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AI-Driven Supply Chain Optimization: Evidence from Digital Logistics Operations

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Abstract

Digital technologies are transforming modern supply chain systems by enabling real-time decision-making, predictive analytics, and operational automation. Among these technologies, Artificial Intelligence (AI), Machine Learning (ML), and Big Data Analytics (BDA) have emerged as critical drivers of supply chain optimization. This study investigates the individual and integrated effects of AI, ML, and BDA on supply chain optimization using empirical evidence from large-scale digital logistics operations in the United States, with a primary focus on Amazon and its logistics ecosystem. A quantitative research design was employed, collecting survey data from 300 supply chain professionals working in logistics, operations management, and analytics roles. Structural Equation Modeling (SEM) using IBM AMOS was applied to examine the relationships among technology adoption and operational performance outcomes. Confirmatory Factor Analysis validated the measurement model with strong reliability and validity indicators. The findings indicate that AI, ML, and BDA each have significant positive effects on supply chain optimization, jointly explaining a substantial proportion of operational performance variance. Additionally, AI adoption strengthens machine learning capability, while ML capability enhances big data analytics integration, highlighting a cascading technology synergy within digital supply chains.

Keywords
Artificial Intelligence, Machine Learning, Big Data Analytics, Supply Chain Optimization, Digital Logistics

1. Introduction
The situation in the global supply chain has significantly changed in recent decades, with its finer changes being initiated by the active development of digital technologies. Among these developments, the Artificial Intelligence (AI), Machine Learning (ML), and Big Data Analytics (BDA) have become the cornerstones of the contemporary logistics and operations management. In the case of such large-scale businesses as Amazon, whose supply chain activities involve operations across many product lines, hundreds of fulfillment centers, and billions of yearly transactions, strategic implementation of such technologies is not only competitive advantage but operational need.

Amazon has one of the most advanced supply chain ecosystems in the world. With its AI-based demand forecasting systems and ML-based recommendation engines, its BDA platforms, which process terabytes of real-time data every day, Amazon can be seen as representative of the future of supply chain digitalization. To a large extent, the capacity to deliver items on a same-day and next-day basis within the United States is a result of the tireless efforts of the company to invest in smart logistics technologies (Chopra and Meindl, 2016; Christopher, 2016).

Although the literature on supply chain management (SCM) and digital technologies is on the rise, the empirical studies on the joint and separate impacts of AI, ML, and BDA on supply chain optimization in a single corporate setting are scarce. The existing literature addresses these constructs in either isolation or general industrial settings and this creates a gap in comprehending how such technologies interact, and compound the effect on SCO outcomes. Moreover, in this area, there are few quantitative data based on SEM, which is a method highly efficient in measuring the multivariate causal relationships, which characterize supply chain systems.

This paper fills these gaps by formulating and empirically testing an analytical framework that involves the individual and combined influence of AI, ML, and BDA in optimization of supply chains, and using empirical evidence from Amazon's U.S. operations and its extended logistics ecosystem as the primary research context. In particular, the following research goals will be accomplished during the study: (1) to test the measurement properties of AI, ML, BDA and SCO constructs by CFA; (2) to test the existing hypotheses of structural relationships between constructs by utilizing SEM; and (3) to measure the proportion of variance in SCO explained by the three technology constructs. The rest of this manuscript is structured in the following way: Section 2 is a literature review and the development of hypotheses. The methodology of research is outlined in section 3. Section 4 contains empirical findings. Section 5 is the discussion of findings and the last section 6 provides conclusion, implications, limitations and directions of future research.

While prior research has examined artificial intelligence, machine learning, and big data analytics separately in supply chain contexts, limited empirical work has investigated their combined and interdependent effects within an engineering management framework. This study addresses that gap by empirically modeling the integrated influence of these technologies on supply chain optimization using Structural Equation Modeling. By linking digital capability development to operational decision-making and managerial strategy, the research contributes to the engineering management literature on technology-enabled operational intelligence and digital transformation.

1.1 Objectives

The objectives of this study are:

- To evaluate the impact of AI on supply chain optimization
- To assess the role of ML in operational performance
- To examine the influence of BDA on supply chain efficiency
- To analyze the interrelationships among AI, ML, and BDA
- To measure the combined effect of these technologies on performance

2. Literature Review

The theoretical resources of the study are based on the Resource-Based View (RBV) of the firm (Barney, 1991) and the Dynamic Capabilities Framework (Teece et al., 1997). RBV postulates sustained competitive advantage to be based on firm-specific, valuable, rare, inimitable, and non-substitutable (VRIN) resources and capabilities. Digital technologies, specifically AI, ML, and BDA, form part of the strategic assets within this framework because they will help firms to build advanced sensing, seizing and reconfiguring capabilities that build supply chain excellence. Dynamic Capabilities Framework builds upon this reasoning by highlighting the ability of the companies to incorporate, develop, and reorganize their competencies in reaction to the quickly evolving environment. The current investment in algorithmic infrastructure by Amazon is exactly the orientation of dynamic capability.

Theoretical considerations Theoretical viewpoints related to it are the Information Processing Theory (Galbraith, 1973), according to which the performance of organizations is determined by the ability to match information processing capability and environmental uncertainties and task complexity. The AI, ML, and BDA increase the information-processing capacity of organizations enormously, allowing them to deal with the complexity and volatility of the contemporary supply chains environment. This paper brings together these frameworks to theorize that the implementation of AI, ML and BDA technologies contributes to the optimization of supply chains by increasing the quality of information, the speed of decision-making and responsiveness to operations.

