Available on: https://jefrr.ep-journals.org/ E-ISSN: 3051-3650, P-ISSN: 3051-3642

Journal of Economic Finance Research and Review

Volume: 02 Issue: 08 August 2026

AI-Driven Demand Forecasting and Inventory Optimization in U.S. Car Rental Supply Chain Operations: A Technology-Organization-Environment and Resource-Based View Analysis

Salami Abdul Mohammed

College of Business, Westcliff University, Irvine, California, USA. ORCID: 0009-0004-4729-1658

Published Date: August 22, 2026 **Article DOI: 10.65150/EP-jefrr/V2E8/2026-10**

ABSTRACT: This paper examines AI-driven demand forecasting adoption as the independent variable and fleet inventory accuracy and supply chain cost efficiency as the dependent variables in United States car rental operations. The United States car rental industry generated revenues of approximately $43.9 billion in 2024, with the five largest operators accounting for 65 percent of global market revenue. Car rental supply chain performance, specifically the ability to match vehicle availability by class and location to reservation demand in real time, is a primary determinant of both fleet utilization rates and customer satisfaction outcomes. Traditional rule-based and statistical demand forecasting methods fail to capture the complex, multi-variable demand patterns that drive vehicle class shortfalls, excess inventory costs, and emergency procurement premiums in car rental supply chains. Drawing on the Resource-Based View of the firm, the Technology-Organization-Environment framework, and the meta-analytic findings of a 2025 study across 174 studies and 104,296 informants confirming analytics capability as a positive driver of supply chain performance, this paper conducts a systematic narrative literature review, maps five AI technique categories applicable to car rental supply chain forecasting, applies the TOE framework to adoption barriers, develops five testable hypotheses, and proposes an empirical validation design. The analysis finds that AI-driven demand forecasting capability satisfies the Resource-Based View conditions for sustained competitive advantage in car rental supply chain management, and that the primary barriers to realizing this advantage are organizational rather than technological.

KEYWORDS: Data-driven procurement, Fleet management intelligence, Logistics analytics adoption, Predictive fleet analytics, Vendor coordination strategy

1. INTRODUCTION

Car rental supply chain management is one of the most operationally complex inventory matching problems in the United States service sector. Unlike manufacturing inventory systems that manage physical goods with predictable demand cycles, car rental supply chains must match perishable, high-value vehicle inventory to geographically dispersed, time-sensitive customer demand across multiple vehicle classes simultaneously. A vehicle that is unavailable in the requested class at the time of reservation pickup cannotbe substituted forward in time, cannot be held indefinitely without cost, and cannot be repositioned without incurring transportation expense. The cost of supply-demand mismatch in this context manifests in three forms: customer dissatisfaction from vehicle class unavailability documented by Khwaja and Yang (2022) to directly reduce customer retention, excess inventory carrying costs from vehicles that sit idle in oversupplied locations, and emergency procurement premiums paid to source vehicles from vendors or competitors when demand exceeds local supply.

The United States car rental market generated revenues of approximately $43.9 billion in 2024 and is projected to grow at a compound annual rate of approximately 8 percent through 2030, with online booking channels accounting for 72.23 percent of total revenue (Grand View Research, 2024; Mordor Intelligence, 2025). The global market is dominated by five operators, including Enterprise Holdings, Avis Budget Group, Hertz Global Holdings, Sixt, and Europcar, collectively accounting for 65 percent of global market revenue (Euromonitor International, 2024). These operators manage fleets of hundreds of thousands of vehicles across thousands of locations, making supply chain demand forecasting decisions that determine whether each location has the right vehicles available in the right class at the right time.

