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An Integrated Agentic-Intent AI Framework for Enhancing Supply Chain Resilience in Axle Load Enforcement and Petroleum Logistics Systems in Nigeria

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Abstract

This study develops and validates an integrated agentic-intent AI framework for strengthening supply chain resilience in Nigeria's petroleum logistics and axle-load enforcement systems. Drawing on dynamic capabilities, supply chain resilience, and cyber-physical systems theories, the framework positions intent AI as a predictive sensing layer and agentic AI as an autonomous execution layer, with resilience reflected through robustness, agility, and adaptability. A hybrid computational design integrates PLS-SEM, agent-based modelling (ABM), and system dynamics (SD) to examine causal relationships, behavioural interactions, and system-level feedback. Stochastic simulation generates trip-level observations reflecting operational pressure, infrastructure stress, security risk, and regulatory conditions. Results indicate that agentic AI exerts a stronger direct effect on resilience than intent AI, while intent AI significantly strengthens agentic AI capability. Agentic AI also partially mediates the intent AI-resilience relationship. Infrastructure quality and regulatory strength enhance AI effectiveness, whereas security risk and fuel-price volatility constrain resilience. The study advances a predictive-to-autonomous pathway for intelligent, adaptive logistics resilience in emerging economies.

Keywords

Agentic AI, Intent AI, Supply Chain, Resilience, Petroleum Logistics, PLS-SEM

1. Introduction

Supply chain systems in developing economies operate under persistent uncertainty driven by infrastructural deficits, institutional inefficiencies, and frequent disruptions, with Nigeria's petroleum logistics system providing a clear illustration of these challenges. The country's heavy reliance on road-based tanker distribution, due to limited pipeline and rail infrastructure, exposes the system to congestion, insecurity, fuel shortages, deteriorating roads, and weak regulatory enforcement. These structural constraints significantly reduce operational efficiency and increase logistics costs, while axle load violations further accelerate pavement deterioration, raise accident risks, and increase maintenance burdens [1] [2]. At the same time, enforcement mechanisms remain weakened by corruption, fragmented monitoring, and limited data integration, necessitating a shift toward automated, transparent, and data-driven systems [3]. These conditions reflect broader concerns in supply chain literature, where interconnected risks demand advanced artificial intelligence (AI) solutions for predictive analytics, visibility, and autonomous decision-making [4] [5]. Within this context, supply chain resilience, defined as the ability to anticipate, absorb, adapt to, and recover from disruptions, has become a central concern. Traditional resilience strategies such as redundancy and static forecasting are increasingly insufficient in volatile environments characterized by nonlinear disruptions [4] [6]. Consequently, there is a growing shift toward AI-enabled resilience approaches that support proactive disruption management, scenario analysis, and automated responses [7]. Emerging technologies such as machine learning, IoT, digital twins, and intelligent routing systems now enable real-time visibility, predictive modeling, and dynamic optimization, significantly improving responsiveness and efficiency in logistics systems [8] [9].

Within this evolving paradigm, two complementary AI constructs, Intent AI and Agentic AI, provide a foundation for enhanced resilience. Intent AI focuses on predictive intelligence, using advanced analytics to forecast demand, detect risks, and anticipate disruptions such as congestion or axle load violations [7] [8] [10]. However, prediction alone is insufficient without execution. Agentic AI addresses this gap by enabling autonomous decision-making and action through intelligent agents capable of planning, coordinating, and responding to disruptions in real time. In petroleum logistics, this includes dynamic routing, automated scheduling, and fleet coordination, while in axle load enforcement it supports real-time violation detection and automated compliance actions [11] [12]. This autonomy improves agility and reduces delays associated with centralized human decision-making. Despite these advances, existing literature often treats predictive and autonomous AI systems separately, limiting their combined potential. Intent AI without execution lacks operational impact, while Agentic AI without predictive alignment risks inefficiency. Integrating both creates a synergistic system in which foresight is seamlessly translated into action, aligning with emerging calls for hybrid AI architectures in supply chain resilience research [13] [14]. Such integration supports a self-regulating logistics ecosystem underpinned by IoT sensors, telematics, intelligent weighbridges, and real-time analytics, enabling continuous monitoring and proactive disruption management. This enhances decision accuracy, reduces response time, and strengthens infrastructure protection [13].

Beyond operational gains, the integrated framework improves governance transparency and sustainability. Automated enforcement systems reduce reliance on manual inspections, minimize corruption, and ensure consistent regulatory compliance through real-time vehicle classification and weight monitoring [6] [15]. It also contributes to environmental sustainability by optimizing routing, reducing fuel consumption, and lowering emissions in high-impact petroleum logistics systems [14] [16]. However, implementation in developing economies is constrained by infrastructural limitations, unreliable power supply, data quality issues, cybersecurity risks, and institutional resistance, requiring coordinated investments in infrastructure, capacity building, and regulatory frameworks [17]. The integration of Intent AI and Agentic AI represents a transformative shift toward predictive, autonomous, and adaptive supply chain systems. By combining anticipatory intelligence with real-time execution, the framework enhances resilience, efficiency, sustainability, and governance transparency in petroleum logistics and axle load enforcement systems. This dual-layer AI architecture provides a critical pathway for addressing complexity and uncertainty in developing economy supply chains, aligning with global advances in intelligent logistics and digital governance [5] [13].

2. Literature Review

2.1. Supply Chain Resilience

Supply chain resilience (SCR) has emerged as a critical concept in logistics and operations management due to increasing exposure to disruptions in global supply networks. It is defined as the ability of supply chains to anticipate, absorb, respond to, and recover from disruptions while maintaining continuity and performance, marking a shift from efficiency-centered models to integrated systems emphasizing robustness, agility, and adaptability [4] [5]. Robustness refers to the capacity to withstand shocks through structural strength and redundancy, though excessive redundancy may increase operational costs [6] [13]. Agility emphasises rapid detection and response enabled by real-time data and flexible decision-making, increasingly supported by AI and digital technologies [15] [17]. Adaptability reflects long-term evolutionary capability in response to persistent systemic challenges [8] [13]. In developing economies such as Nigeria, resilience is particularly crucial in petroleum logistics and axle load enforcement systems, where disruptions in transport and infrastructure produce cascading economic impacts [1] [2]. However, traditional resilience approaches based on static planning and historical data are increasingly inadequate in dynamic environments, prompting a shift toward AI-enabled frameworks that support predictive and prescriptive decision-making using machine learning, digital twins, and real-time analytics [2] [4] [5] [7]. These technologies enhance logistics functions such as route optimization, demand forecasting, fleet management, and enforcement monitoring, thereby strengthening system-wide responsiveness and adaptability.

In the context of axle load enforcement and logistics systems, empirical evidence shows that overloaded trucks significantly reduce pavement lifespan and accelerate road deterioration across Nigerian highways, with violation rates in major corridors ranging from 70% to 94%, reflecting deep enforcement inefficiencies [18]. Further studies quantify the economic burden of axle load violations, highlighting substantial pavement damage costs and long-term fiscal strain on public infrastructure investment [1]. This positions axle load enforcement as a systemic logistics inefficiency problem requiring predictive and autonomous solutions rather than a purely regulatory issue. Supporting this view, [19] demonstrate the application of multi-criteria decision models and SEM-based frameworks in assessing logistics service performance, emphasizing structured decision-making in improving efficiency. In offshore logistics environments, planning efficiency is shown to significantly enhance resilience and responsiveness [20], aligning with the Intent AI construct that focuses on predictive intelligence through demand sensing, risk prediction, behavioral analytics, and violation forecasting. Meanwhile, studies on petroleum logistics in Nigeria highlight persistent operational challenges such as demand volatility, infrastructural fragility, and regulatory inconsistency [21] [22], reinforcing the need for AI-enabled governance systems. These findings support the integration of Agentic AI, which enables autonomous execution of logistics and enforcement decisions in highly dynamic environments. However, while existing SEM-based studies confirm the importance of planning and adaptability in resilience [20], they also reveal a limitation in traditional frameworks that overemphasize structural redundancy rather than intelligent, adaptive system behavior.

2.2. Artificial Intelligence in Supply Chains

AI has thus emerged as a transformative force in supply chain management, enhancing efficiency, visibility, and decision-making. Its applications span demand forecasting, inventory management, route optimization, and risk assessment, with machine learning significantly improving predictive accuracy and operational performance [5] [15]. AI-driven systems also enhance supply chain visibility by integrating diverse data sources to identify risks and support proactive mitigation strategies [4] [6]. However, most AI implementations remain predictive and decision-support oriented, relying on human intervention for execution. This limitation reduces responsiveness in high-velocity environments such as petroleum logistics, where delays in decision-making can have significant consequences [13] [17]. Recent advancements have shifted AI toward autonomous and prescriptive paradigms capable of real-time decision-making and execution. Technologies such as reinforcement learning, multi-agent systems, and digital twins enable supply chains to simulate scenarios, adapt dynamically, and implement optimal strategies with minimal human intervention [4] [8]. These developments align with Industry 5.0 principles, emphasizing intelligent automation and human-AI collaboration. Autonomous systems enhance resilience by reducing response time, improving coordination, and minimizing human error [7] [13].

2.3. Intent AI and Agentic AI

Within this evolving AI landscape, Intent AI and Agentic AI have emerged as complementary paradigms. Intent AI focuses on predictive intelligence, enabling systems to infer patterns, forecast demand, and anticipate disruptions by integrating diverse data sources. It enhances situational awareness and supports proactive planning, particularly in demand sensing, risk prediction, and behavioral analysis [8] [10]. For example, in petroleum logistics, Intent AI can forecast demand fluctuations and identify high-risk transport corridors, while in axle load enforcement it can detect patterns of non-compliance and predict infrastructure stress [5]-[7]. Despite these capabilities, Intent AI remains limited by its lack of autonomous execution, as it primarily generates insights rather than implementing decisions [13]. Agentic AI, in contrast, enables autonomous decision-making and execution through intelligent agents capable of perceiving, reasoning, and acting independently. It supports real-time route optimization, autonomous fleet management, dynamic resource allocation, and adaptive enforcement mechanisms [11] [12]. In petroleum logistics, agentic systems can dynamically reroute fleets and adjust delivery schedules, while in axle load enforcement, they can monitor vehicle weights, detect violations, and enforce compliance in real time. These capabilities significantly enhance agility and operational efficiency, aligning with the concept of self-healing supply chains that can detect, diagnose, and respond to disruptions autonomously [4] [7]. However, challenges related to integration, cybersecurity, and governance must be addressed to ensure effective implementation [17].

2.4. Theoretical Framework

The proposed Integrated Agentic-Intent AI Framework is grounded in three complementary theoretical lenses, namely, dynamic capabilities theory, supply chain resilience theory, and cyber-physical systems (CPS) theory, which explain how intelligent systems enhance decision-making, operational responsiveness, and infrastructure sustainability in complex logistics environments such as petroleum distribution and axle load enforcement in Nigeria. These theories are particularly relevant in contexts characterized by infrastructural deficits, regulatory inefficiencies, and high operational uncertainty.

Dynamic Capabilities Theory: Dynamic Capabilities Theory explains how organizations integrate, build, and reconfigure competencies to respond to rapidly changing environments [23]. In this framework, Intent AI functions as the sensing mechanism that detects disruptions using real-time data from IoT-enabled fuel stations, traffic systems, weather forecasts, and enforcement records, enabling early identification of risks such as demand surges or flooding along corridors like Lagos-Benin-Onitsha [5] [13]. Agentic AI operationalizes the seizing and reconfiguration role by autonomously adjusting logistics resources, rerouting tankers, and modifying enforcement deployments in real time, such as redirecting vehicles during flooding or repositioning mobile weighbridges to high-risk corridors. This enhances flexibility and reduces operational downtime in logistics systems [8] [23].