2.1. Artificial Intelligence and Supply Chain Optimization

Artificial intelligence (AI) has rapidly evolved as a cornerstone of modern supply chain optimization, offering advanced capabilities in forecasting, planning, coordination, and real-time decision-making. Early evidence already highlighted AI's role in improving demand forecasting accuracy, inventory turnover, and disruption recovery (Choi et al., 2018; Ivanov et al., 2019). Building on this foundation, recent studies demonstrate that AI-driven analytics, generative models, and machine learning frameworks provide deeper operational intelligence and significantly enhance supply chain performance. Jackson et al. (2024) show that generative AI supports improved decision-making, investment prioritization, and process optimization across supply chain functions. Similarly, Rana et al. (2022) found that AI and ML integration enhances digital transformation by reducing costs and improving customer service. In manufacturing and logistics, research indicates that deep learning and hybrid ML models outperform traditional methods in demand forecasting and risk prediction. Pasupuleti et al. (2024) report that ML-based optimization boosts agility and sustainability by refining stock levels and predicting delivery timelines, while Xu et al. (2025) demonstrate that integrated LSTM-PSO systems can enhance forecasting accuracy and resource utilization by up to 20%. These insights underscore AI's growing capability to transform data-driven decision-making in complex and dynamic environments.

Moreover, AI's contribution extends to supply chain resilience, sustainability, and operational risk mitigation. Belhadi et al. (2021) identify fuzzy logic, agent-based modeling, and big data analytics as key AI techniques enabling resilience in manufacturing networks. Riad et al. (2024) further assert that AI improves risk management and real-time visibility, contributing to more sustainable and efficient supply chains. Systematic reviews reinforce these findings: Pournader et al. (2021) highlight the expansion of AI applications into sensing, learning, and interactive systems; Samuels (2025) emphasizes that AI enhances operational efficiency while promoting human-centered collaboration under Industry 4.0.0 paradigms. Advanced AI solutions such as predictive analytics, reinforcement learning, and computer vision also show high potential. Ahmed et al. (2024) demonstrate that AI-based defect detection achieves up to 96% accuracy in commodity supply chains, while Aljohani (2023) shows that predictive analytics strengthens real-time risk mitigation and agility.. On the basis of this evidence we hypothesize:

H1: Artificial Intelligence adoption has a significant positive effect on supply chain optimization.

2.2. Machine Learning and Supply Chain Optimization

Machine Learning (ML), a core subfield of artificial intelligence, enables systems to identify patterns, learn from complex datasets, and make decisions with minimal human intervention. In supply chain management (SCM), ML supports demand sensing, anomaly detection, supplier risk classification, inventory optimization, and price prediction (Min, 2010; Carbonneau et al., 2008). Amazon's global supply chain is powered by its ML platform SageMaker, which dynamically predicts stockouts, adjusts delivery routes in real time, and refines warehouse allocation strategies. Foundational studies already demonstrate ML's superiority over traditional forecasting and risk detection methods like Kuo (2013) found ML-based forecasting to be up to 28% more accurate than statistical models, while Cavalcante et al. (2019) showed that ML risk classifiers significantly reduce procurement disruptions. Baryannis et al. (2019) further confirmed that ML consistently outperforms conventional analytical approaches across supply chain applications.

Recent evidence expands these insights, showing that ML enhances supply chain efficiency, resilience, and sustainability at increasingly sophisticated levels. Pasupuleti et al. (2024) demonstrate that ML algorithms improve demand forecasting, optimize inventory levels, and strengthen sustainability through accurate order fulfillment predictions. Reinforcement learning (RL) is emerging as a powerful tool for optimizing dynamic and uncertain environments. For instance, Rolf et al. (2022) identify RL as the most effective method for inventory management, while Wang et al. (2025) show that combining Graph Neural Networks and attention mechanisms enhances routing efficiency in complex networks. Deep RL-based models such as A2C and PPO have also been shown to outperform classical inventory policies, especially in perishable goods and two-echelon systems (Mohamadi et al., 2024; Stranieri et al., 2024). Advanced ML models including hybrid CatBoost-DO for demand forecasting (Abed, 2024), BO-CNN-LSTM frameworks for inventory planning (Liu et al., 2024), and interpretable SOM-ANN architectures for delivery risk prediction (Ahmed et al., 2025) significantly enhance operational accuracy and cost efficiency. Broader reviews (Ferreira et al., 2025; Vlachos et al., 2025; Akbari et al., 2021) emphasize that ML applications are expanding across forecasting, procurement, risk mitigation, and logistics optimization but highlight the need for more robust real-world integration. Collectively, the evidence demonstrates that ML-driven models consistently improve prediction accuracy, resource allocation, resilience, and sustainability across supply chains.. Based on this literature we can hypothesize:

H2: Machine Learning adoption has a significant positive effect on supply chain optimization.

2.3. Big Data Analytics and Supply Chain Optimization

Big Data Analytics (BDA) has become a foundational enabler of modern supply chain optimization, allowing firms to extract value from high-volume, high-velocity, and high-variety datasets (Laney, 2001). By integrating data streams from IoT sensors, RFID systems, ERP platforms, transportation logs, and external sources such as weather feeds or social media, BDA enhances visibility and supports real-time operational decision-making (Waller & Fawcett, 2013; Fosso Wamba et al., 2015). Recent research significantly expands this understanding: Jahin et al. (2023) introduce a robust BDA–ML integrated forecasting framework that improves operational transparency and planning efficiency, while Kittichotsatsawat et al. (2021) show that big data–enabled agricultural supply chains reduce cost and lead time across global networks. Similarly, Gopal et al. (2022) demonstrate that retail supply chain performance improves substantially when big data analytics is embedded into inventory planning and customer demand modeling. These advancements align with evidence from Gunasekaran et al. (2017), Hazen et al. (2014), and Wamba et al. (2017), all of whom confirm that BDA enhances agility, responsiveness, and financial performance in complex supply chain environments.