Traditional demand forecasting in car rental supply chains relies on historical utilization averages, seasonal adjustment factors, and manager experience. These approaches fail systematically in contexts of demand volatility, local event-driven demand spikes, competitive pricing changes, and post-disruption demand recovery. Filani, Olajide, and Osho (2023), examining AI applications in supply chain demand forecasting and inventory optimization, document that conventional forecasting methods relying on historical data fail to adapt to real-time market fluctuations, producing both overstocking and stockout conditions that generate direct cost and service quality consequences. AI-driven forecasting approaches, specifically machine learning models including gradient boosting, recurrent neural networks, and transformer architectures, outperform traditional statistical methods on precisely the complex, volatile, multi-variable demand patterns that characterize car rental supply chains.

This paper examines AI-driven demand forecasting adoption as the independent variable and fleet inventory accuracy and supply chain cost efficiency as the dependent variables in United States car rental operations. It draws on the Resource-Based View (Barney, 1991) to explain why

AI demand forecasting capability generates sustained competitive advantage when developed effectively, the Technology-Organization-Environment framework (Tornatzky and Fleischer, 1990) to explain why adoption barriers are primarily organizational rather than technological, and the meta-analytic findings of Raj, Kumar, Narayanan, Kirca, and Jeyaraj (2025) to provide the empirical foundation linking analytics capability to supply chain performance outcomes across 174 prior studies and 104,296 informants.

The paper is organized as follows. Section 2 presents the industry and supply chain context. Section 3 presents the theoretical framework. Section 4 reviews the literature. Section 5 maps five AI technique categories applicable to car rental supply chain forecasting. Section 6 applies the TOE framework to adoption barriers. Section 7 develops five testable hypotheses. Section 8 presents the proposed empirical validation design. Section 9 discusses implications. Section 10 concludes.

2. INDUSTRY AND SUPPLY CHAIN CONTEXT

2.1 The Scale of the Car Rental Supply Chain Challenge

Table 1 presents verified industry and supply chain statistics establishing the context for this analysis.

Table 1. U.S. Car Rental Industry and Supply Chain Context (2022 to 2025)

Metric	Value	Source
U.S. car rental market revenue (2024)	$43.9 billion	Grand View Research (2024)
Global market: top 5 operators' revenue share	65% of global revenue	Euromonitor International (2024)
U.S. car rental online booking share (2024)	72.23% of total revenue	Mordor Intelligence (2025)
Global car rental market forecast to 2029	20% growth to USD 108 billion	Euromonitor International (2024)
U.S. hotel labor cost as % of revenue (2023)	32.4%	CBRE Hotels Research (2024)
Hotel labor cost year-over-year increase (2022-2023)	11.9%	CBRE Hotels Research (2024)
U.S. service sector labor productivity growth (2023)	1.2% , below 2.7% all-nonfarm average	BLS (2024)
AI adoption rate in U.S. supply chain operations	Growing rapidly; estimated 44% of large firms deploying AI forecasting by 2024	Filani, Olajide, and Osho (2023)
Cost of poor demand forecasting (stockouts and overstock)	Estimated 10-30% of inventory carrying costs in service supply chains	Raj et al. (2025)

Sources: Grand View Research (2024); Euromonitor International (2024); Mordor Intelligence (2025); CBRE Hotels Research (2024); BLS (2024); Filani, Olajide, and Osho (2023); Raj et al. (2025).

The statistics in Table 1 reveal a structural tension at the core of car rental supply chain management: a market growing at 8 percent annually and generating 72.23 percent of revenue through digital channels where customers set precise class and location expectations, managed by a supply chain that predominantly relies on historical averages and managerial judgment for demand forecasting. The consequence of this tension is systematic supply-demand mismatch whose costs, spanning vehicle class unavailability, idle inventory, and emergency procurement premiums, reduce both the customer experience quality and the supply chain cost efficiency that determine competitive position in a market where five operators control 65 percent of global revenue.