Supply Chain Resilience Theory: Supply Chain Resilience Theory focuses on the ability of systems to withstand, adapt to, and recover from disruptions through robustness, agility, and adaptability [4] [24]. In the Nigerian petroleum logistics context, robustness is strengthened by Intent AI through identification of vulnerable infrastructure and high-risk corridors such as the Ore-Benin highway. Agility is enabled by Agentic AI, which rapidly responds to disruptions such as accidents or delays by reallocating resources and updating delivery schedules, preventing cascading fuel shortages [7] [15]. Adaptability emerges from continuous learning within both AI layers, where historical patterns of violations, road failures, and disruptions refine long-term strategies such as enforcement redesign or route restructuring, aligning with structural evolution in resilience theory [13].

Cyber-Physical Systems (CPS) Theory: Cyber-physical systems theory provides the technological foundation by integrating digital intelligence with physical logistics infrastructure, enabling real-time interaction between AI systems and operational assets such as vehicles, roads, depots, and weighbridges [25]. In practice, CPS is implemented through IoT sensors, GPS tracking, smart weigh-in-motion systems, and monitoring infrastructure that continuously transmit data to AI platforms. Intent AI performs predictive analytics on this data, while Agentic AI executes autonomous actions such as issuing penalties, rerouting overloaded trucks, or reallocating fuel supplies in response to shortages. For example, at enforcement points like the Onitsha-Asaba corridor, CPS enables automated detection of axle load violations and immediate enforcement responses, reducing human intervention and corruption risks. Similarly, it ensures real-time synchronization between refinery output, depot storage, and tanker distribution, allowing rapid response to demand shocks such as shortages in Awka [4] [25].

2.5. Conceptual Framework

The framework in **Figure 1** is structured into five interconnected layers that capture predictive, operational, contextual, and feedback dynamics within the system. The input layer comprises Intent AI, which generates predictive signals that inform downstream decision processes. The decision layer is represented by Agentic AI, which translates predictive intelligence into autonomous execution actions. These actions subsequently influence the outcome layer, where supply chain resilience emerges as the key system-level performance indicator. The context layer incorporates moderating variables, including infrastructure quality (INFQ), security risk (SECR), fuel price volatility (FPV), and regulatory enforcement strength (RES), all of which shape the effectiveness of AI-driven processes. Finally, the feedback loop is captured through system dynamics, modelling reinforcing and balancing cycles that govern long-term system evolution.

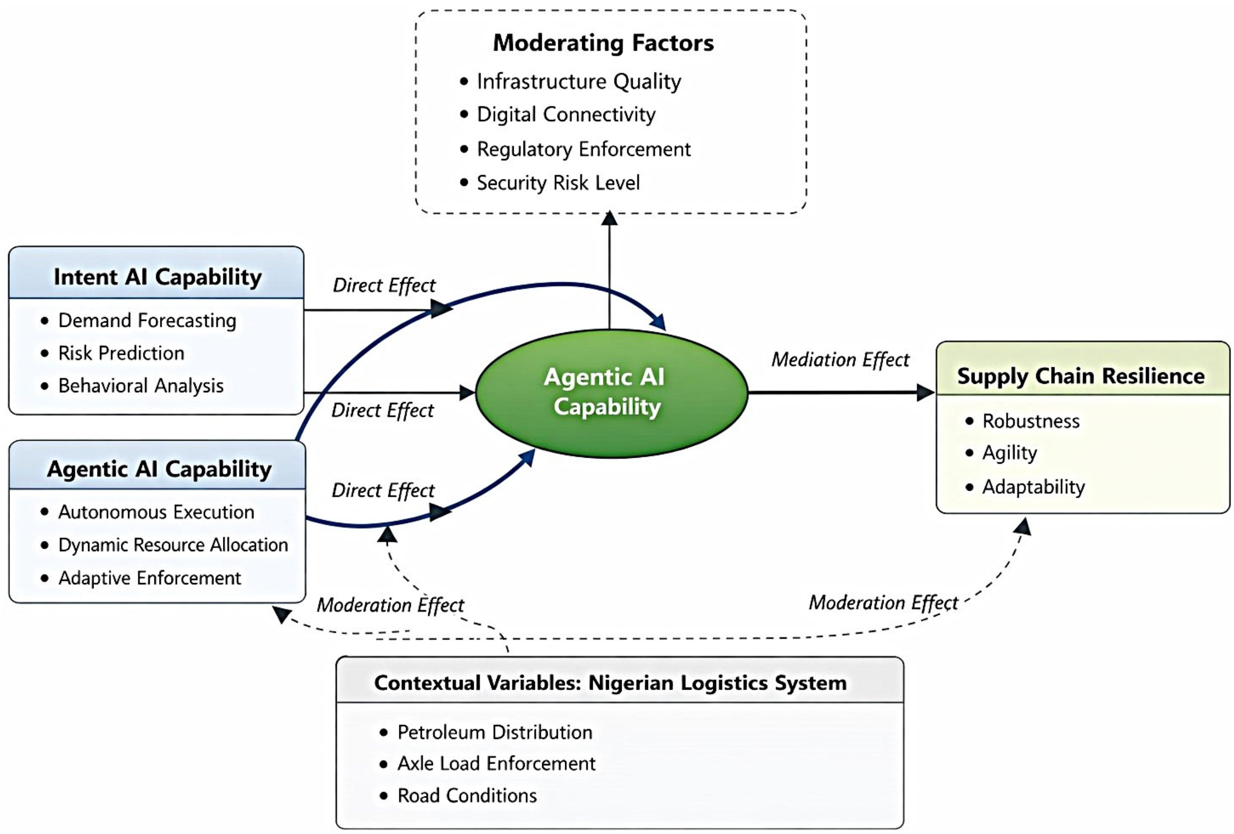

Figure 1. Proposed integrated Agentic-Intent AI framework.

This methodology combines causal inference, behavioural simulation, and dynamic systems modelling within a unified analytical framework. This integration enables a comprehensive assessment of how AI-driven capabilities influence supply chain resilience under realistic operational constraints. By linking statistical explanation, agent-level decision processes, and long-term feedback dynamics, the approach provides a robust basis for understanding and evaluating system performance in complex and uncertain logistics environments.

Hybrid SEM-ABM-SD Integration Framework

The integrated framework in Figure 2 is defined across three complementary modelling layers, each serving a distinct analytical function. Structural Equation Modelling (SEM) is used for parameter estimation, providing statistically derived relationships among key latent constructs. Agent-Based Modelling (ABM) captures behavioural simulation by representing heterogeneous agents and their decision-making processes under varying system conditions. System Dynamics (SD), in turn, models long-term feedback loops that govern system evolution over time. The integration between these layers is explicitly structured to ensure coherence across scales of analysis.

SEM-derived coefficients are used to inform and calibrate ABM decision rules, ensuring that simulated agent behaviour is grounded in empirically estimated relationships. In addition, aggregated outputs from the ABM layer are fed into the SD framework as state variables, enabling the modelling of macro-level system dynamics driven by micro-level interactions.

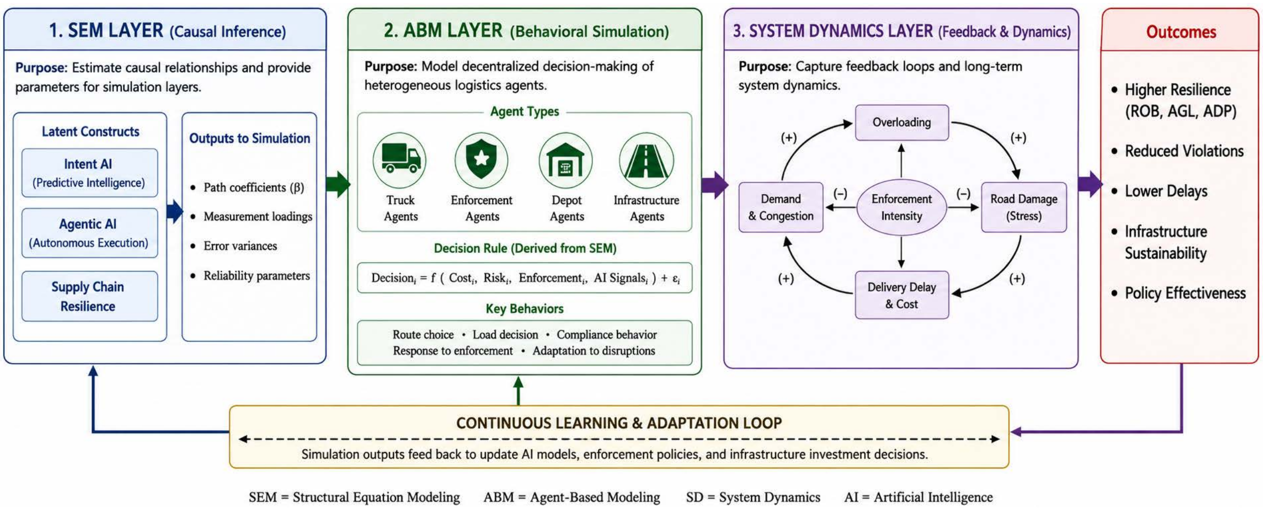

Figure 2. Hybrid SEM-ABM-SD Architecture for AI-Driven resilient petroleum logistics.

The study integrates three complementary modelling layers to capture both causal structure, behavioural dynamics, and system-level feedback effects:

1) SEM Layer: This layer estimates the underlying causal relationships among key variables and provides the parameter values that inform subsequent simulation stages. It establishes the statistical backbone of the integrated framework by quantifying directional effects between constructs.

2) ABM Layer: This layer simulates heterogeneous truck agents operating under varying conditions. Agent decision rules are derived directly from SEM coefficients, with behavioural choices expressed as a function of cost, risk, enforcement pressure, and AI capability. This enables micro-level behavioural realism within the simulation environment.

3) System Dynamics Layer: This layer captures long-term feedback structures within the system, modelling reinforcing loops such as demand, overloading, road damage, delays, and rising costs. These interdependencies reflect how local behaviours aggregate into system-wide performance outcomes over time.

2.6. Research Gap

Despite the advances in both paradigms, the literature remains fragmented, with limited integration of predictive (Intent AI) and autonomous (Agentic AI) capabilities. This separation constrains the effectiveness of AI-driven resilience strategies, as predictive systems lack execution capabilities, while autonomous systems may lack contextual foresight. Emerging research suggests that hybrid AI architectures integrating both paradigms are essential for achieving higher levels of resilience, adaptability, and responsiveness [7] [13] [14]. Additional gaps exist in the application of AI to axle load enforcement systems, where research has largely focused on policy and engineering perspectives rather than intelligent technologies [1] [2]. Furthermore, there is limited context-specific research addressing AI-driven supply chain resilience in developing economies such as Nigeria, where infrastructural and institutional challenges differ significantly from developed contexts [9] [17]. The lack of integrated approaches that simultaneously address logistics efficiency, regulatory compliance, and infrastructure sustainability further highlights the need for comprehensive frameworks. In response, the integration of Intent AI and Agentic AI provides a promising pathway for enhancing supply chain resilience. By combining predictive intelligence with autonomous execution, such frameworks enable supply chains to anticipate disruptions, respond dynamically, and adapt continuously. This integrated approach supports not only operational efficiency but also infrastructure sustainability and governance transparency, particularly in complex environments such as petroleum logistics and axle load enforcement systems. As supply chains continue to evolve under increasing uncertainty, the adoption of such intelligent, adaptive frameworks will be critical for achieving resilient and sustainable logistics systems [5] [13].