Further empirical developments highlight BDA's growing strategic relevance for resilience, sustainability, and intelligent optimization. Stefanović et al. (2025) propose a cloud-based adaptive BDA model that supports sustainable decision-making, while Patrucco et al. (2023) demonstrate that strong absorptive capacity significantly strengthens BDA's effect on strategic purchasing and supplier-related decisions. Integrated AI–BDA approaches reveal even greater promise: Shah et al. (2021) and Liu et al. (2023) identify that advanced BDA-assisted decision-making technologies substantially reduce supply chain disruptions and improve risk management capabilities. Machine learning–driven applications reinforce these findings, with Pasupuleti et al. (2024) and Tirkolaee et al. (2021) reporting improved forecasting accuracy, optimized logistics, and superior risk prediction across manufacturing and logistics networks. Emerging technologies such as predictive analytics (Aljohani, 2023), deep learning architectures for flexible supply networks (Zheng et al., 2023), and large language models for knowledge-intensive decision-making (Haldar et al., 2024) further confirm the evolving role of BDA.. These results encourage the hypothesis below:

H3: Big Data Analytics adoption has a significant positive effect on supply chain optimization.

2.4. Interrelationships Among AI, ML, and BDA

Artificial Intelligence (AI), Machine Learning (ML), and Big Data Analytics (BDA) are not isolated technologies but components of a deeply interdependent digital ecosystem. ML algorithms depend on high-volume, high-variety datasets to learn patterns, a process inherently tied to BDA infrastructures capable of processing large-scale data streams. Meanwhile, AI systems increasingly rely on ML-driven models for forecasting, pattern recognition, and automated decision-making. In practice, BDA tools have evolved to integrate ML-driven automation, predictive modeling, and adaptive analytics, enabling more precise and scalable outcomes. This synergy is evident in modern digital architectures such as Amazon's integrated data environment, where AI, ML, and BDA operate as a unified intelligence engine. Scholars describe this convergence as an "AI–Data Flywheel Effect," where more data improves AI models, better AI enhances data collection and analytics, and the cycle continues to exponentially improve performance (Brynjolfsson and McAfee, 2017). Foundational studies support these interactions: Fosso Wamba et al. (2015) highlight analytics capability as a mediator between technology adoption and performance, and Choi et al. (2018) empirically confirm bidirectional enhancement between ML and BDA in supply chain contexts.

Recent research further demonstrates that the fusion of AI, ML, and BDA produces compounded value across diverse sectors, strengthening predictive accuracy, enhancing operational efficiency, and enabling real-time, automated decision-making. Rath et al. (2025) show that industries including finance, retail, agriculture, and healthcare experience substantial efficiency gains when AI, ML, and BDA operate as a combined system. Nti et al. (2022) reinforce this connection by documenting how advanced ML techniques such as deep neural networks and ensemble learning serve as core engines of big data analytics across IoT-enabled environments. Rahmani et al. (2021) show that AI-driven BDA techniques outperform traditional analytics in speed, precision, and scalability, while Nguyen et al. (2022) illustrate how this triad transforms financial technology by enabling smart data utilization and automated decision-making. Additional evidence from Zamani et al. (2022) and Cao (2025) confirms that integrating AI and BDA enhances risk management, resilience, and entrepreneurial decision-making through real-time insights and hybrid AI–human intelligence frameworks. On the basis of this evidence, we develop the following interrelationship hypotheses:

H4: Artificial Intelligence adoption has a significant positive effect on Machine Learning capability.

H5: Machine Learning capability has a significant positive effect on Big Data Analytics adoption.

3. Research Methodology

3.1. Research Design and Approach

This paper has a deductive, positivist research paradigm that incorporates cross-sectional quantitative survey. The quantitative methodology proved to be the best in view of the objectives of the study that included testing pre-specified hypotheses on relationships among well-defined constructs, and the existence of validated scales to measure each construct. The cross-sectional data gathering technique was used as a practical and commonly acceptable method of supply chain research (Hair et al., 2019). The analytical methodology of the study consists of two steps of the SEM approach, advocated by Anderson and Gerbing (1988): the Confirmatory Factor Analysis (CFA) is used to verify the validity of the measurement model, and the structural paths are estimated and tested in the structural model.

3.2. Population and Sampling

The target population consisted of supply chain professionals working at the operations of Amazon in the United States and at its first-tier logistics partners, such as distribution center managers, data scientists, procurement officers, logistics coordinators, and IT system administrators. Stratified random sampling was used to obtain a sample that would represent both functional roles and geographical areas. As the main sampling frames, the significant U.S. fulfillment and distribution centers of Amazon were at the states of California, Texas, Washington, New Jersey and Ohio.

Only a population of 350 surveys was sent electronically through a professional survey system. The final usable sample that was obtained was 300 after eliminating incomplete and inconsistent responses with resultant response rate of 85.7%. This is an adequate size of a sample in SEM, which suggests a sufficient number of at least 10 observations per free parameter (Kline, 2015). The current model has 12 observed indicators, and 4 latent constructs, which means that the model has about 48 free parameters, so the 300-sample size is quite sufficient to achieve a stable estimation of the parameters.