2.2 The Vehicle Demand Forecasting Problem in Car Rental Operations

Vehicle demand in car rental operations is driven by a complex interaction of factors that traditional statistical forecasting methods cannot adequately capture. Reservation volume varies by vehicle class, pickup location, rental duration, booking channel, and advance booking window. Demand for specific vehicle classes is sensitive to local event calendars, competitive pricing changes, airline schedule disruptions, and weather patterns. Cancellation rates vary by customer segment and booking channel in ways that affect net demand at the time of vehicle pickup. Khwaja and Yang (2022), using proprietary data from a U.S. car rental company, found that vehicle class downgrade events, which occur when a customer arrives for a reserved vehicle class that is unavailable, directly reduce customer retention even when the substituted vehicle is provided at no additional cost. This finding establishes that supply chain forecasting accuracy in car rental operations has a direct and measurable customer relationship consequence, not merely an inventory cost consequence.

Soppert, Oliveira, Angeles, and Steinhardt (2024), in the Journal of Business Economics, demonstrate that fleet composition optimization at the strategic level, specifically the integration of car rental and car sharing demand into a unified fleet management model, generates both cost and utilization benefits that neither service concept achieves in isolation. Their finding that unified fleet management reduces the total number of vehicles required for a given level of mobility service is directly applicable to AI demand forecasting: operators that can accurately forecast demand by class and location can right-size their fleet at each location, reducing the excess inventory that idle vehicles represent while ensuring the availability that customer retention requires.

3. THEORETICAL FRAMEWORK

3.1 Resource-Based View of the Firm

The Resource-Based View (Barney, 1991), published in the Journal of Management, identifies four conditions under which a firm resource generates sustained competitive advantage: the resource must be valuable, rare, imperfectly imitable, and non-substitutable. Applied to AI-driven demand forecasting capability in car rental supply chain operations, each condition is examined in the current industry environment.

AI demand forecasting capability is valuable because it directly reduces the supply-demand mismatch that generates excess inventory costs, emergency procurement premiums, and vehicle class unavailability events that damage customer retention. It is relatively rare because, as the TOE barrier analysis in Section 6 documents, the combination of integrated data infrastructure, organizational analytics capability, and AI model governance required to realize forecasting accuracy improvements is not yet widely deployed across car rental operators. It is imperfectly imitable because it is accumulated through the integration of historical demand data, operational learning, and organizational capability development over time, and cannot be purchased off-the-shelf without the data infrastructure and human capability required to govern the systems effectively. It lacks straightforward strategic substitutes because, as Filani, Olajide, and Osho (2023) document, traditional statistical forecasting methods produce systematically inferior performance on the volatile, multi-variable demand patterns that characterize car rental operations.

The meta-analytic evidence of Raj, Kumar, Narayanan, Kirca, and Jeyaraj (2025), drawing on 174 prior studies and 104,296 informants, confirms that analytics capability is positively and significantly associated with supply chain performance across firm types and contexts, and that the performance benefits flow through supply chain integration, flexibility, and resilience as mediating mechanisms. This establishes the empirical foundation for the Resource-Based View prediction that AI demand forecasting capability generates measurable and sustained supply chain performance advantages.

3.2 Technology-Organization-Environment Framework

The Technology-Organization-Environment framework (Tornatzky and Fleischer, 1990) provides the structural lens for understanding why AI demand forecasting adoption in car rental supply chains varies systematically across operators and why deployment does not automatically translate into performance improvement. The technological dimension identifies the availability and compatibility of AI forecasting platforms with existing reservation and fleet management systems. The organizational dimension captures the internal capability constraints, specifically supply chain manager analytical capability and data integration quality, that determine whether deployed AI systems generate their theoretical forecasting accuracy improvements. The environmental dimension identifies the competitive, regulatory, and market conditions shaping adoption incentives. Nikopoulou, Kourouthanassis, Chasapi, Pateli, and Mylonas (2023), applying the TOE framework to digital technology adoption across 502 hospitality operators, found that organizational readiness, specifically management digital capability and data infrastructure quality, is the binding constraint on productive technology adoption. This finding is directly applicable to AI demand forecasting in car rental supply chains, where the organizational dimension barriers, particularly supply chain manager analytical capability gaps and data fragmentation across reservation, fleet, and maintenance systems, are the primary constraints preventing operators from realizing the forecasting accuracy improvements that deployed AI systems are designed to generate.