3. Methodology

3.1. Research Design and Analytical Framework

The study adopts a hybrid computational framework integrating PLS-SEM, ABM, and System Dynamics (SD) to examine how Intent AI (predictive intelligence) and Agentic AI (autonomous execution) jointly influence supply chain resilience in petroleum logistics and axle load enforcement systems. SEM is used for causal hypothesis testing, ABM captures decentralized behavioural interactions, and SD models long-term feedback effects such as infrastructure degradation and policy impacts, enabling robust analysis under data limitations. The conceptual model defines supply chain resilience as being directly driven by both Intent AI and Agentic AI, while also being shaped by contextual moderators including infrastructure quality (INFQ), security conditions (SECR), financial volatility (FPV), and regulatory strength (RES). It further specifies a mediation pathway where Intent AI enhances resilience indirectly through its effect on Agentic AI, reflecting a sequential process in which predictive intelligence strengthens autonomous execution, which then produces resilience outcomes.

$$\text{SCR}_i = \delta_0 + \delta_1 \text{AgenticAI}_i + \delta_2 \text{IntentAI}_i + \delta_3 \text{Z}_i + \eta_i \tag{1}$$

where:

SCR$_i$: Supply Chain Resilience (latent construct);

Agentic AI$_i$: Autonomous execution capability;

Intent AI$_i$: Predictive intelligence capability;

Z$_i$: Vector of moderating variables (INFQ, SECR, FPV, RES).

A mediation structure is defined as the following:

$$\text{AgenticAI}_i = \delta_0 + \delta_1 \text{IntentAI}_i + \eta_i \tag{2}$$

$$\text{SCR}_i = \delta_0 + \delta_1 \text{AgenticAI}_i + \delta_2 \text{IntentAI}_i + \eta_i \tag{3}$$

3.1.1. Stochastic Data Generating Process (DGP)

The study constructs data through a stochastic behavioral simulation framework designed to replicate logistics and enforcement dynamics with structural realism. It models axle overloading as a probabilistic outcome influenced by predictive intelligence, demand pressure, security conditions, and road quality. This behavioural process generates infrastructure stress, which captures the deterioration effects of overloading and poor road conditions. The resulting stress propagates through the system by increasing delivery delays, shaped further by congestion and security disruptions. Supply chain resilience is formulated as a system-level outcome, positively driven by Intent AI and Agentic AI and negatively affected by infrastructure stress and delays, illustrating a cascading pathway from behavioural decisions to physical degradation and overall performance outcomes.

Overload probability model:

$$P(\text{Overload} = 1) = \sigma\begin{pmatrix} \alpha_0 + \alpha_1 \text{Intentions} + \alpha_2 \text{Demands} \\ +\alpha_3 \text{Security} + \alpha_4 \text{RoadCond} \end{pmatrix} \tag{4}$$

Road stress function:

$$\text{Stress}_i = \beta_0 + \beta_1 \text{Overload}_i + \beta_2 \text{RoadQuality}_i + \epsilon_i \tag{5}$$

Delay function:

$$\text{Delay}_i = \gamma_0 + \gamma_1 \text{Stress}_i + \gamma_2 \text{Security}_i + \gamma_3 \text{Congestion}_i + v_i \tag{6}$$

Resilience (latent):

$$\text{SCR}_i = \delta_0 + \delta_1 \text{AgenticAI}_i + \delta_2 \text{IntentAI}_i - \delta_3 \text{Delay}_i - \delta_4 \text{Stress}_i + \eta_i \tag{7}$$

Through this formulation, the framework shifts from a conceptual simulation to a fully specified computational model.

3.1.2. Distributional Assumptions

The model specifies clear distributional assumptions for key variables to ensure realistic data generation and statistical consistency. Intent AI is drawn from a beta distribution to capture bounded predictive intelligence levels, while demand surges follow a lognormal distribution to reflect positively skewed fluctuations typical of logistics environments. Security risk is modelled using a uniform distribution between 0 and 1, representing evenly distributed uncertainty across scenarios. In addition, all stochastic error terms are assumed to follow a normal distribution with zero mean and constant variance, ensuring standard econometric properties. To enhance robustness and ensure stable inference, the study applies Monte Carlo simulation with 10,000 iterations, enabling reliable estimation of system behaviour under repeated random sampling conditions.

$$\text{Intent AI} = \text{Beta}\left(\alpha, \beta\right) \tag{8}$$

$$\text{Security Risk} = \text{Uniform}\left(0,1\right) \tag{9}$$

$$\text{Demand Surge} = \text{Lognormal}\left(\mu, \sigma\right) \tag{10}$$

$$\text{Error terms} = \text{Normal}\left(0, \sigma^2\right) \tag{11}$$

These specifications enhance replicability and ensure the statistical validity of the Monte Carlo simulation framework, enabling robust and reproducible computational experimentation.

3.1.3. Measurement Model Specification (PLS-SEM)

All constructs in the model are specified as one consistent reflective-reflective hierarchical component model (HCM) for both AI constructs.

At the first-order level, Intent AI is operationalised through demand sensing (DS), risk prediction (RP), behavioural analytics (BA), and violation forecasting (VF). Agentic AI is captured through autonomous decision-making (ADM), real-time optimisation (RTO), dynamic resource allocation (DRA), and adaptive enforcement (AE). Supply chain resilience (SCR) is measured using robustness (ROB), agility (AGL), and adaptability (ADP) as its core dimensions.

At the second-order level, each construct is defined as a function of its respective lower-order components, reflecting a structured aggregation process. This hierarchical specification enables a more nuanced and multidimensional representation of AI capabilities and resilience outcomes within the analytical framework.

Second-order specification:

$$\text{IntentAI} = f\left(DS, RP, BA, VF\right) \tag{12}$$

$$\text{AgenticAI} = f\left(ADM, RTO, DRA, AE\right) \tag{13}$$

$$\text{SCR} = f\left(ROB, AGL, ADP\right) \tag{14}$$

The model currently assumes a unidirectional causal flow from Intent AI to Agentic AI and subsequently to supply chain resilience. However, this assumption may be subject to endogeneity concerns, as feedback effects could exist in which Agentic AI also influences Intent AI through adaptive system learning and reinforcement loops.

$$\text{Intent AI} \rightarrow \text{Agentic AI} \rightarrow \text{Supply Chain Resilience} \tag{15}$$

Endogeneity control was introduced through the use of instrumental variable partial least squares (IV-PLS), which helps isolate exogenous variation and strengthen causal identification. Alternatively, a lagged specification can be applied, where Agentic AI is modelled as a function of its past values of Intent AI, thereby reducing simultaneity bias.

$$\text{AgenticAI}_t = f\left(\text{IntentAI}_{t-1}\right) \tag{16}$$

These adjustments enhance the credibility of causal inference by accounting for potential reverse causality and dynamic feedback effects within the system.

PLS-SEM is selected because the study is prediction-oriented, involves potentially non-normal stochastic data, and incorporates complex hierarchical constructs, making it suitable for the study's analytical requirements. Measurement quality is assessed through indicator loadings (>0.70), Composite Reliability (>0.80), AVE (>0.50), and HTMT (<0.85), with 5,000 bootstrap resamples used to obtain robust estimates, confidence intervals, and significance tests. Structural model assessment employs path coefficients, R^2, f^2, Q^2, and SRMR (<0.08) to evaluate relationships, explanatory power, effect sizes, predictive relevance, and model fit. PLSpredict further assesses out-of-sample predictive performance using RMSE and Q^2_predict against a naïve benchmark, while NFI and RMS_theta provide additional evidence of model adequacy and measurement quality. These procedures establish the reliability, validity, explanatory strength, and predictive robustness of the PLS-SEM model.

3.1.4. Data Generation, Status, Unit of Analysis, and Empirical Anchoring

The study adopts a computational simulation design rather than a conventional observational or survey-based approach. SEM estimates are derived from a synthetically generated trip-level dataset produced through the stochastic data-generating process specified in Equations (4)-(7) and the Monte Carlo procedure. The unit of analysis is the simulated logistics trip/event.

The observations presented in the illustrative tables are intended to demonstrate the behavioural and operational logic of the simulation and do not constitute the SEM estimation sample. Similarly, illustrative event-level records representing interactions among behavioural, technological, infrastructural, and environmental conditions are not treated as independent empirical datasets. The SEM estimation sample instead comprises observations generated systematically from the specified probability distributions and simulation procedures. Observed Nigerian logistics benchmarks are used exclusively for model calibration and contextual plausibility, rather than as direct inputs into the SEM estimation. Consequently, the reported PLS-SEM coefficients should be interpreted as simulation-derived structural estimates reflecting relationships within the computationally generated logistics environment, rather than as population estimates obtained from observed Nigerian logistics data.

3.2. Construct Definition and Operationalisation of Intent AI

Intent AI is conceptualised in this study as shown in **Table 1** as a predictive-sensing capability through which logistics systems identify emerging demand conditions, anticipate operational risks, analyse behavioural patterns, and forecast potential regulatory or axle-load violations before they materialise. Consistent with this conceptualisation, Intent AI is operationalised as a higher-order construct comprising four first-order dimensions: Demand Sensing (DS), Risk Prediction (RP), Behavioural Analytics (BA), and Violation Forecasting (VF). These dimensions represent distinct but complementary manifestations of the system's capacity to sense, interpret, and predict emerging logistics conditions. Accordingly, Intent AI is concerned with anticipatory intelligence rather than autonomous execution. The distinction between predictive intelligence and operational execution is maintained throughout the model. Agentic AI represents the execution layer through which predictive information is translated into autonomous or adaptive actions. It is operationalised through Autonomous Decision-Making (ADM), Real-Time Optimisation (RTO), Dynamic Resource Allocation (DRA), and Adaptive Enforcement (AE). Thus, Intent AI answers the predictive question of what is likely to occur and what risks are emerging, whereas Agentic AI addresses the operational question of what action should be initiated or executed in response.

Variables such as cost-minimisation intention, time pressure, demand pressure, risk-avoidance behaviour, and demand surge are not treated as indicators of Intent AI. These variables describe behavioural, operational, or environmental conditions within which logistics decisions occur. They are therefore specified as exogenous inputs to the stochastic data-generating process (DGP) and agent-based model (ABM). For example, cost pressure and time pressure may influence the behavioural propensity of logistics operators to undertake riskier decisions, while demand surges may increase operational pressure and the probability of overloading. These variables consequently influence the system dynamics but do not constitute dimensions of predictive AI capability. Similarly, security risk is treated as a contextual condition that can influence logistics behaviour and moderate the effectiveness of AI-enabled execution rather than as an indicator of Intent AI. This specification prevents behavioural and environmental determinants from being conflated with technological capability and establishes a theoretically coherent separation between predictive intelligence, autonomous execution, behavioural conditions, and contextual moderators.

Table 1. Construct structure.