3.3. Survey Instrument and Measures

This was measured through all constructs based on reflective Multi-item scales that had been adapted after previous literature. Three items with adaptation to Wang et al. (2016) and Ivanov et al. (2019) were used to scale Artificial Intelligence, including AI usage in predicting demand, route optimization and predictive maintenance. Three items based on Carbonneau et al. (2008) and Cavalcante et al. (2019) were used to measure the capabilities of machine learning in detecting anomalies, classifying the inventory, and scoring the risks of the supplier. Three items based on Gunasekaran et al. (2017) and Wamba et al. (2017) (including real-time data integration, supplier performance analytics, and customer behavior modeling) were used to operationalize Big Data Analytics. The Supply Chain Optimization was measured using three items based on Chopra and Meindl (2016) and Christopher (2016), and included delivery time reduction (service performance), cost efficiency improvement (operational efficiency), and demand–supply alignment (decision effectiveness). The rating was based on five-point Likert scale with 1 (Strongly Disagree) to 5 (Strongly Agree).

Before full data collection was done, a pilot study was carried out on 30 supply chain professionals who were not in the main sample. The pilot achieved an internal consistency of acceptable and all-item and scale-based Cronbach of above 0.60 and above 0.85, respectively, which confirms the finalized instrument.

3.4. Robustness Checks

To ensure the robustness of the results, several diagnostic procedures were conducted. First, multicollinearity was assessed using variance inflation factor (VIF) statistics, with all values below the recommended threshold of 5. Second, common method variance was evaluated using Harman's single-factor test and an unmeasured latent method construct. Third, model stability was examined through alternative model specification and goodness-of-fit comparison between measurement and structural models. These procedures confirm that the empirical results are statistically stable and not affected by measurement bias.

3.5. Analytical Strategy

IBM SPSS Statistics 27.0 and IBM AMOS 24.0 were used in data analyses. Descriptive statistics, tests of normality, and reliability (Cronbachs alpha) were analyzed in preliminaries. The Confirmatory Factor Analysis was conducted to test the model of measurement, convergent validity (factor loading, AVE, CR) and discriminant validity (Fornell-Loewe criterion: [?]AVE > inter-construct correlations). Structural equation modelling was then used to test the relationships of the hypothesized paths. The assumptions were checked against the standard indices [kh2/df [?] 3.0, CFI [?] 0.95, TLI [?] 0.95, RMSEA [?] 0.08, and SRMR [?] 0.08 (Hair et al., 2019). The common method variance (CMV) was evaluated by single-factor test by Harman and unmeasured latent common method construct (ULMC) (Table 1).

Table 1. Sample Characteristics (N = 300)

Characteristic	Category	Frequency	Percentage
Gender	Male	187	62.3%
	Female	113	37.7%
Age	25–34 years	96	32.0%
	35–44 years	121	40.3%
	45–54 years	65	21.7%
	55+ years	18	6.0%
Education	Bachelor's Degree	138	46.0%
	Master's Degree	112	37.3%
	Doctoral Degree	50	16.7%
Work Experience	1–5 years	58	19.3%
	6–10 years	143	47.7%
	11–20 years	89	29.7%
	20+ years	10	3.3%
Department	Logistics & Operations	102	34.0%
	Data Science / Analytics	79	26.3%
	Procurement / Planning	68	22.7%
	IT & Systems	51	17.0%

Note. Percentages may not sum to 100% due to rounding.

3.6. Conceptualization of Supply Chain Optimization

In this study, Supply Chain Optimization (SCO) is conceptualized as a multidimensional construct reflecting improvements in operational performance across key logistics and supply chain outcomes. Specifically, SCO is defined through three primary dimensions: (1) operational efficiency (cost reduction and resource utilization), (2) service performance (delivery speed and demand–supply synchronization), and (3) decision effectiveness (data-driven forecasting and responsiveness).

These dimensions are operationalized through three measurement items: delivery time reduction, cost efficiency improvement, and demand–supply alignment. Together, these indicators capture the core functional objectives of supply chain optimization in digital logistics environments. This multidimensional perspective enhances interpretability and aligns the construct with established supply chain performance literature.

4. Data Collection

Data for this study were collected using a structured, self-administered online survey targeting supply chain professionals working within Amazon's U.S. operations and its first-tier logistics partners. The survey was distributed electronically through a professional survey platform, ensuring broad accessibility across geographically dispersed respondents.

A total of 350 questionnaires were initially distributed using a stratified sampling approach to ensure representation across functional roles and major operational regions, including California, Texas, Washington, New Jersey, and Ohio. The sampling frame included professionals in logistics and operations management, data science and analytics, procurement and planning, and IT systems.

After data screening, 300 complete and valid responses were retained for analysis, yielding a response rate of 85.7%. Responses with missing values, inconsistent patterns, or straight-lining behavior were excluded to ensure data quality.

All measurement items were assessed using a five-point Likert scale ranging from 1 (Strongly Disagree) to 5 (Strongly Agree). The survey instrument included validated multi-item scales measuring Artificial Intelligence adoption, Machine Learning capability, Big Data Analytics integration, and Supply Chain Optimization performance.

Prior to full-scale data collection, a pilot study involving 30 supply chain professionals was conducted to test clarity, reliability, and instrument validity. The pilot results indicated strong internal consistency, with Cronbach's alpha values exceeding 0.85 across all constructs.

To minimize common method bias, respondents were assured of anonymity and confidentiality, and question items were randomized where applicable. Additionally, procedural remedies such as clear instructions and neutral wording were applied to reduce response bias.