Figure 1 presents the integrated conceptual framework.

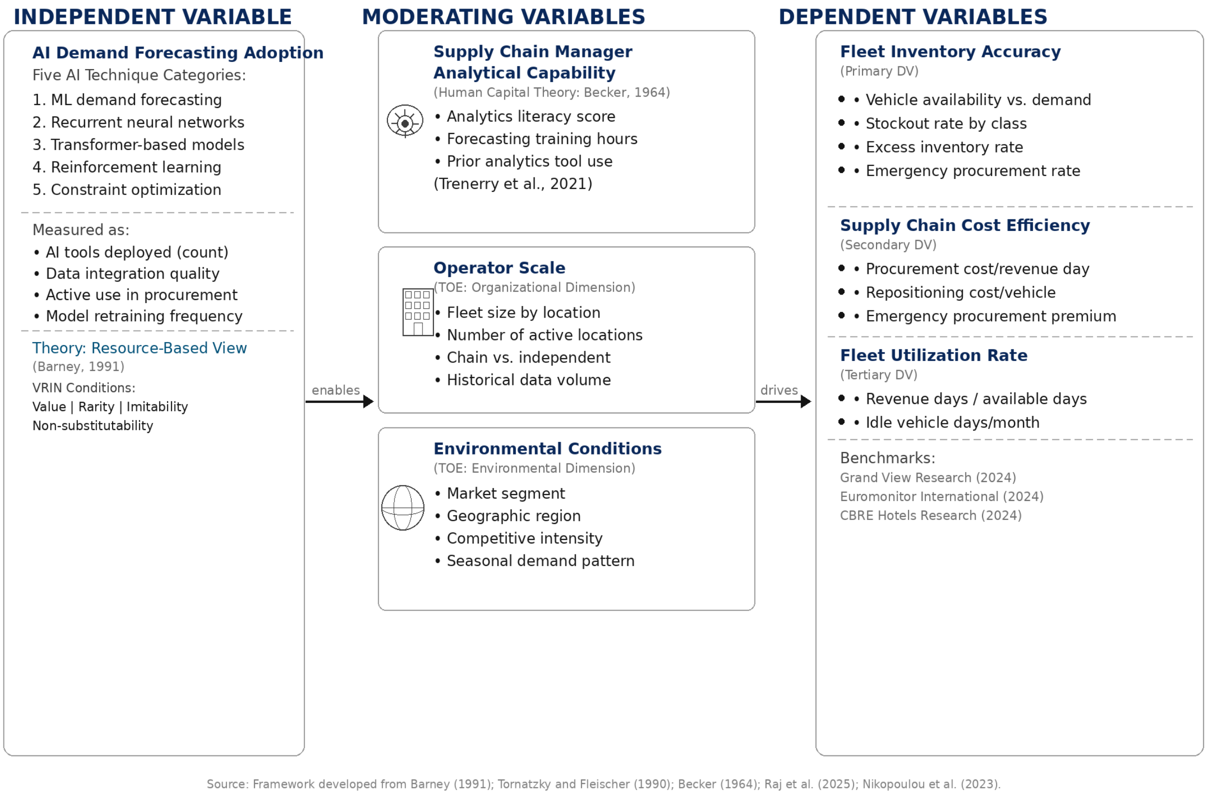

Figure 1. Conceptual Framework: AI-Driven Demand Forecasting Adoption and Supply Chain Performance in U.S. Car Rental Operations

Source: Framework developed from Barney (1991); Tornatzky and Fleischer (1990); Becker (1964); Raj et al. (2025); Nikopoulou et al. (2023).