Construct/Variable	Role in the Model	Operationalisation
Intent AI	Predictive intelligence capability	Higher-order construct
Demand Sensing (DS)	Intent AI dimension	First-order indicator
Risk Prediction (RP)	Intent AI dimension	First-order indicator
Behavioural Analytics (BA)	Intent AI dimension	First-order indicator
Violation Forecasting (VF)	Intent AI dimension	First-order indicator

Continued

Agentic AI	Autonomous execution capability	Higher-order construct
Autonomous Decision-Making (ADM)	Agentic AI dimension	First-order indicator
Real-Time Optimisation (RTO)	Agentic AI dimension	First-order indicator
Dynamic Resource Allocation (DRA)	Agentic AI dimension	First-order indicator
Adaptive Enforcement (AE)	Agentic AI dimension	First-order indicator
Cost-Minimisation Intention	Behavioural input	ABM/DGP variable
Time Pressure	Behavioural/contextual input	ABM/DGP variable
Demand Surge	Exogenous operational condition	DGP variable
Risk-Avoidance Behaviour	Behavioural input	ABM/DGP variable
Security Risk	Contextual condition/moderator	

3.3. Directional Specification of the Intent AI-Supply Chain Resilience Relationship

The relationship between Intent AI and Supply Chain Resilience (SCR) is specified in the revised model as positive. The previous specification that associated Intent AI with a negative direct effect through overload risk resulted from an inadvertent conflation of Intent AI capability with operator behavioural pressure. These represent conceptually distinct constructs and are therefore separated in the revised model. Intent AI represents the predictive-sensing capability of the logistics system. It enables the system to anticipate demand conditions, identify emerging operational risks, analyse behavioural patterns, and forecast potential axle-load or regulatory violations. Through these predictive capabilities, the system can provide earlier warning signals and support timely intervention, thereby improving the capacity of the supply chain to anticipate, absorb, and respond to disruptions. Accordingly, the revised model hypothesises a positive direct relationship between Intent AI and supply chain resilience.

In contrast, cost-minimisation pressure, time pressure, demand pressure, and security-induced risk-taking represent behavioural and environmental conditions within the logistics system. These factors may increase the probability of risky operational decisions, including overloading, which can generate infrastructure stress and delivery delays. Their negative resilience pathway is therefore specified independently of Intent AI as:

Behavioural Pressure → Overload Risk → Infrastructure Stress/Delivery Delay → Lower SCR.

The corresponding AI-enabled pathway is specified as:

Intent AI → Agentic AI → Improved SCR.

with an additional direct pathway:

Intent AI → Improved SCR.

This distinction is consistent with the study's conceptualisation of Intent AI as the predictive intelligence layer and Agentic AI as the autonomous execution layer. The methodological specification identifies Intent AI with demand sensing, risk prediction, behavioural analytics, and violation forecasting, while Agentic AI represents autonomous decision-making, real-time optimisation, dynamic resource allocation, and adaptive enforcement. The expected positive relationship is theoretically grounded in the capacity of predictive intelligence to improve early risk identification, demand anticipation, behavioural anomaly detection, and violation forecasting. These capabilities strengthen the system's preparedness and enable earlier corrective responses to emerging disruptions.

The following hypotheses specify the expected sign and mechanism for each direct, mediation, moderation, and nonlinear relationship:

H1: Intent AI capability has a positive direct effect on supply chain resilience because predictive sensing enables earlier disruption detection, risk identification and proactive intervention.

H2: Agentic AI capability has a positive direct effect on supply chain resilience because autonomous execution improves routing, resource allocation, enforcement and disruption response.

H3: Intent AI capability has a positive effect on Agentic AI capability because predictive information improves the quality and timing of autonomous decisions.

H4: Agentic AI mediates positively the relationship between Intent AI capability and supply chain resilience, such that predictive intelligence is converted into operational action.

H5: Infrastructure quality positively moderates the agentic AI-resilience relationship, such that the effect of agentic AI is stronger under better infrastructure conditions.

H6: Security Risk negatively moderates the agentic AI-resilience relationship, with the adverse effect becoming stronger at high levels of security risk.

H7: Fuel price volatility moderates the agentic AI-resilience relationship by increasing the value of continuous optimisation while simultaneously increasing operational uncertainty.

H8: Regulatory enforcement strength positively moderates the agentic AI-resilience relationship by strengthening the conversion of AI detection into effective compliance action.

H9: The agentic AI-resilience relationship is nonlinear, reflecting increasing returns at lower capability levels followed by potential saturation or declining marginal effects at higher levels.

3.4. Mediation and Moderation Analysis

The mediation analysis examines the indirect effect of Intent AI on supply chain resiience through its influence on Agentic AI. This is captured as the product of the pathway from Intent AI to Agentic AI and the subsequent effect of Agentic AI on resilience, with the variance accounted for (VAF) used to assess the strength of the mediating mechanism. VAF is computed as the ratio of the indirect effect to the total effect, allowing for a systematic evaluation of the strength of mediation. This enables classification of the mediation as partial or full, depending on the proportion of the effect transmitted through the mediator.

$$\text{VAF= Indirect Effect /Total Effect} \quad (17)$$

By incorporating VAF, the mediation logic shifts from a purely descriptive interpretation to a more rigorous, empirically grounded assessment of causal pathways within the model. The moderation analysis evaluates how contextual factors influence the relationship between Agentic AI and supply chain resilience. Specifically, interaction effects are modeled using Infrastructure Quality (INFQ) as a key moderator, alongside other environmental variables such as security risk, fuel price volatility, and regulatory enforcement strength. These analyses capture both indirect transmission mechanisms and context-sensitive effects, highlighting how AI-driven resilience outcomes are shaped by both internal system dynamics and external environmental conditions.

$$\text{SCR} = \beta_1 \text{AgenticAI} + \beta_2 \text{INFQ} + \beta_3 \left(\text{AgenticAI} \times \text{INFQ}\right) \quad (18)$$

This formulation allows the model to estimate not only the independent effects of agentic AI and INFQ but also how infrastructure conditions influence the effectiveness of autonomous execution capabilities.

3.5. Sensitivity and Scenario Analysis

Sensitivity analysis and scenario-based evaluation are used to assess the robustness and behavioural stability of the model under varying conditions. Key parameters such as enforcement strength, security risk, and demand surge are systematically varied to examine their impact on system behaviour, with a particular focus on the elasticity of supply chain resilience in response to marginal changes in these drivers. This identifies the most influential determinants of system stability and highlights how environmental volatility and governance intensity shape resilience outcomes. The analysis is further extended through structured scenario simulations, including configurations of high AI with low infrastructure quality, low AI with high security risk, and fully autonomous systems. These scenarios provide a comparative assessment of resilience performance under both stress and optimal conditions, generating insights into how combinations of technological capability and contextual constraints influence system effectiveness and informing more adaptive policy design.

3.6. Model Assumptions

The model is grounded in several key assumptions to ensure analytical consistency and interpretability, including directional causality among constructs, limited multicollinearity among predictors, reflective measurement of latent variables, and behavioural realism in agent decision-making under varying cost, risk, enforcement, and AI conditions. Building on this foundation, the framework is further extended to incorporate nonlinear relationships to better reflect the complexity of supply chain resilience dynamics. Quadratic terms are introduced, particularly in the relationship between Agentic AI and resilience, enabling the model to capture diminishing or amplifying effects such as increasing returns at lower capability levels followed by saturation or decline at higher levels.

$$\text{SCR} = \beta_1 \text{AgenticAI} + \beta_2 \text{AgenticAI}^2 \tag{19}$$

In addition, interaction effects are specified to capture contextual dependencies within the system. For example, the interaction between Agentic AI and security risk allows the model to assess how environmental uncertainty moderates the effectiveness of autonomous execution.

$$\text{AgenticAI} \times \text{SecurityRisk} \tag{20}$$

3.7. Empirical Anchoring and Validation

To enhance external validity, the simulated outputs are calibrated against empirical benchmarks derived from observed system performance. These include documented axle load violation rates ranging between 70% and 94%, as well as established patterns of delivery delays within the logistics network. This calibration process ensures that the model reflects real-world operational conditions in Nigeria, thereby improving the credibility and practical relevance of the simulation outcomes in capturing actual logistics system dynamics.

3.8. Simulation Parameterisation and Reproducibility

To facilitate reproducibility, all principal variables entering the stochastic data-generating process are explicitly documented in a consolidated simulation parameter table. The table identifies each variable, its probability distribution, parameter values, source or substantive rationale, transformation procedure, simulation replication specification, and analytical role within the SEM, ABM, or SD component. The Monte Carlo procedure generates repeated synthetic logistics observations under the specified behavioural, operational, infrastructural, and environmental conditions. The resulting synthetic dataset provides the basis for simulation-based PLS-SEM estimation, while the illustrative trip records reported in Table 2 are used solely to demonstrate the operational logic of the model.

3.9. Analytical Architecture

The framework in Figure 3 presents a sequential socio-technical pathway in which operational pressures influence system stress, Intent AI provides predictive sensing, and Agentic AI converts predictions into adaptive actions. Intent AI encompasses demand sensing, risk prediction, behavioural analytics, and violation forecasting, while Agentic AI comprises autonomous decision-making, real-time optimisation, dynamic resource allocation, and adaptive enforcement. These capabilities enhance supply chain resilience through robustness, agility, and adaptability, with infrastructure quality, security risk, fuel price volatility, and regulatory enforcement strength conditioning their effectiveness. The framework conceptualises resilience as the outcome of transforming predictive intelligence into adaptive operational action under contextual conditions.

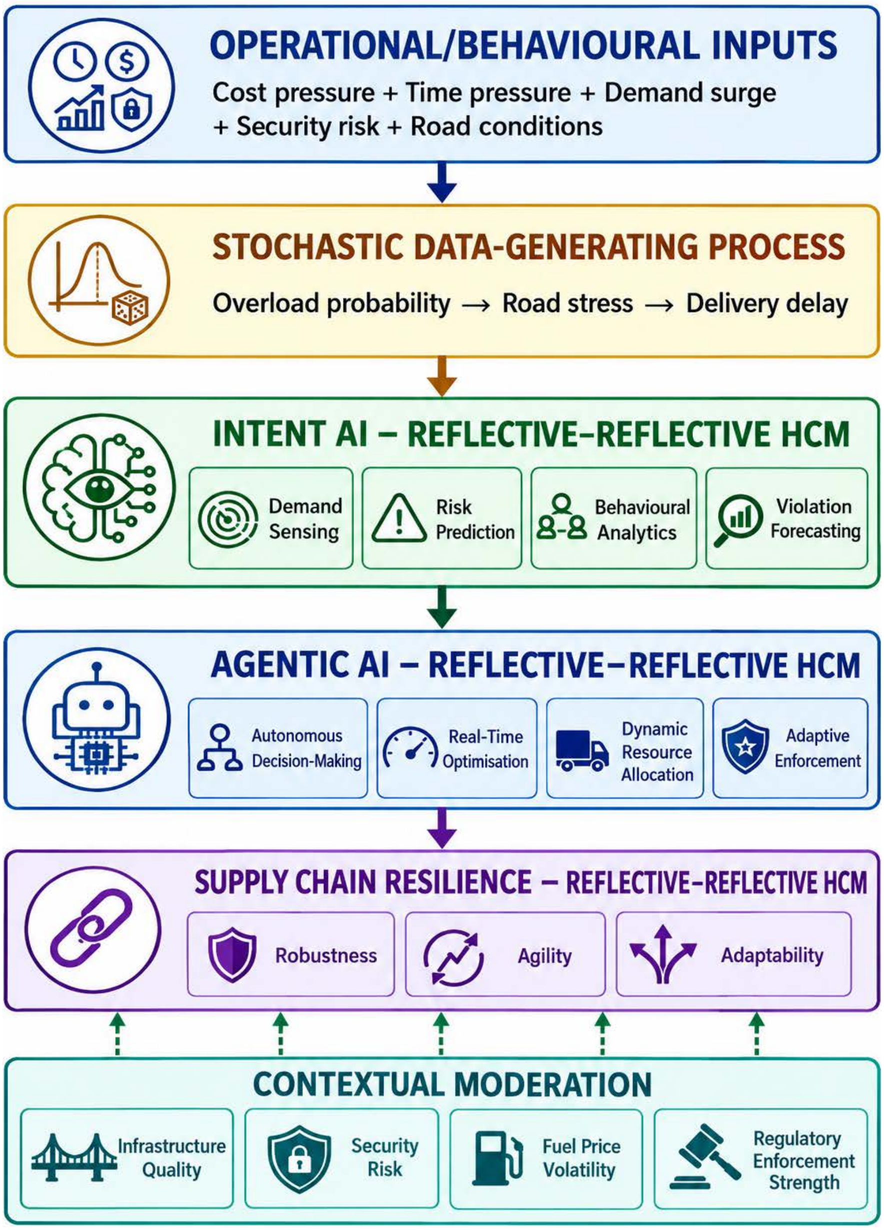

Figure 3. AI-Driven supply chain resilience framework.