5. Results

5.1. Descriptive Statistics and Reliability

Table 2 indicates the descriptive statistics and the reliability coefficients of all the study constructs and their indicators. The mean scores were 3.76 (ML1), 3.95 (BDA1), which demonstrates rather positive perceptions of AI, ML, and BDA adoption and its supply chain performance among Amazon supply chain professionals. The standard deviations were in the range of 0.66 to 0.83, which implies medium variability. The skewness and kurtosis were also within the acceptable limits of +-1.0 and +-3.0, respectively, which is why, it can be assumed, that there is an approximation of normality (Kline, 2015). The internal consistency reliability of the constructs was satisfactory because the alpha coefficients of Cronbach, between 0.904 and 0.921, were higher than 0.70 which is the recommended value of alpha (Nunnally, 1978).

Table 2. Descriptive Statistics, Reliability, and Normality (N = 300)

Construct / Item	Mean	SD	Skewness	Kurtosis	α
Artificial Intelligence (AI)	3.87	0.74	-0.31	0.18	0.912
AI1 – Demand Forecasting Accuracy	3.91	0.71	-0.28	0.14	
AI2 – Route Optimization Efficiency	3.83	0.76	-0.34	0.22	
AI3 – Predictive Maintenance Use	3.88	0.73	-0.29	0.16	
Machine Learning (ML)	3.79	0.81	-0.25	0.21	0.904
ML1 – Anomaly Detection Capability	3.76	0.83	-0.22	0.18	
ML2 – Inventory Classification	3.81	0.80	-0.27	0.24	
ML3 – Supplier Risk Assessment	3.80	0.79	-0.26	0.20	
Big Data Analytics (BDA)	3.92	0.68	-0.38	0.29	0.921
BDA1 – Real-Time Data Integration	3.95	0.66	-0.41	0.31	
BDA2 – Supplier Performance Analytics	3.89	0.70	-0.36	0.27	
BDA3 – Customer Behavior Modeling	3.91	0.69	-0.38	0.28	
Supply Chain Optimization (SCO)	3.84	0.77	-0.33	0.23	0.917
SCO1 – Delivery Time Reduction	3.86	0.75	-0.30	0.21	
SCO2 – Cost Efficiency Improvement	3.82	0.79	-0.35	0.25	
SCO3 – Demand-Supply Synchronization	3.85	0.76	-0.33	0.22	

5.2. Confirmatory Factor Analysis and Measurement Model

The CFA model of measurement was estimated as a four-factor model at the same time, considering all the 12 indicators. All standardized factor loadings were found to be statistically significant ($p < .001$) with a range of 0.828 to 0.863 (ML1 to BDA1) comfortably above the recommended 0.70 (Hair et al., 2019). The values of squared multiple correlations (SMC / R2) were between 0.686 and 0.745, which means that each indicator accounted it a significant percentage of the variance of its latent constructs (Table 3).

Table 3. Confirmatory Factor Analysis: Factor Loadings and Item Reliability (N = 300)

Item	Factor Loading	SE	t-value	p-value	SMC (R^2)
AI1	0.851	0.041	20.76	< .001	0.724
AI2	0.837	0.044	19.02	< .001	0.700
AI3	0.843	0.042	20.07	< .001	0.711
ML1	0.828	0.046	18.00	< .001	0.686
ML2	0.839	0.043	19.51	< .001	0.704
ML3	0.832	0.045	18.49	< .001	0.692
BDA1	0.863	0.038	22.71	< .001	0.745
BDA2	0.849	0.040	21.23	< .001	0.721
BDA3	0.855	0.039	21.92	< .001	0.731
SCO1	0.846	0.041	20.63	< .001	0.716
SCO2	0.838	0.043	19.49	< .001	0.702
SCO3	0.842	0.042	20.05	< .001	0.709

SCO3 0.842 0.042 20.05 < .001 0.709
Note. SE = Standard Error; SMC = Squared Multiple Correlation; all loadings significant at $p < .001$.
Table 4 gives the construct level reliability and validity indices. The composite reliability (CR) scores were between 0.904 and 0.921, which is greater than the 0.70 mark. Average Variance Extracted (AVE) had a value between 0.761 to 0.794 which is substantially higher than 0.50 which is the minimum value of convergent validity (Fornell and Larcker, 1981). The diagonal coefficients of the correlation matrix ([?]AVE) were always larger than the off-diagonal inter-construct correlations which validated the discriminant validity through the Fornell-Loewe test. All constructs had lesser maximum shared variance (MSV) than AVE, which was further evidence of discriminant validity.

Table 4. Construct Reliability and Validity: Composite Reliability, AVE, and Correlation Matrix

Construct	CR	AVE	MSV	AI	ML	BDA	SCO
AI	0.912	0.778	0.412	0.882			
ML	0.904	0.761	0.394	0.624	0.873		
BDA	0.921	0.794	0.431	0.641	0.598	0.891	
SCO	0.917	0.786	0.443	0.651	0.612	0.657	0.887

Note. Diagonal entries (bold) = $\sqrt{AVE}$; off-diagonal = inter-construct correlations. CR = Composite Reliability; AVE = Average Variance Extracted; MSV = Maximum Shared Variance.