4. LITERATURE REVIEW

4.1 AI Applications in Supply Chain Demand Forecasting

The application of AI to supply chain demand forecasting has expanded substantially across industries over the past decade, driven by the availability of large historical datasets, reduced cost of computational infrastructure, and demonstrated accuracy advantages of machine learning models over traditional statistical approaches. Filani, Olajide, and Osho (2023), examining AI in demand forecasting and inventory optimization across supply chain contexts, establish that AI algorithms including machine learning and neural networks resolve the core limitation of conventional forecasting methods by processing real-time data streams, identifying complex non-linear demand patterns, and adapting to market volatility without requiring manual parameter adjustment. Their review documents that AI-powered demand forecasting specifically addresses the overstocking and stockout conditions that generate the most significant inventory cost consequences in service supply chains.

Hasan, Islam, and Rahman (2025), examining AI demand forecasting implementations in U.S. supply chains, find that recurrent neural networks and transformer-based architectures show the strongest performance on volatile, time-series demand patterns, outperforming traditional ARIMA and exponential smoothing approaches on both accuracy and adaptability metrics. Their finding that data quality is the primary determinant of AI forecasting performance, rather than model architecture selection, has direct implications for car rental supply chain analytics adoption: operators with fragmented or inconsistent historical demand data will not realize the accuracy improvements that AI forecasting is theoretically capable of generating regardless of the sophistication of the model deployed.

Table 2 presents the structured comparison of prior literature most directly relevant to this paper's analysis.

Table 2. Prior Literature on AI Demand Forecasting and Supply Chain Performance in Service Contexts

Study	Context	Key Finding	Relevance to Car Rental
Raj, Kumar, Narayanan, Kirca, and Jeyaraj (2025)	Meta-analysis: 174 studies, 104,296 informants	Analytics capability positively and significantly associated with operational performance through supply chain integration, flexibility, and resilience as mediating mechanisms	Directly establishes the empirical foundation that AI-driven supply chain analytics improves operational performance in service contexts
Filani, Olajide, and Osho (2023)	Supply chain management, cross-sector	AI-powered demand forecasting transforms traditional supply chain management by enabling more accurate demand prediction and efficient inventory optimization; machine learning and deep learning outperform traditional statistical methods in volatile demand environments	Provides the foundational evidence that AI forecasting outperforms traditional methods in the inventory and supply chain optimization context relevant to car rental fleet management
Soppert, Oliveira, Angeles, and Steinhardt (2024)	Car rental and car sharing combined operations, strategic level	Combining car rental and car sharing with a unified fleet reduces total vehicles required for a given level of mobility service, increasing fleet utilization and reducing the carbon intensity per trip served	Directly applicable to car rental supply chain optimization; demonstrates that fleet composition analytics at the strategic level generates both cost and efficiency benefits
Khwaja and Yang (2022)	U.S. car rental company, proprietary operational data	Frontline employee engagement positively and causally linked to customer satisfaction and retention; service disruptions including vehicle downgrades from fleet readiness problems dampen this relationship	Establishes that supply chain-driven fleet availability directly affects customer outcomes in car rental operations, motivating the business case for AI demand forecasting
Hasan, Islam, and Rahman (2025)	U.S. supply chains, cross-sector	AI-driven demand forecasting models outperform traditional approaches in accuracy and responsiveness; recurrent neural networks and transformer-based models show strongest performance on volatile demand patterns	Provides the most recent evidence on AI forecasting model performance in the U.S. supply chain context directly applicable to car rental demand forecasting
Nikopoulou, Kourouthanassis, Chasapi, Pateli, and Mylonas (2023)	502 hoteliers, Greece, hospitality sector	Organizational readiness and management digital capability are the primary constraints on effective technology adoption outcomes; technology alone does not generate operational improvements	Establishes the human capability gap that moderates AI forecasting adoption effectiveness in service operations , directly applicable to car rental supply chain analytics governance

Sources: Raj et al. (2025); Filani, Olajide, and Osho (2023); Soppert, Oliveira, Angeles, and Steinhardt (2024); Khwaja and Yang (2022); Hasan, Islam, and Rahman (2025); Nikopoulou et al. (2023).