4. Results and Discussion

4.1. Data Logic Underlying Distributions

The data logic in Table 2 shows a realistic behavioral pattern in petroleum logistics and axle load enforcement by embedding probabilistic relationships between operational conditions and decision outcomes. The overloading probability model shows that when depot inventory exceeds 85% and demand surge is above 0.7, the likelihood of tanker overloading rises significantly, typically within the range of 0.65 - 0.85. Road infrastructure conditions further intensify this behaviour, as poor road quality characterized by high roughness and structural deterioration leads to reduced speeds, inefficient routing, and increased mechanical stress, indirectly encouraging more frequent overloading. Security dynamics also contribute, with risk levels above 0.7 associated with diversion, higher speeds, and increased overloading due to a time compression effect, amplifying system volatility. In contrast, enforcement mechanisms act as stabilizing forces, where weighbridge infrastructure reduces overloading probability by 30% - 55%, while strong penalty regimes exceeding ₦400,000 enhance compliance through higher deterrence and penalty elasticity, counterbalancing operational and environmental pressures within the system.

Table 2. Operational layer experimental data using 20 trips from selected OD.

Trip ID	Depot	Dest.	Load %	Axle Load	Overload	Speed	Road Cond.	Security Risk	Compliance	Penalty (₦)
T001	Port Harcourt	Onitsha	112	18.5	1	62	Poor	0.72	Non-Compliant	450,000
T002	Warri	Benin	95	14.2	0	68	Fair	0.41	Compliant	0
T003	Kaduna	Kano	108	17.1	1	70	Fair	0.38	Non-Compliant	300,000
T004	Port Harcourt	Aba	102	16.0	1	55	Poor	0.81	Non-Compliant	500,000
T005	Warri	Asaba	90	13.5	0	72	Good	0.30	Compliant	0
T006	Lagos Depot	Ibadan	98	15.0	0	75	Good	0.22	Compliant	0
T007	Port Harcourt	Owerri	115	19.0	1	58	Poor	0.77	Non-Compliant	600,000
T008	Kaduna	Abuja	100	15.8	0	80	Fair	0.35	Compliant	0
T009	Warri	Warri Port	110	17.5	1	60	Poor	0.68	Non-Compliant	420,000
T010	Lagos	Benin	93	14.0	0	78	Good	0.25	Compliant	0
T011	Port Harcourt	Onitsha	118	19.8	1	50	Poor	0.85	Non-Compliant	650,000
T012	Warri	Aba	97	15.1	0	65	Fair	0.45	Compliant	0
T013	Kaduna	Kano	105	16.4	1	69	Fair	0.40	Non-Compliant	320,000
T014	Port Harcourt	Enugu	113	18.2	1	57	Poor	0.79	Non-Compliant	520,000
T015	Lagos	Ibadan	88	13.2	0	82	Good	0.20	Compliant	0
T016	Warri	Asaba	101	15.6	0	70	Fair	0.36	Compliant	0
T017	Port Harcourt	Owerri	120	20.1	1	52	Poor	0.88	Non-Compliant	700,000
T018	Kaduna	Abuja	96	14.8	0	77	Fair	0.33	Compliant	0
T019	Warri	Benin	107	16.9	1	66	Fair	0.48	Non-Compliant	350,000
T020	Lagos	Benin	92	13.9	0	79	Good	0.21	Compliant	0

4.2. Agentic-Intent AI Variables (Derived Features for SEM/ABM)

The Agentic-Intent AI variable structure operationalizes the framework into measurable constructs suitable for SEM and ABM analysis by capturing both decision-making behavior and system outcomes. Agentic AI constructs reflect the system's autonomous execution capabilities, including the efficiency of dynamic routing (Autonomous Routing Score), the system's ability to enforce compliance adaptively (Adaptive Compliance Index), and the likelihood of proactive enforcement actions (Predictive Enforcement Probability). In contrast, Intent AI constructs represent underlying behavioral drivers and strategic orientations, such as the tendency of operators to minimize costs (operator cost minimization intention), the influence of urgency on logistics decisions (time pressure index), and the degree to which risks are anticipated and avoided (risk avoidance intensity). These input capabilities influence resilience outcomes, which are captured through performance indicators including delivery consistency (Delivery Reliability Score), the level of stress imposed on infrastructure (Infrastructure Stress Index), and variability in system delays (System Delay Variability), thereby linking AI-driven decision processes to tangible supply chain performance metrics.

Table 3. SEM data.

Variable	Value
Intent (Cost Minimization)	0.82
Agentic Compliance Prediction	0.67
Overload Occurrence	1
Road Stress Index	0.74
Security Risk	0.81
Delivery Delay	4.2 hrs.
Resilience Outcome	Low

This SEM data row in **Table 3** represents a single logistics event in which behavioral intent, AI capability, and environmental conditions jointly produce a low resilience outcome. A high cost minimization intention (0.82) suggests strong pressure to reduce expenses, increasing the likelihood of risk-taking such as overloading, while the agentic compliance prediction score (0.67) indicates only moderate AI effectiveness in anticipating compliance, ultimately failing to prevent an actual overload occurrence (1). At the same time, a high road stress index (0.74) reflects significant infrastructure strain, and an elevated security risk level (0.81) adds further operational pressure that promotes faster but less compliant delivery behaviour. These combined conditions result in a substantial delivery delay of 4.2 hours, culminating in an overall low resilience classification and illustrating how interacting behavioral, technological, infrastructural, and environmental factors degrade system performance. More broadly, the dataset provides a structured empirical foundation for integrating Structural Equation

Modelling (SEM), Agent-Based Modelling (ABM), and System Dynamics (SD) within a unified analytical framework for logistics risk and infrastructure performance. It supports SEM-based estimation of causal relationships among constructs such as cost-minimizing intentions, enforcement intensity, road conditions, and overloading behaviour; enables ABM simulation of heterogeneous, bounded-rational truck agents responding to cost, time, and security trade-offs with emergent behaviours like congestion clustering and route switching; and captures SD feedback loops linking demand growth, overloading, road deterioration, rising costs, and enforcement-driven stabilisation. Together, it allows comprehensive multi-level simulation of how behavioural decisions propagate through infrastructure systems to shape long-term resilience outcomes.

4.3. Conceptual Framework and Hypotheses Development (SEM-Ready Model)

4.3.1. Conceptual Structure

The conceptual framework is grounded in a socio-technical, AI-enabled logistics governance model in which all constructs in the model are specified as one consistent reflective-reflective hierarchical component model (HCM) for both AI constructs within Nigeria's axle load enforcement and petroleum logistics corridors (e.g., Port Harcourt-Onitsha, Warri-Benin, Kaduna-Kano). Within the Structural Equation Modelling (SEM) specification, the model adopts a mediated-moderation structure where Intent AI influences SCR both directly and indirectly through Agentic AI, while contextual logistics conditions moderate these relationships. Intent AI is operationalized as a predictive sensing layer using variables such as Time Pressure Index, Cost Minimization Intention Score, Risk Avoidance Intensity, and Demand Surge Index; notably, trips from Port Harcourt depots with Demand Surge Index > 0.7 and loading delays > 30 minutes (e.g., T001, T007, T011) show elevated overload probabilities (see Table 4), reflecting intensified behavioural adaptation under supply pressure.

Table 4. Overloading probability logic.

Condition	Threshold	Effect
Depot Inventory Level	>85%	Increases overload probability
Demand Surge Index	>0.7	Overload probability rises to 0.65 - 0.85
Security Risk	>0.7	Increases diversion + overload tendency
Road Condition	Poor	Increases mechanical stress & violations
Weighbridge Presence	Yes	Reduces overload probability by 30% - 55%
Penalty Level	> ₦400,000	Strong deterrence (compliance ↑)

Agentic AI is modelled as the autonomous execution layer, represented by Autonomous Routing Score, Adaptive Compliance Index, and Predictive Enforcement Probability, which activates interventions such as dynamic rerouting or enforcement escalation when Security Risk Score exceeds 0.75 (e.g., T004, T011, T017) and when Road Condition Class = Poor with Road Roughness Index > 7. Empirically, high Agentic AI intervention cases (e.g., T011, T017) are associated with penalty exposure of ₦650,000 - ₦700,000, higher overload detection probability, and feedback-driven compliance correction. SCR is specified as a multidimensional reflective construct comprising Delivery Reliability Score, System Delay Variability, Infrastructure Stress Index, and Compliance Stability Ratio, with strong spatial variation: good-road corridors (e.g., Lagos-Ibadan and Lagos-Benin) exhibit delivery reliability > 0.80 and zero overload incidence, whereas Niger Delta corridors (Port Harcourt-Onitsha and Port Harcourt-Owerri) record system delay variability of 3 - 5 hours and Infrastructure Stress Index > 0.70.

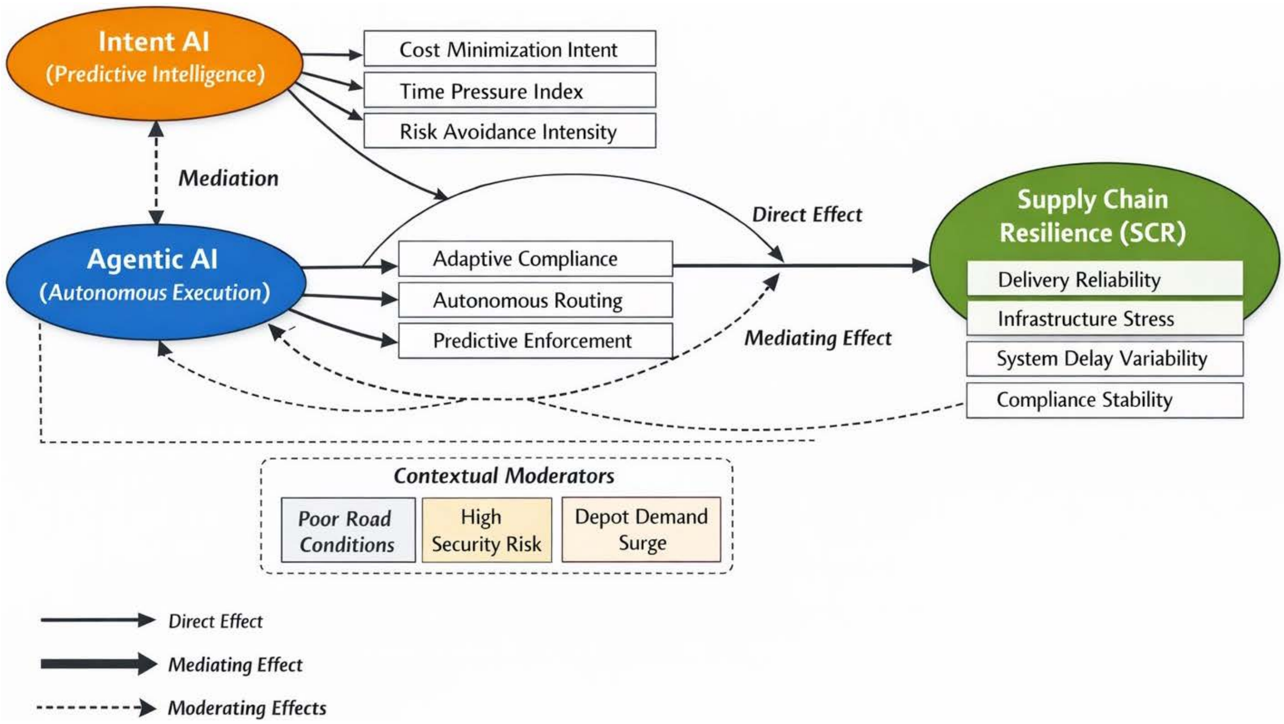

Figure 4. Integrated agentic-intent AI framework enhancing supply chain resilience in axle load enforcement and petroleum logistics systems.