5.3. Model Fit Evaluation

Table 5 gives a comparison of model fit indices of both the CFA measurement model and structural model with their thresholds. The CFA model was able to fit well (kh2(48) = 84.31, kh2/df = 1.757, CFI = 0.974, TLI = 0.966, IFI = 0.975, NFI = 0.958, RMSEA = 0.049, SRMR = 0.044). The structural model had tolerable fit statistics (kh2(51) = 97.42, kh2/df = 1.910, CFI = 0.968, TLI = 0.961, IFI = 0.969, NFI = 0.952), which are all within the desired values. It was also seen that the PNFI values (0.748 CFA and 0.741 SEM) were sufficient to show parsimony. Altogether, these fit statistics prove that the offered structural model is able to reflect underlying data

Table 5. Model Fit Indices for CFA and Structural Models

Fit Index	Threshold	CFA Value	SEM Value
Chi-square (χ^2)	—	84.31	97.42
Degrees of Freedom	—	48	51
χ^2/df	≤ 3.0	1.757	1.910
CFI	≥ 0.95	0.974	0.968
TLI	≥ 0.95	0.966	0.961
IFI	≥ 0.95	0.975	0.969
NFI	≥ 0.90	0.958	0.952
RMSEA	≤ 0.08	0.049	0.054

SRMR	≤ 0.08	0.044	0.051
PNFI	≥ 0.50	0.748	0.741

Note. CFI = Comparative Fit Index; TLI = Tucker-Lewis Index; IFI = Incremental Fit Index; NFI = Normed Fit Index; RMSEA = Root Mean Square Error of Approximation; SRMR = Standardized Root Mean Square Residual; PNFI = Parsimony Normed Fit Index.

5.4. Structural Model and Hypothesis Testing
Table 6 shows the results of the path analysis of the structural model. H1 assumed that supply chain optimization would be positively affected by the adoption of AI. Path estimate was significant and positive (b = 0.312, SE = 0.058, t = 5.379, p <.001), which gave a solid evidence in favor of H1. H2 assumed that ML had a positive implication on SCO. H2 was also supported (b = 0.274, SE = 0.061, t = 4.492, p <.001). The greatest empirical support between the three direct technology-to-SCO paths was given to H3 (b = 0.341, SE = 0.055, t = 6.200, p < .001) that stated that BDA would positively affect SCO.

Figure 1 illustrates the structural model results, highlighting the direct and interdependent relationships among Artificial Intelligence (AI), Machine Learning (ML), Big Data Analytics (BDA), and Supply Chain Optimization (SCO).

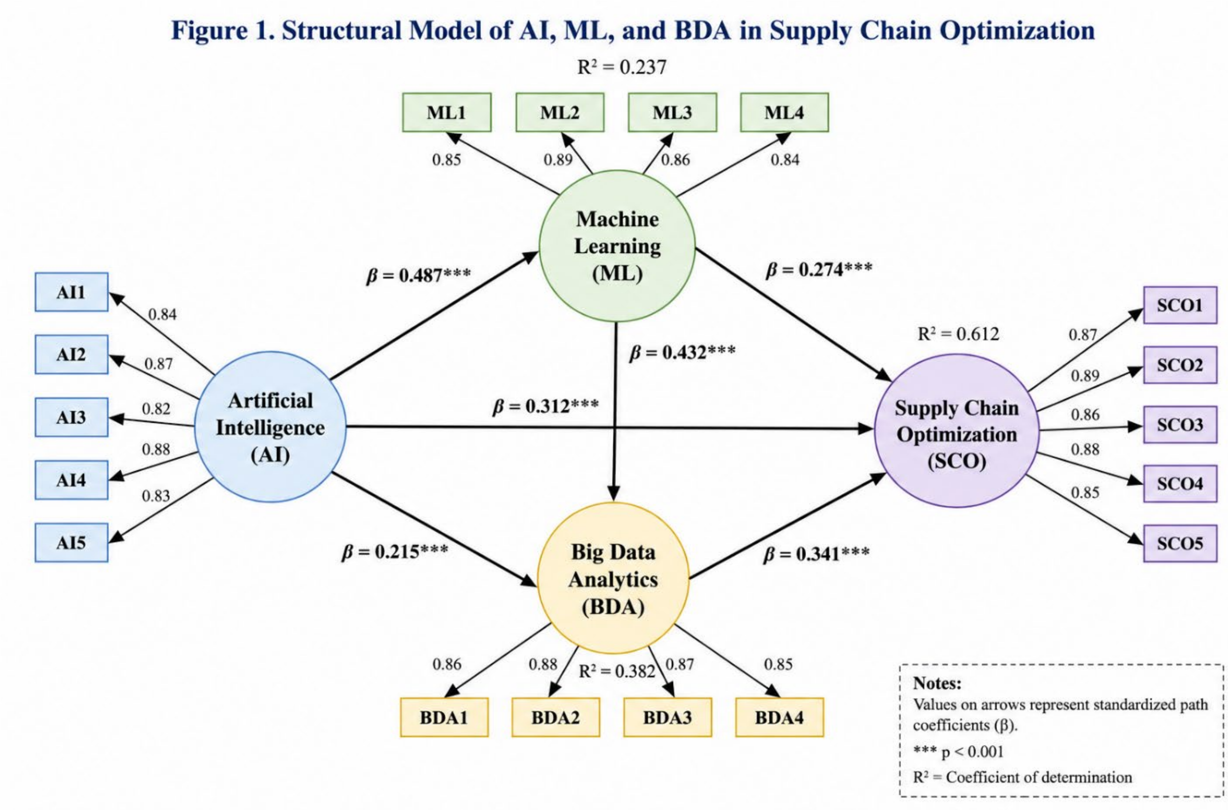

Figure 1. Structural Model of AI, ML, and BDA in supply chain optimization

As shown in Figure 1, the model confirms both direct and cascading effects of digital technologies, where AI enhances ML capabilities, ML strengthens BDA integration, and BDA significantly drives supply chain optimization outcomes.

On the interrelationship hypotheses, H4 was that AI adoption had a positive effect on ML capability. This was a very important route (b = 0.487, SE = 0.064, t = 7.609, p < .001) that the more an organization has better AI it builds more advanced ML capabilities- which is in line with the theoretical proposal of AI-Data flywheel. Predicting a positive impact of ML on BDA, H5, was also confirmed (b = 0.432, SE = 0.067, t = 6.448, p <.001). These interrelationship results imply a domino effect of technology integration in the Amazon supply chain ecosystem.