4.2 Analytics Capability and Supply Chain Performance

Raj, Kumar, Narayanan, Kirca, and Jeyaraj (2025), in the Journal of Operations Management, provide the most comprehensive empirical foundation for the analytics capability-supply chain performance relationship. Their meta-analytic study, synthesizing 405 effect sizes from 174 prior empirical studies based on data from 104,296 informants, finds that analytics capability is positively and significantly associated with operational performance across firm types and sectors. Critically for the car rental context, they identify supply chain integration, flexibility, and resilience as the three mediating mechanisms through which analytics capability generates operational performance improvements. Each of these mechanisms maps directly onto the car rental supply chain challenge: AI demand forecasting improves supply chain integration by enabling demand signals to flow from reservation systems directly into procurement decisions, improves flexibility by allowing operators to adjust fleet composition in response to forecasted demand shifts, and improves resilience by enabling the anticipation of demand disruptions before they generate inventory shortfalls.

Brynjolfsson, Mitchell, and Rock (2018) establish the critical complementarity finding: technology adoption generates operational performance improvements only when complementary human capability investments are made simultaneously. Applied to AI demand forecasting in car rental supply chains, this prediction, which this paper designates as the human capability moderation hypothesis, specifically states that AI forecasting adoption generates stronger inventory accuracy and cost efficiency improvements at operators where supply chain managers have the analytical capability to interpret forecasting outputs, evaluate model performance, and make evidence-based procurement decisions than at operators who deploy the same technology without the corresponding capability investment.

4.3 Literature Gap

The application of AI demand forecasting frameworks specifically to car rental supply chain operations represents a genuine gap in the academic literature. Prior work has examined AI forecasting in retail inventory, airline capacity management, hotel demand forecasting, and logistics route optimization, but has not addressed the specific operational structure of car rental supply chains, where the inventory unit is a high-value, class-differentiated, location-specific, perishable asset whose demand is simultaneously driven by multiple competing channels with heterogeneous booking lead times and cancellation rates. This paper addresses that gap by applying established theoretical frameworks, specifically the Resource-Based View and the TOE framework, to a new operational context, and by developing the first sector-specific hypothesis framework for AI demand forecasting adoption and supply chain performance in car rental operations.

5. AI TECHNIQUE CATEGORIES FOR CAR RENTAL SUPPLY CHAIN FORECASTING

Based on the literature review and the Resource-Based View framework, five AI technique categories are identified as applicable to car rental supply chain demand forecasting and inventory optimization. Table 3 maps each category to its application, advantage, and data requirements in the car rental context.

Table 3. AI Technique Categories for Car Rental Supply Chain Demand Forecasting and Inventory Optimization

AI Technique	Application in Car Rental Supply Chain	Advantage	Data Required
Machine learning demand forecasting (gradient boosting, random forest)	Predicts vehicle demand by class, location, time period, and channel using historical reservation data, seasonal patterns, local events, and economic indicators	Interpretable outputs; outperforms traditional statistical methods on volatile demand; integrates with existing reservation management systems	Historical reservation data; occupancy and utilization records; event calendars; pricing data; channel mix data
Recurrent neural networks and LSTM models	Time-series forecasting of vehicle demand patterns capturing complex temporal dependencies including seasonality, trend, and cyclical variation	Captures multi-period temporal patterns; adapts to non-linear demand relationships; outperforms statistical methods on datasets with strong seasonal patterns	Minimum 2-3 years of daily reservation and utilization data; vehicle class breakdown; geographic location data
Transformer-based models	Large-scale demand forecasting incorporating multiple demand signals simultaneously; excels in high-complexity, multi-location fleet networks	Best performance on complex, multi-variable demand environments; captures cross-location demand substitution effects	Multi-location demand data; pricing history; competitive data; macroeconomic signals; event and weather data
Reinforcement learning for dynamic replenishment	Agent-based optimization of vehicle procurement and repositioning decisions in response to real-time demand signals and fleet availability data	Adapts dynamically to changing demand without requiring pre-labeled training data; optimizes multi-period procurement decisions	Real-time reservation and cancellation data; fleet status by location; vendor lead times; repositioning cost data
Inventory optimization algorithms (constraint satisfaction and mixed-integer programming with ML demand inputs)	Combines AI demand forecasts with optimization algorithms to generate fleet procurement, repositioning, and surplus vehicle decisions that minimize both excess and shortage costs	Guarantees feasibility of generated decisions against operational constraints; balances cost optimization with service level requirements	AI demand forecast outputs; fleet maintenance schedules; vendor capacity and lead time constraints; target utilization and service level parameters