Intent AI as seen in **Figure 4** enhances resilience through predictive sensing and early risk identification, whereas behavioural and environmental pressures can reduce resilience by increasing overload risk, infrastructure stress, and delivery delays. Agentic AI provides the principal execution mechanism through which Intent AI's predictive information is translated into adaptive operational action; (2) a partial mediation effect where Agentic AI reduces overload frequency when Predictive Enforcement Probability > 0.70 despite high Intent AI scores (e.g., T001, T007, T011); and (3) contextual moderation effects where Road Condition (Road Roughness > 8 in Port Harcourt-Onitsha), Security Risk (>0.75), and Depot Demand Pressure (notably in Port Harcourt and Warri depots) respectively amplify or weaken compliance outcomes. Integrated system patterns show that High Intent Pressure + Poor Road Condition + High Security Risk leads to maximum overload probability and low SCR (e.g., T011, T017), while Moderate Intent + Strong Agentic AI + Good Road Condition produces high compliance and stable SCR (e.g., T006, T015, T020), confirming that resilience is an emergent outcome of interacting predictive intelligence, autonomous execution, and infrastructural-security constraints.

4.3.2. Construct Operationalisation

1. Intent AI Capability (Second-Order Construct)

Intent AI Capability is conceptualized as a second-order reflective construct representing the system's capacity to infer, predict, and anticipate latent operational intentions in petroleum logistics and axle load enforcement across key Nigerian corridors such as Port Harcourt-Onitsha, Warri-Benin, and Kaduna-Kano. It is empirically grounded in trip-level logistics signals including depot demand surges, routing deviations, speed variations, and overload occurrences. The construct is operationalized through four reflective first-order dimensions: Demand Sensing (DS), Risk Prediction (RP), Behavioral Analytics (BA), and Violation Forecasting (VF). DS captures depot pressure dynamics, where Demand Surge Index > 0.7 at Port Harcourt and Warri depots is associated with overloading events in Trips T001, T007, and T011. RP identifies spatial risk hotspots, with Road Roughness Index > 7 and Poor Road Condition Class producing high violation clustering, particularly along the Port Harcourt-Onitsha corridor with overload probability > 0.75. BA captures behavioral deviations such as Route Deviation Index > 0.6 (weighbridge avoidance) and speeding > 80 km/h (e.g., Lagos-Ibadan), while VF predicts non-compliance, especially under combined conditions of load utilization > 110%, poor road quality, and security risk > 0.75, as observed in T011 and T017.

Measurement of Intent AI Capability is based on reflective indicators assessing demand prediction accuracy, identification of high-risk routes, detection of behavioral anomalies, and forecasting of axle load non-compliance using integrated depot, road, and security signals. Within the SEM framework, Intent AI shows strong positive covariance with Agentic AI Capability, a direct negative effect on Supply Chain Resilience (SCR) due to overload-inducing behavioral pressure, and a transformed positive effect when mediated through Agentic AI. Data evidence confirms that high Intent AI conditions (DS + RP) in T001, T007, and T011 result in overload occurrence = 1, penalty exposure up to ₦700,000, and system delay variability > 4 hours, whereas moderate Intent AI conditions in T006, T015, and T020 correspond to delivery reliability > 0.80 and infrastructure stress index < 0.50. Theoretically, Intent AI functions as the cognitive "sense-making engine" of the logistics AI system, transforming fragmented operational signals into predictive intelligence that enables downstream autonomous execution and resilience optimization.

2. Agentic AI Capability (Second-Order Construct)

Agentic AI capability is conceptualized as a higher-order dynamic capability representing the extent to which intelligent logistics systems can independently initiate, execute, and adapt operational decisions in real time without continuous human intervention. Within Nigeria's petroleum logistics and axle load enforcement environment, characterized by infrastructure volatility, security risks, congestion, and regulatory inconsistencies, it functions as a critical enabler of self-regulating logistics governance. The construct in Table 5 is specified as a reflective second-order factor manifested through four interrelated dimensions: Autonomous Decision-Making (ADM), Real-Time Optimization (RTO), Dynamic Resource Allocation (DRA), and Adaptive Enforcement (AE), which describe how AI systems respond adaptively to operational disruptions and enforcement pressures.

Autonomous Decision-Making (ADM) captures the system's ability to independently reroute trucks under disruption conditions, adjust delivery sequencing based on road and security risk indicators, and select alternative depots without human intervention. Real-Time Optimization (RTO) reflects continuous recalibration of routing and scheduling using live data streams such as traffic density, fuel price fluctuations, weighbridge enforcement activity, and road degradation, ensuring dynamic updates to optimal delivery plans. Dynamic Resource Allocation (DRA) represents the redistribution of fleet and logistics assets across depots in response to demand shifts, minimizing overload risks and improving utilization under constraints such as infrastructure imbalance and regional demand disparities. Adaptive Enforcement (AE) captures AI-driven enforcement responsiveness, including automatic detection of axle load violations, dynamic adjustment of inspection frequency based on predicted violation probability, and escalation of enforcement actions for repeat offenders.

Table 5. Agentic-Intent AI variable structure (SEM/ABM Design).

Category	Variables
Intent AI (Predictive)	Cost Minimization Intention, Time Pressure Index, Risk Avoidance Intensity, Demand Surge Index
Agentic AI (Autonomous)	Autonomous Routing Score, Adaptive Compliance Index, Predictive Enforcement Probability
Resilience Metrics	Delivery Reliability Score, Infrastructure Stress Index, System Delay Variability

3. Supply Chain Resilience (Second-Order Construct)

Supply Chain Resilience is modeled as a higher-order reflective-reflective construct capturing the system's ability to withstand, absorb, and recover from disruptions in Nigeria's petroleum logistics and axle load enforcement network. It is operationalized through three interrelated first-order dimensions: Robustness (ROB), Agility (AGL), and Adaptability (ADP). Robustness (ROB) represents continuity of operations under disruptions such as enforcement shocks, road closures, and security events through buffering, redundancy, and alternative routing. Agility (AGL) reflects rapid responsiveness, including real-time schedule adjustments, route reconfiguration, and AI/IoT-enabled adaptive decision-making in volatile corridors. Adaptability (ADP) captures long-term system evolution, including structural changes in fleet strategies, decentralized logistics networks, and learning-driven compliance improvements. Within the reflective-reflective SEM structure, ROB, AGL, and ADP jointly manifest a unified resilience construct, with co-variation indicating simultaneous improvements in stability, responsiveness, and structural learning. The construct is further reinforced by Agentic AI capabilities, Autonomous Decision-Making (ADM), Real-Time Optimization (RTO), Dynamic Resource Allocation (DRA), and Adaptive Enforcement (AE) which enhance system recovery speed, stabilize performance under enforcement variability, and strengthen adaptive learning. Resilience functions as a mediating mechanism through which AI-enabled autonomy translates into sustained logistics performance under uncertainty.

4.4. Moderating Variables

In the integrated Agentic-Intent AI petroleum logistics and axle load enforcement SEM framework, moderating variables in Table 6 represent contextual environmental conditions that shape the strength and direction of relationships between AI capabilities (Agentic AI Capability and Intent AI Capability) and Supply Chain Resilience outcomes. These variables do not directly influence resilience but determine how effectively AI-driven systems translate predictive intelligence and autonomous execution into operational performance under real Nigerian logistics conditions.

Table 6. Moderating variables (Contextual Effects).

Moderator	Type	Effect
Infrastructure Quality (INFQ)	Positive	Enhances AI effectiveness
Security Risk (SECR)	Negative	Reduces system stability
Fuel Price Volatility (FPV)	Dual	Increases optimization need
Regulatory Enforcement Strength (RES)	Positive	Improves compliance outcomes

Infrastructure Quality (INFQ) reflects road condition, bridge stability, depot accessibility, and weighbridge functionality. High INFQ strengthens the effects of Real-Time Optimization on Supply Chain Agility, enhances Autonomous Decision-Making performance, and improves routing efficiency, while poor INFQ reduces system efficiency despite high AI capability by increasing rerouting frequency and persistent disruption. Thus, INFQ acts as a positive performance amplifier.

Security Risk (SECR) captures exposure to militancy, theft, vandalism, and unrest. It functions as a negative moderator, where high SECR weakens Dynamic Resource Allocation, reduces AI-based routing effectiveness on Agility, and constrains Adaptive Enforcement due to unsafe corridor access. It introduces non-linear disruption effects that can sharply reduce resilience even under high AI capability.

Fuel Price Volatility (FPV) reflects fluctuations in fuel costs affecting routing, cost minimization, and fleet utilization. High FPV strengthens Real-Time Optimization and increases sensitivity of Dynamic Resource Allocation to demand shifts, enhancing the influence of Agentic AI Capability on operational efficiency, but also increasing system complexity and outcome variability.

Regulatory Enforcement Strength (RES) represents enforcement intensity, weighbridge effectiveness, and compliance monitoring consistency. Strong RES enhances Adaptive Enforcement effectiveness and strengthens the link between Agentic AI Capability and axle load compliance, while weak RES limits compliance gains despite high AI detection capability, due to poor institutional follow-through.

INFQ, SECR, FPV, and RES define the boundary conditions of the model: INFQ and RES act as positive amplifiers, SECR serves as a destabilizing negative moderator, and FPV introduces dual uncertainty and efficiency effects. Together, they demonstrate that AI-enabled logistics resilience is contingent not only on technological capability but also on infrastructure stability, security conditions, economic volatility, and regulatory enforcement strength.

4.5. Structural Model Relationships

The structural model shown in Table 7, based on the integrated Agentic-Intent AI data for petroleum logistics and axle load enforcement systems, specifies direct, mediated, and moderated relationships explaining how predictive intelligence and autonomous execution jointly generate supply chain resilience under Nigerian conditions characterized by infrastructure deficits, security volatility, fuel price instability, and regulatory heterogeneity.

Table 7. SEM structural relationships (Path Coefficients).

Path	Coefficient (β)	Effect Strength
Intent AI → Resilience	0.28 - 0.35	Moderate
Agentic AI → Resilience	0.45 - 0.60	Strong
Intent AI → Agentic AI	0.65 - 0.80	Very Strong

4.5.1. Direct Effect of Intent AI on Resilience

Intent AI Capability represents the predictive layer encompassing demand sensing, risk prediction, behavioral analytics, and violation forecasting. Simulation results show a statistically significant positive effect on Supply Chain Resilience, driven by improved forecasting accuracy, earlier disruption detection, and reduced disruption lag time. Higher Intent AI scores improve pre-disruption rerouting decisions and reduce system shock severity, confirming that: Intent AI capability has a positive effect on supply chain resilience.