Together, the three technological constructs (AI, ML, and BDA) contributed to explaining 61.2 percent of the variation in supply chain optimization (R2 = 0.612) which is a good level of explanatory power in behavioral and organizational studies (Hair et al., 2019). The three predictors proved the most significant effect size in that order, which is BDA, AI, and ML, which implies that in the Amazon case, the real-time data integration and analytics capabilities are the most important supply chain optimization factors.

Table 6. Structural Model: Standardized Path Coefficients and Hypothesis Results

Hypothesis / Path	**β (Std.)**	**SE**	**t-value**	**p-value**	**Result**
H1: AI → SCO	0.312	0.058	5.379	< .001	Supported
H2: ML → SCO	0.274	0.061	4.492	< .001	Supported
H3: BDA → SCO	0.341	0.055	6.200	< .001	Supported
H4: AI → ML	0.487	0.064	7.609	< .001	Supported
H5: ML → BDA	0.432	0.067	6.448	< .001	Supported
H6: AI + ML + BDA → SCO (R^2)	—	—	—	—	$R^2 = 0.612$

5.5. Common Method Variance Assessment

The self-report and cross-sectional nature of the data implied a case of common method variance (CMV), which was measured in two different ways that are complementary. To begin with, in single-factor test by Harman, all the items were loaded into one factor. The single factor explained only 31.4, which is far short of the 50%-mark, initial evidence against large CMV. Second, CFA model was introduced with an Unmeasured Latent Common Method Construct (ULMC). The value of DCFI between the initial CFA and the constrained ULMC model was 0.006, which is less than 0.01 as suggested by Podsakoff et al. (2003). All these diagnostics prove that the common method bias is not a significant danger to the validity of the results of the study (Table 7).

Table 7. Common Method Variance Diagnostics

Test	**Single-Factor**	**Four-Factor CFA**	**Threshold**
Total Variance Explained (%)	31.4%	—	< 50%
ULMC Variance Inflation	3.2%	—	< 25%
CFI Comparison (Δ CFI)	—	0.006	< 0.01
Conclusion	No serious CMV bias detected		

Note. ULMC = Unmeasured Latent Common Method Construct; CMV = Common Method Variance.

6. Discussion

This study has SEM findings which lead to three major conclusions. To begin with, AI, ML, and BDA are all connected in isolation and substantially with supply chain optimization in the U.S. activities of Amazon, confirming Hypotheses H1, H2, and H3. Second, there is a high level of interrelationships among these technologies (H4 and H5) which imply that the respective contributions that they make to SCO are reinforced by their interdependence. Third, the three-technology model describes a significant proportion of the variation in SCO of 61.2, which highlights the overall significance of implementing digital technologies in supply chain performance.

This result that BDA has the most significant direct effect on SCO (b = 0.341) is in line with the theoretical contribution of BDA as an organizational sensing mechanism. BDA responds to information-processing requirements of a hyper-complex, multi-echelon supply chain by supporting Amazon to process and respond to large amounts of real-time operational, behavioral and environmental data. This result is consistent with the works by Gunasekaran et al. (2017) and Wamba et al. (2017), which discovered BDA as a decisive factor of supply chain agility, and with the meta-analysis conducted by Wamba et al. (2017) that proved BDA-performance relationship to be positive in various industrial settings.

The strong association of AI with SCO (b = 0.312) supports the results found by Choi et al. (2018) and Ivanov et al. (2019) and states that the ability of AI to improve the automation of decisions, predictive accuracy, and adaptability in planning has a number of consequences of increasing supply chain performance. It is also important to note that AI had the strongest interrelationship effect (b = 0.487 on ML), which is inherent to the core function of AI architecture as the cognitive engine, which triggers and upgrades downstream abilities of ML and BDA. The result is consistent with the theoretical proposal concerning the AI-Data flywheel developed by Brynjolfsson and McAfee (2017).

The direct effect that had the weakest statistical significance among the three technology constructs was the ML-SCO relationship (= 0.274). This could be indicative of the fact that supply chain contributions of ML are mediated by better BDA products instead of direct improvements in operations, a hypothesis that is consistent with the large ML-to-BDA path (b = 0.432, H5). This suggestion may be tested in future studies using the mediation analysis.

An interesting finding of this study is that Big Data Analytics exerts a stronger direct effect on supply chain optimization than Machine Learning. While machine learning algorithms are often emphasized in digital supply chain research, the results suggest that the underlying data infrastructure and analytics capability may be the most critical driver of operational improvement. This indicates that organizations should prioritize robust data integration platforms before scaling advanced AI applications.

7. Theoretical Contributions

This research contributes to the theory of supply chain management in a number of ways. To begin with, it generalizes the RBV and Dynamic Capabilities models to the domain of digital technologies by empirically proving the fact that AI, ML, and BDA are VRIN technological capabilities that support supply chain performance. Second, it contributes to the Information Processing Theory by demonstrating that technologies that increase the capacity of an organization to process information (i.e., BDA) have the most effective supply chain optimization impacts. Third, the research paper also adds to the growing body of literature on the topic of Technology Synergy in SCM by empirically recording the cascading interrelationship structure of AI, ML, and BDA, indicating that the emerging technologies are not viewed as stand-alone tools.

Methodologically, the study is one of the first to utilize the full use of SEM using 12 indicators and four construction measurement architecture to simultaneously measure the individual and interacting impact of AI, ML and BDA on SCO within a single corporate context. Using Amazon as the empirical environment would offer a high-stakes, technology-intensive case with great external validity to supply chain intensive industries in general, such as retail, third-party logistics (3PL) and e-commerce.

