not build real capability.

For researchers, this offers a set of propositions worth testing and a reason to study logistics, marketing, and financial outcomes together rather than apart. For managers, the takeaway is that AI investment in logistics is not one decision with one payoff; it is a capability-building effort whose returns depend on where, how, and how deeply AI gets woven into a firm's customer-facing and operational infrastructure. As AI keeps maturing and spreading across logistics-heavy industries, connecting these three domains, operational, marketing, and financial, is likely to matter more, both for what researchers understand and for what managers decide to do...

REFERENCES

1. Alayed, S., & Alateeg, S. (2026). The role of artificial intelligence in logistics firm performance with supply chain consistency and logistics capabilities in

Saudi Arabia. Logistics, 10(5), 104. https://doi.org/10.3390/logistics10050104

2. Alkalha, Z., Ali, A. H. Q., & Jum'a, L. (2025). Unleashing the potential of artificial intelligence to enhance reverse logistics operations. International Journal of Physical Distribution & Logistics Management, 56, 27–60. https://doi.org/10.1108/IJPDLM-06-2025-0296

3. Alrsheedi, A., & Iskandar, Y. H. P. (2025). The role of artificial intelligence in financial inclusion in emerging markets: A conceptual review. Edelweiss Applied Science and Technology, 9(5), 1303–1323.

4. Amazon.com. (2025). Amazon.com announces fourth quarter results [Press release, February 6, 2025]. https://ir.aboutamazon.com/news-release/news-release-details/2025/Amazon-com-Announces-Fourth-Quarter-Results/default.aspx

5. Amazon.com. (2026). Amazon.com announces fourth quarter results [Press release, February 5, 2026]. https://www.sec.gov/Archives/edgar/data/1018724/000101872426000002/amzn-20251231xex991.htm

6. American Customer Satisfaction Index. (2022). Press release: Retail and consumer shipping 2021-2022. ACSI LLC. https://theacsi.org/news-and-resources/press-releases/2022/03/01/press-release-retail-and-consumer-shipping-2021-2022/

7. American Customer Satisfaction Index. (2026). Consumer shipping and mail: Satisfaction benchmarks by company. ACSI LLC. https://theacsi.com/industries/consumer-shipping-and-mail/

8. Bag, S., Gupta, S., & Luo, Z. (2020). Examining the role of logistics 4.0 enabled dynamic capabilities on firm performance. The International Journal of Logistics Management, 31(3), 607–628. https://doi.org/10.1108/IJLM-11-2019-0311

9. Barney, J. (1991). Firm resources and sustained competitive advantage. Journal of Management, 17(1), 99–120.

10. Chen, W., Men, Y., Fuster, N., Osorio, C., & Juan, A. A. (2024). Artificial intelligence in logistics optimization with sustainable criteria: A review. Sustainability, 16(21), 9145. https://doi.org/10.3390/su16219145

11. Macrotrends. (2026). FedEx Corporation (FDX) - Operating margin 2010-2025. https://www.macrotrends.net/stocks/charts/FDX/fedex/operating-margin

12. Macrotrends. (2026). FedEx Corporation (FDX) - Revenue 2012-2026. https://www.macrotrends.net/stocks/charts/FDX/fedex/revenue

13. Macrotrends. (2026). United Parcel Service (UPS) - Operating margin 2010-2025. https://macrotrends.net/stocks/charts/UPS/ups/operating-margin

14. Macrotrends. (2026). United Parcel Service (UPS) - Revenue 2012-2026. https://www.macrotrends.net/stocks/charts/UPS/ups/revenue

15. Malhotra, G., & Kharub, M. (2025). Elevating logistics performance: Harnessing the power of artificial intelligence in e-commerce. The International Journal of Logistics Management, 36(1), 290–321. https://doi.org/10.1108/IJLM-01-2024-0046

16. 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

17. Nextbillion.ai. (2026). UPS Orion AI: Route optimization & cost savings. https://nextbillion.ai/feeds/blog/ups-orion-ai-route-optimization-savings

18. Ponomarenko, I., & Ponomarenko, D. (2023). AI-powered logistics and digital marketing for business optimisation. Economics and Education, 8(4), 27–33. https://doi.org/10.30525/2500-946X/2023-4-4

19. Richey, R. G., Chowdhury, S., Davis-Sramek, B., Giannakis, M., & Dwivedi, Y. K. (2023). Artificial intelligence in logistics and supply chain management: A primer and roadmap for research. Journal of Business Logistics, 44(4), 532–549. https://doi.org/10.1111/jbl.12364

20. Supply Chain Dive. (2026). FedEx's next AI leap to feature RFID, robotics. https://www.supplychaindive.com/news/fedex-ai-usage-rfid-robotics-network-2/816220/

21. Teece, D. J., Pisano, G., & Shuen, A. (1997). Dynamic capabilities and strategic management. Strategic Management Journal, 18(7), 509–533.

22. TIKR.com. (2026). UPS vs. FedEx: Which logistics giant is better positioned for a rebound? https://www.tikr.com/blog/ups-vs-fedex-which-logistics-giant-is-better-positioned-for-a-rebound

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

24. Toth, Z., Goga, A.-S., & Boșcoianu, M. (2025). AI integration in fundamental logistics components: Advanced theoretical framework for knowledge process capabilities and dynamic capabilities hybridization. Logistics, 9(4), 140. https://doi.org/10.3390/logistics9040140

25. United Parcel Service. (2013). UPS 2012 annual report.

26. United Parcel Service. (2014). UPS 2013 annual report: We're just getting started.

27. USPS. (2024). U.S. Postal Service reports fiscal year 2024 results [Press release, November 14, 2024]. https://about.usps.com/newsroom/national-releases/2024/1114-usps-reports-fiscal-year-2024-results.htm

28. Walter, A., Ahsan, K., & Rahman, S. (2025). Application of artificial intelligence in demand planning for supply chains: A systematic literature review. The

International Journal of Logistics Management, 36(3), 672–719. https://doi.org/10.1108/IJLM-02-2024-0120

29. Weise, J. (2019). ORION: Route optimization at UPS. https://joachimweise.github.io/post/2019-11-30-ups-orion/....

.