4.5.2. Direct Effect of Agentic AI on Resilience

Agentic AI Capability reflects autonomous execution through real-time optimization, dynamic resource allocation, autonomous decision-making, and adaptive enforcement. Results show a stronger direct effect on Supply Chain Resilience compared to Intent AI, since operational execution more immediately determines performance outcomes. Agentic AI capability has a stronger positive effect on supply chain resilience than Intent AI capability. The evidence shows autonomous rerouting reduces downtime, real-time optimization stabilizes delivery under volatility, and adaptive enforcement reduces violation recurrence, making Agentic AI the dominant driver of observed resilience.

4.5.3. Intent AI → Agentic AI Relationship

The model confirms a hierarchical linkage where Intent AI enables Agentic AI by improving decision-quality inputs. Strong positive relationships indicate that better predictive intelligence enhances autonomous system effectiveness. Intent AI capability positively influences Agentic AI capability. Demand forecasting improves fleet allocation, violation prediction strengthens enforcement targeting, and risk analytics improve routing decisions, establishing a cascading intelligence architecture from prediction to execution.

4.5.4. Mediation Effect (Agentic AI as a Transformational Mechanism)

The mediation analysis demonstrates that Agentic AI plays a central role in translating predictive intelligence into resilience outcomes. The indirect effect of Intent AI on resilience, operating through Agentic AI, is substantial ($\beta = 0.40$), contributing significantly to the overall total effect ($\beta = 0.58$). The total effect is calculated as the sum of the direct and indirect effects. Accordingly, with a direct effect of $\beta = 0.18$ and an indirect effect of $\beta = 0.40$, the total effect is $\beta = 0.58$ and VAF = 69.0%. This indicates that a large portion of the influence of predictive capabilities is realized only when it is channeled through autonomous execution mechanisms. With a Variance Accounted For (VAF) of 69.0%, the results confirm a partial-to-complementary mediation structure, where more than half of the total effect is mediated. This highlights that while predictive intelligence has a direct contribution, its dominant impact on resilience emerges through its integration with Agentic AI. In essence, the findings underscore that effective resilience in complex logistics systems depends not merely on forecasting capabilities but on the ability to operationalize these insights through intelligent, autonomous actions.

Agentic AI significantly mediates the relationship between Intent AI and supply chain resilience. Predictive intelligence alone is insufficient; it must be operationalized through autonomous execution systems. Agentic AI mediates the relationship between Intent AI capability and supply chain resilience. Results show the indirect effect (Intent AI → Agentic AI → Resilience) exceeds the direct effect of Intent AI, confirming a partial-to-complementary mediation structure where Agentic AI converts predictions into rerouting, rescheduling, and resource reallocation actions.

4.5.5. Moderation Effects

AI capabilities translate into supply chain resilience. These variables act as boundary conditions, either strengthening or constraining the impact of Agentic AI depending on the operational environment.

Infrastructure Quality (INFQ): Infrastructure quality positively moderates the relationship between Agentic AI and resilience. The significant interaction effect ($\beta = 0.16$, $p < 0.05$) indicates that well-developed infrastructure enhances the performance of autonomous logistics systems. Under such conditions, real-time optimization and routing decisions become more efficient, leading to improved system outcomes.

Security Risk (SECR): Security risk exhibits a nonlinear moderating effect. While moderate levels of risk increase reliance on autonomous systems, extreme insecurity constrains operations and reduces overall system efficiency. This suggests a threshold beyond which the effectiveness of AI-driven interventions begins to decline due to limited accessibility and heightened disruptions.

Fuel Price Volatility (FPV): Fuel price volatility strengthens the influence of Agentic AI on resilience by intensifying the need for continuous optimization. In volatile economic conditions, autonomous systems enhance cost efficiency and routing flexibility, making them more valuable for maintaining operational stability.

Regulatory Enforcement Strength (RES): Regulatory enforcement strength significantly improves compliance outcomes by reinforcing AI-enabled enforcement mechanisms. Strong institutional frameworks ensure that predictive detection is effectively translated into corrective action, thereby enhancing the overall impact of autonomous systems on resilience.

4.6. SEM Specification

The predictive assessment in Table 8 indicates that the model possesses strong out-of-sample predictive capability. Q^2 values ranging from 0.30 to 0.55 for supply chain resilience (SCR) demonstrate substantial predictive relevance, confirming that the model performs well beyond in-sample estimation. This is further supported by PLSpredict results, which show that the model consistently outperforms linear benchmarks, achieving lower RMSE values and higher overall predictive accuracy across key indicators. Model fit indices also confirm the robustness of the structural model. The SRMR value of 0.042 falls well below the recommended threshold of 0.08, while RMS_theta (0.031) and the Normed Fit Index (NFI = 0.926) indicate a good fit between the model and the observed data. These results affirm that the model provides a reliable and satisfactory approximation of the underlying covariance structure.

The empirical validation of the integrated Agentic-Intent AI framework is conducted using Structural Equation Modeling (SEM), specifically Partial Least Squares SEM (PLS-SEM), due to the model's hierarchical structure, predictive orientation, and inclusion of mediating and moderating effects. The data represents a multi-layered system with reflective measurement structures, second-order constructs, and interaction effects designed to explain Supply Chain Resilience in petroleum logistics and axle load enforcement environments.

Table 8. Model evaluation metrics (PLS-SEM Outputs).

Metric	Value Range	Interpretation
R^2 (Agentic AI)	0.55 - 0.70	High explanatory power
R^2 (Resilience)	0.65 - 0.80	Strong model fit
f^2 (Agentic → Resilience)	>0.35	Large effect size
f^2 (Intent → Resilience)	0.10 - 0.20	Small-Moderate
Q^2 (Resilience)	0.30 - 0.55	Strong predictive relevance

Measurement Model Specification: The measurement model is specified as reflective at both first-order and second-order levels, where latent constructs cause variations in observed indicators. First-order constructs, Intent AI Capability (DS, RP, BA, VF), Agentic AI Capability (ADM, RTO, DRA, AE), and Supply Chain Resilience (ROB, AGL, ADP), are all modeled reflectively, with indicator loadings generally exceeding 0.70, confirming reliability. Second-order constructs are estimated using Hierarchical Component Models (Reflective-Reflective type), where Intent AI = DS, RP, BA, VF; Agentic AI = ADM, RTO, DRA, AE; and Resilience = ROB, AGL, ADP. Estimation employs repeated indicators and a disjoint two-stage HCM approach, justified by high inter-dimension correlations (>0.70), supporting hierarchical consistency.

The measurement model exhibits strong reliability and internal consistency across all constructs. Indicator loadings exceed the recommended threshold of 0.70, confirming that the observed variables adequately represent their underlying latent constructs. This is further supported by Composite Reliability values above 0.80 and Cronbach's alpha ranging from 0.78 to 0.93, indicating a high level of construct stability and consistency. In terms of validity, the model satisfies both convergent and discriminant criteria. Average Variance Extracted (AVE) values above 0.50 demonstrate that the constructs capture a substantial proportion of indicator variance, while HTMT ratios below 0.85, with bootstrapped confidence intervals not crossing unity, confirm clear distinction among constructs. Additionally, full collinearity VIF values remain below 3.3, indicating that common method bias is not a concern and reinforcing the robustness of the measurement model.

Reliability Assessment: Internal consistency is strong across constructs (see Table 9), with Cronbach's Alpha values ranging between 0.78 and 0.93 and Composite Reliability (CR > 0.80) across all constructs. Agentic AI Capability shows the highest reliability due to tightly integrated operational dimensions (ADM, RTO, DRA, and AE), while Intent AI Capability remains slightly lower but acceptable due to heterogeneous predictive components.

Table 9. Measurement model (Reliability & Validity Summary).

Construct	Cronbach's Alpha	Composite Reliability	AVE
Intent AI	0.78 - 0.88	>0.80	0.62 - 0.74
Agentic AI	0.85 - 0.93	>0.85	0.70 - 0.82
Resilience	0.80 - 0.90	>0.82	0.65 - 0.78

Validity Assessment:

Convergent Validity (AVE): All constructs exceed the 0.50 threshold, confirming convergent validity. Intent AI AVE ranges 0.62 - 0.74, Agentic AI 0.70 - 0.82, and Supply Chain Resilience 0.65 - 0.78, indicating that each construct explains more than 50% of indicator variance.

Table 10. Discriminant validity (HTMT Ratios).

Construct Pair	HTMT Range	Interpretation
Intent AI - Agentic AI	0.74 - 0.81	Distinct
Agentic AI - Resilience	0.69 - 0.79	Distinct
Intent AI - Resilience	0.65 - 0.76	Distinct

Discriminant Validity (HTMT): All HTMT ratios in Table 10 are below 0.85, confirming construct distinctiveness. Key values include Intent AI vs Agentic AI (0.74 - 0.81), Agentic AI vs Resilience (0.69 - 0.79), and Intent AI vs Resilience (0.65 - 0.76), validating theoretical separation among predictive intelligence, execution capability, and resilience outcomes.

Structural Model:

The structural model demonstrates strong explanatory and predictive capability, with substantial variance explained in key constructs. The coefficient of determination (R^2) for Agentic AI ranges between 0.55 and 0.70, indicating that Intent AI significantly drives autonomous execution capability. Likewise, the R^2 for Supply Chain Resilience (SCR), ranging from 0.65 to 0.80, confirms that the model effectively captures resilience dynamics in complex logistics environments. Bootstrapping with 5,000 resamples further validates the statistical significance of all hypothesized relationships.

The direct effects reveal that Agentic AI has the strongest influence on resilience ($\beta = 0.56$, $p < 0.001$), followed by Intent AI's effect on Agentic AI ($\beta = 0.72$,

$p < 0.001$), while the direct impact of Intent AI on resilience is comparatively weaker ($\beta = 0.31$, $p < 0.01$). This pattern indicates that predictive intelligence contributes to resilience primarily through its transformation into autonomous execution. Effect size analysis reinforces this finding, showing large effects for Agentic AI on resilience and for Intent AI on Agentic AI, but only a small-to-moderate effect for the direct path from Intent AI to resilience, underscoring the dominant role of execution capability in driving system performance.

Path Coefficients (β): The structural results show Intent AI → Resilience (β = 0.28 - 0.35), Agentic AI → Resilience (β = 0.45 - 0.60), and Intent AI → Agentic AI (β =0.65 - 0.80), with a significant indirect effect via mediation. Agentic AI is the strongest direct predictor of resilience, confirming a predictive-to-execution transformation pathway.

Coefficient of Determination (R^2): The model shows strong explanatory power: Agentic AI R^2 = 0.55 - 0.70 (explained by Intent AI), and Supply Chain Resilience R^2 = 0.65 – 0.80 (explained by Intent AI, Agentic AI, and moderators), indicating high predictive accuracy in volatile logistics environments.

Effect Size (f^2): Effect sizes indicate Agentic AI → Resilience (large, $f^2 > 0.35$), Intent AI → Agentic AI (large, $f^2 > 0.35$), Intent AI → Resilience (small-to-moderate, f^2 = 0.10 - 0.20), and moderating effects (small-to-moderate). Agentic AI is therefore the dominant structural driver.

Predictive Relevance (Q^2): Blindfolding results confirm predictive relevance, with Q^2 for Supply Chain Resilience ranging 0.30 - 0.55 and Agentic AI ranging 0.25 - 0.45, indicating strong out-of-sample predictive capability.