Sources: Synthesized from Filani, Olajide, and Osho (2023); Hasan, Islam, and Rahman (2025); Raj et al. (2025); Soppert, Oliveira, Angeles, and Steinhardt (2024); Grand View Research (2024).

The five technique categories form a progression from accessible, interpretable forecasting methods suitable for operators with moderate data infrastructure to sophisticated optimization approaches that require substantial data integration and governance capability. Machine learning demand forecasting, Category 1, represents the most accessible entry point for car rental operators without existing AI infrastructure, as it can be trained on standard reservation management system exports and produces interpretable outputs that supply chain managers can evaluate and override with documented rationale. Transformer-based models, Category 3, represent the highest accuracy ceiling but require the most substantial data infrastructure and generate the least interpretable outputs, making them best suited for operators with mature analytics governance capability and large multi-location demand datasets.

The selection of AI technique category should be driven by the operator's current data infrastructure maturity, supply chain manager analytical capability, and organizational readiness rather than by the theoretical accuracy ceiling of the most sophisticated model. This finding is consistent with the TOE framework prediction that organizational readiness is the binding constraint on technology adoption effectiveness, and with the Human Capital Theory prediction that the returns to technology investment are moderated by the human capability available to govern the deployed system.

6. TOE FRAMEWORK ANALYSIS: BARRIERS TO AI DEMAND FORECASTING ADOPTION

Table 4 applies the Technology-Organization-Environment framework to map the specific barriers constraining effective AI demand forecasting adoption in U.S. car rental supply chain operations.

Table 4. TOE Framework Analysis: Barriers to AI Demand Forecasting Adoption in U.S. Car Rental Supply Chain Operations

TOE Dimension	Enabling Conditions	Constraining Conditions
Technological	Cloud-based fleet management and reservation systems provide the data infrastructure for AI forecasting integration; telematics platforms generate real-time vehicle availability and utilization data; commercial AI forecasting platforms (including Blue Yonder and Oracle) provide accessible solutions for mid-scale operators	Data fragmentation across reservation systems, fleet management platforms, and maintenance records prevents the integrated demand signal that AI forecasting requires; inconsistent data quality and classification standards across locations reduce forecasting accuracy; most car rental operators below the top tier lack the data science capability to configure and govern AI forecasting models
Organizational	Major operators (Enterprise, Avis Budget Group, Hertz) have dedicated analytics and technology teams capable of deploying and governing AI forecasting systems; operational structure of car rental provides natural experimental data for model training and validation; high-volume reservation data creates favorable conditions for supervised learning models	Operations managers at the location level are trained in customer service and fleet management rather than data analytics; Human Capital Theory (Becker, 1964; Schultz, 1961) predicts systematic underinvestment in analytics capability in high-turnover operating environments; small and independent operators lack the data volume and organizational resources to deploy AI forecasting effectively
Environmental	Competitive pressure from digitally advanced major operators creates adoption incentive for all market participants; rising customer expectations for vehicle availability and service reliability reward operators with accurate demand management; dynamic pricing already adopted across the industry creates existing data infrastructure for demand signal integration	Absence of industry-wide standards for supply chain analytics capability; no regulatory mandate for AI-driven demand management; price competition limits discretionary technology investment particularly for independent operators; economic cycles and external demand shocks (pandemic, fuel price volatility) can invalidate forecasting models trained on pre-disruption data

Sources: Tornatzky and Fleischer (1990); Barney (1991); Becker (1964); Nikopoulou et al. (2023); Filani, Olajide, and Osho (2023); Grand View Research (2024); Euromonitor International (2024).