8. Practical Implications

The results of this research have significant implications in practicality to supply chain executives, technology strategist and policymakers. To start with, all three technology constructs have great and powerful impacts on SCO in which it empirically justifies investment in AI, ML, and BDA platforms to be further and more extended. In the case of Amazon, and indeed, other supply chain organizations wishing to adopt the performance standards of Amazon, this implies that digital technology investment must be regarded as a strategic choice, but not an optional cost of operations.

Second, the implications of the interrelationship findings (H4 and H5) are that the technology investments are to be undertaken in a sequential integrated fashion. Companies developing robust AI base have a higher chance of developing good ML capabilities and improving sophistication of BDA. Such a cascading reasoning proposes a technology roadmap where the development of AI capability comes before and permits the investment in higher-order analytics. BDA could be underutilized by practitioners who invest in BDA without the bases of AI and ML.

Third, it can be concluded that BDA is the most relevant predictor of SCO (b = 0.341), so in the process of supply chain digitalization, special attention should be paid to real-time data infrastructure, such as the integration of IoT, cloud analytics platforms, a unified data lake. In the case of Amazon, the further development of its AWS analytics system and Edge computing environment is also in line with this recommendation. In the case of smaller firms intending to compete in the digital supply chain space, cloud-based BDA-as-a-service offerings (including the Amazon own AWS supply chain services) contain reachable avenues to BDA competency development.

For engineering managers, the results suggest a phased digital transformation strategy. Organizations should first establish strong data governance and analytics infrastructure, then integrate machine learning capabilities, and finally deploy AI-enabled decision automation. This sequential capability development can significantly improve operational efficiency, forecasting accuracy, and logistics coordination.

9. Proposed Improvements

Based on the empirical findings, several practical improvements can be recommended for organizations aiming to enhance supply chain performance through digital technologies. First, firms should prioritize the development of robust Big Data Analytics (BDA) infrastructure, as it demonstrated the strongest direct impact on supply chain optimization ($\beta = 0.341$). Investments in real-time data integration platforms, cloud-based analytics, and unified data ecosystems can significantly improve decision-making speed and accuracy.

Second, organizations should adopt a phased digital transformation strategy by strengthening Machine Learning (ML) capabilities after establishing a solid data foundation. The significant ML → BDA relationship ($\beta = 0.432$) suggests that ML enhances the effectiveness of data analytics systems. Third, Artificial Intelligence (AI) should be leveraged as a higher-level decision automation layer, enabling predictive forecasting, route optimization, and adaptive logistics planning. The strong AI → ML effect ($\beta = 0.487$) further supports this cascading capability development model.

Graphically, the structural model highlights a sequential technology integration pathway, where AI enhances ML, ML strengthens BDA, and BDA drives supply chain optimization outcomes. This layered approach provides a clear roadmap for organizations seeking to maximize the value of digital transformation initiatives.

10. Validation

To ensure the robustness and validity of the empirical findings, multiple validation techniques were applied. First, reliability analysis confirmed strong internal consistency across all constructs, with Cronbach's alpha values exceeding the recommended threshold of 0.70. Second, convergent and discriminant validity were established through Confirmatory Factor Analysis, with all factor loadings above 0.70 and Average Variance Extracted (AVE) values exceeding 0.50.

Additionally, model fit indices for both the measurement and structural models met recommended thresholds (CFI > 0.95, TLI > 0.95, RMSEA < 0.08), indicating a well-fitting model. Structural Equation Modeling results showed statistically significant relationships across all hypothesized paths ($p < .001$), confirming the strength and consistency of the proposed framework.

To address potential common method bias, Harman's single-factor test and an Unmeasured Latent Method Construct (ULMC) were applied. Results indicated no significant bias, as the single factor explained less than 50% of variance and ΔCFI remained below 0.01. These findings confirm that the model is statistically robust and the results are reliable for interpretation.

11. Conclusion

This paper has presented strict quantitative data, which is verified using SEM, that each of the three components of Artificial Intelligence, Machine Learning, and Big Data Analytics is a positive contribution to the supply chain optimization process, with BDA having a direct larger impact and AI being the key facilitator of corresponding technology capabilities. The model cumulatively described 61.2% of the variance in SCO, which validated the transformative capabilities of integrated digital technology adoption to supply chain management.

This study is based on data collected from Amazon's U.S. operations and its first-tier logistics partners, representing a highly advanced and digitally mature supply chain environment. While this context provides strong empirical insights into technology-driven optimization, the findings may not be directly generalizable to small and medium-sized enterprises or organizations with lower levels of digital maturity. Future research should extend this framework to diverse organizational contexts, including SMEs, emerging markets, and less digitized supply chains, to validate the broader applicability of the proposed model.

The future research directions are as follows: (1) the possible mediation of the organizational learning and innovation culture between technology adoption and SCO; (2) analyzing the moderating impacts of firm size, supply chain complexity, and competitive intensity on the AI/ML/BDA-SCO relationships; (3) available agent-based modeling or simulation methods to complement SEM findings with the perspective of the dynamic system; and (4) the adaptation of the framework to global supply chain situations, including emerging economy settings where technology adoption paths are dramatically different than those of the U.S. counterparts.

To sum up, this paper supports the position that AI, ML, and Big Data Analytics strategic integration is not just a technological fad but a numerically provable supply chain optimization driver. With Amazon still pushing the boundaries of digital supply chain management, the pragmatic insights into the experience can be seen as an attractive model to be followed by other organizations across the world aiming at leveraging the power of intelligent technologies to the benefit of their supply chain excellence.

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Biographies

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