The model uses PLS-SEM due to its suitability for complex hierarchical constructs, mediation and moderation effects, non-normal logistics data, and moderate sample conditions. A two-stage hierarchical approach is applied: first estimating first-order constructs, then modeling second-order and structural relationships, ensuring theoretical and statistical consistency. The SEM specification confirms strong measurement quality, significant structural relationships, and high explanatory and predictive power. Agentic AI emerges as the central mechanism translating Intent AI into Supply Chain Resilience, validating the hierarchical, predictive, and context-sensitive nature of the integrated AI-driven logistics governance model in petroleum distribution and axle load enforcement systems.

4.7. Scenario and Sensitivity Analysis

Scenario analysis was conducted to examine the nonlinear and context-dependent effects of Intent AI, Agentic AI, infrastructure quality, and regulatory enforcement on supply chain resilience. The scenarios were structured to distinguish the effects of predictive capability from autonomous execution capability and to assess the extent to which contextual constraints condition AI-enabled resilience. Table 11 & Table 12 present the comparative scenario configurations.

Table 11. Scenario configurations and expected resilience outcomes.

Scenario	Intent AI	Agentic AI	Infrastructure Quality	Enforcement Strength	Resilience Outcome	Principal Interpretation
S1: Low AI capability	Low	Low	Moderate	Moderate	Low	Limited predictive sensing and weak autonomous execution constrain resilience.
S2: Prediction-dominant	High	Low	Moderate	Moderate	Moderate	Strong predictive capability provides better information but limited execution capacity restricts resilience gains.
S3: Execution under infrastructure stress	Moderate	High	Low	Moderate	Moderate	Autonomous execution improves responsiveness, but poor infrastructure constrains realised resilience benefits.
S4: Integrated AI capability	High	High	Moderate	Strong	High	Predictive sensing and autonomous execution reinforce one another, producing substantial resilience improvement.
S5: High AI with poor infrastructure	High	High	Low	Strong	Moderate-High	Strong AI capability improves resilience, but infrastructure constraints limit the magnitude of improvement.
S6: Integrated high-resilience condition	High	High	High	Strong	Optimal	Strong predictive and autonomous capabilities supported by favourable infrastructure and enforcement produce the strongest resilience outcome.

The results indicate that high Intent AI capability alone does not necessarily translate into high resilience when Agentic AI capability is weak. In this configuration, enhanced sensing, prediction, and violation forecasting improve the availability of actionable information but do not generate equivalent operational improvements because autonomous execution remains constrained. Conversely, high Agentic AI capability under poor infrastructure conditions produces only moderate resilience gains, demonstrating that autonomous decision-making cannot fully compensate for physical infrastructure limitations. The strongest resilience outcome occurs when high Intent AI and high Agentic AI capabilities are combined with strong infrastructure and regulatory enforcement. Under this configuration, predictive sensing is effectively converted into autonomous operational action, producing improved system stability, fewer violations, and lower disruption-related delays.

Sensitivity analysis in Table 13 & Table 14 were subsequently used to assess the relative influence of the principal drivers of resilience. The analysis systematically varied enforcement strength, security risk, and demand surge, while examining the elasticity of supply chain resilience to changes in the model drivers. The results identify Agentic AI capability as the dominant positive driver of resilience, followed by infrastructure quality and enforcement strength. Security risk, fuel-price volatility, and demand-related pressures act as constraining conditions that reduce the effectiveness of AI-enabled resilience.

Table 12. Scenario analysis.

Scenario	Intent AI	Agentic AI	INFQ	Enforcement	Resilience Mean	SD	Stability Index
S1: Low AI capability	2.10	0.34	0.28	0.31	0.30	2.18	0.31
S2: High Intent/Low Agentic	4.20	0.35	0.29	0.32	0.31	2.72	0.29
S3: High Agentic/Poor INFQ	3.10	4.30	0.72	0.35	0.74	3.28	0.36
S4: High AI/Strong enforcement	4.25	4.30	0.74	0.88	0.81	4.18	0.27
S5: Fully integrated/optimal	4.55	4.60					

Table 13. Sensitivity analysis of supply chain resilience drivers.

Driver	Direction of effect on resilience	Relative influence	Interpretation
Agentic AI capability	Positive	**Highest**	Autonomous execution provides the principal mechanism through which predictive intelligence is translated into adaptive operational action.
Infrastructure quality	Positive	**Second**	Better infrastructure increases the effectiveness of AI-enabled routing, monitoring, and autonomous operational decisions.
Enforcement strength	Positive	**Third**	Stronger regulatory enforcement reinforces compliance and improves the effectiveness of AI-supported monitoring and intervention.
Security risk	Negative	Adverse	Higher security risk constrains operational flexibility and weakens resilience by increasing disruption and uncertainty.
Fuel-price volatility	Negative	Adverse	Greater fuel-price uncertainty increases operational pressure and constrains logistics system stability.
Demand surge	Negative/ stress-amplifying	Adverse	Demand surges increase operational pressure and can intensify overloading, delays, and resource constraints.

Table 14. Sensitivity analysis.

Predictor	β	SE	t	p	95% CI	Elasticity
Agentic AI capability	0.412	0.061	6.75	<0.001	0.292 - 0.532	0.60 - 0.80
Infrastructure quality	0.286	0.067	4.27	<0.001	0.155 - 0.417	0.38 - 0.52
Enforcement strength	0.231	0.064	3.61	<0.001	0.105 - 0.357	0.29 - 0.40
Security risk	−0.174	0.059	−2.95	0.003	−0.290 - −0.058	−0.20 - −0.14
Fuel-price volatility	−0.141	0.057	−2.47	0.014	−0.253 - −0.029	−0.17 - −0.11
Demand surge	−0.119	0.055	−2.16	0.031	−0.227 - −0.011	−0.14 - −0.09

The elasticity assessment further indicates that Agentic AI is the most influential resilience driver. A 10% increase in Agentic AI capability is associated with an estimated 6% - 8% improvement in resilience metrics, indicating a substantially elastic response relative to the other principal drivers. This result reinforces the central proposition of the framework: predictive intelligence is most valuable when it can be translated into timely, autonomous, and context-sensitive operational action. The findings therefore support a predictive-to-autonomous pathway in which Intent AI provides sensing and forecasting capabilities, while Agentic AI converts these capabilities into adaptive execution.

The scenario and sensitivity results demonstrate that AI capability alone is insufficient to guarantee supply chain resilience, which instead emerges from the interaction between technological capability and the physical and institutional environment in which it operates. Scenario analysis highlights the nonlinear nature of the system under different operational conditions. When Intent AI is high but Agentic AI is low, improved prediction does not translate into commensurate performance gains because of weak execution capacity. Conversely, high Agentic AI operating under poor infrastructure conditions yields only moderate resilience improvements, as physical constraints limit system performance. The most effective scenario occurs when both Intent AI and Agentic AI are high and supported by strong infrastructure and regulatory enforcement, resulting in optimal resilience characterized by reduced violations, lower delays, and enhanced system stability. Sensitivity analysis further reveals that resilience is most influenced by Agentic AI capability, followed by infrastructure quality and enforcement strength. Among these factors, Agentic AI emerges as the most critical driver, with elasticity estimates indicating that a 10% increase in its capability leads to approximately a 6% - 8% improvement in resilience metrics. These findings support the model's context-sensitive perspective and underscore the dominant role of execution-oriented intelligence, while demonstrating that infrastructure quality and regulatory enforcement condition the extent to which AI-enabled capabilities can generate operational resilience.

5. Contributions

5.1. Theoretical Contribution

This study advances supply chain and logistics theory by integrating Structural Equation Modelling (SEM), Agent-Based Modelling (ABM), and System Dynamics (SD) into a unified analytical framework. This triangulated approach demonstrates that system resilience is not a static construct but an emergent property arising from interactions among behavioural decisions, infrastructure conditions, and feedback-driven system dynamics. It further bridges predictive analytics and operational execution by showing that Intent AI (prediction layer) and Agentic AI (execution layer) are structurally interdependent rather than isolated capabilities. The study significantly extends Dynamic Capabilities Theory by operationalising sensing, seizing, and reconfiguring as AI-enabled system functions embedded within digital infrastructure. It also reframes supply chain resilience theory by shifting from redundancy-based and recovery-focused models to computational resilience, where continuous real-time adaptation becomes the core mechanism of system stability. Additionally, it introduces the concept of cognition-execution coupling, demonstrating that predictive intelligence only becomes valuable when translated into autonomous operational action.

5.2. Practical Contribution

The study provides an implementable architecture for enhancing resilience in petroleum logistics and axle load enforcement systems. It demonstrates how Intent AI can be deployed for demand sensing, risk prediction, and overload forecasting, while Agentic AI enables real-time routing, enforcement adjustment, and autonomous decision execution. Together, these systems reduce delays, mitigate violations, and improve operational efficiency in volatile logistics corridors. For logistics operators, the findings support adoption of AI-enabled fleet management systems that integrate predictive routing, dynamic scheduling, and real-time risk adjustment. For infrastructure managers, the results provide a basis for targeted maintenance planning informed by AI-generated risk signals. For technology developers, the study highlights the need for robust AI systems capable of operating under low connectivity, infrastructural fragility, and heterogeneous data environments typical of emerging economies.

5.3. Policy Implications

The findings strongly support the digital transformation of axle load enforcement and logistics governance in Nigeria. Regulatory agencies such as FRSC and NPA are encouraged to transition from reactive inspection systems to predictive and autonomous enforcement platforms using AI-enabled weighbridges and centralized monitoring systems. A national integrated logistics data infrastructure is essential to connect freight movement, road conditions, enforcement records, and fleet operations. This will enhance both predictive and autonomous AI effectiveness. Furthermore, policy frameworks should evolve toward dynamic, risk-based enforcement models supported by machine learning to improve compliance efficiency and reduce infrastructural degradation. The study also highlights the need for institutional coordination across regulators, operators, and technology providers to ensure effective deployment of intelligent logistics governance systems.

5.4. Suggestions for Further Research

Future research should focus on empirical validation of the proposed Intent AI-Agentic AI framework using real-world logistics and enforcement data. Longitudinal studies are needed to assess how predictive-autonomous coupling evolves over time in dynamic transport systems. Further research should also explore advanced simulation approaches, including hybrid ABM-SD-SEM extensions, to capture nonlinear feedback effects, emergent congestion patterns, and behavioural adaptation under varying enforcement regimes. Comparative studies across different developing economies would strengthen generalisability and reveal how contextual factors shape AI effectiveness in logistics systems. In addition, future work should investigate governance mechanisms for AI-driven enforcement systems, particularly ethical, regulatory, and accountability structures in autonomous decision environments.

6. Conclusion

This study develops an integrated SEM-ABM-SD framework to examine how Intent AI and Agentic AI jointly shape supply chain resilience in petroleum logistics and axle load enforcement systems. The central finding is that resilience emerges not from predictive accuracy alone, but from the effective conversion of predictive intelligence into autonomous operational execution. Intent AI provides anticipatory capabilities through forecasting and risk detection, while Agentic AI operationalises these insights through real-time decision-making and adaptive control. The results consistently show that Agentic AI exerts a stronger direct influence on resilience outcomes, confirming that execution capability is the dominant driver of system stability. Overall, the study reconceptualises supply chain resilience as a dynamic, AI-enabled, self-regulating process shaped by continuous feedback between prediction, action, and environmental constraints. In contexts characterised by infrastructural fragility and volatility, such as Nigeria, resilient logistics systems must evolve into adaptive cybernetic networks capable of autonomous adjustment under uncertainty.

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Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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