The TOE barrier analysis reveals that the organizational dimension presents the most significant constraints on AI demand forecasting value realization in car rental supply chain operations. The technology exists, is commercially available, and is increasingly affordable for operators above a minimum scale threshold. The binding constraints are in the organizational layer: supply chain managers who cannot evaluate AI forecasting outputs, approve or override procurement recommendations with analytical rationale, or identify when a forecasting model is underperforming due to data quality failures will not generate the inventory accuracy and cost efficiency improvements that deployed AI systems are designed to produce. This finding is consistent with the meta-analytic evidence of Raj et al. (2025), who identify supply chain integration and flexibility as the primary mechanisms through which analytics capability generates operational performance improvements, and with the Nikopoulou et al. (2023) finding that organizational readiness is the binding constraint on hospitality technology adoption outcomes.

7. PROPOSED RESEARCH HYPOTHESES

Drawing on the theoretical frameworks in Section 3, the literature review in Section 4, and the TOE barrier analysis in Section 6, five hypotheses are proposed for empirical validation. Table 5 presents the complete hypothesis set with theoretical grounding.

Table 5. Research Hypotheses: AI Demand Forecasting Adoption and Supply Chain Performance in U.S. Car Rental Operations

Hypothesis	Statement	Theoretical Basis
H1	AI-driven demand forecasting adoption is positively associated with fleet inventory accuracy, measured as the ratio of available vehicles by class to forecasted demand by class at the location level	Resource-Based View (Barney, 1991); Raj et al. (2025) meta-analytic finding on analytics capability and supply chain integration
H2	AI-driven demand forecasting adoption is positively associated with fleet utilization rate, measured as revenue-generating vehicle days as a percentage of total available vehicle days	Filani, Olajide, and Osho (2023); Soppert, Oliveira, Angeles, and Steinhardt (2024)
H3	AI-driven demand forecasting adoption is positively associated with supply chain cost efficiency, measured as vehicle procurement cost per revenue-generating rental day	Raj et al. (2025); Hasan, Islam, and Rahman (2025)
H4	The relationship between AI demand forecasting adoption and fleet inventory accuracy is positively moderated by supply chain manager analytical capability, such that higher capability strengthens the adoption-accuracy relationship	Human Capital Theory (Becker, 1964); Brynjolfsson, Mitchell, and Rock (2018); Nikopoulou et al. (2023)
H5	The operational performance benefits of AI demand forecasting adoption differ by operator scale, with larger operators showing stronger adoption-performance effects than smaller operators due to greater data volume, organizational capability, and technology resources	TOE Framework (Tornatzky and Fleischer, 1990); Barney (1991) VRIN conditions

Sources: Barney (1991); Raj et al. (2025); Filani, Olajide, and Osho (2023); Soppert, Oliveira, Angeles, and Steinhardt (2024); Hasan, Islam, and Rahman (2025); Becker (1964); Brynjolfsson, Mitchell, and Rock (2018); Nikopoulou et al. (2023); Tornatzky and Fleischer (1990).

H1 and H2 test the core adoption-performance relationship at the inventory accuracy and fleet utilization levels respectively. The Resource-Based View prediction that valuable, rare, and imperfectly imitable capabilities generate competitive performance advantages is tested at the operational metric level against the fleet management benchmarks documented by Grand View Research (2024) and Euromonitor International (2024). H3 tests the cost efficiency dimension of the analytics-performance relationship, generating a specific, measurable prediction that operators with AI demand forecasting deployed should show lower emergency procurement premium rates and repositioning costs than operators without it, controlling for fleet size and market segment.

H4 is the paper's most distinctive theoretical contribution. It tests the Brynjolfsson, Mitchell, and Rock (2018) complementarity prediction in the car rental supply chain context: that the same AI forecasting technology generates stronger inventory accuracy improvements at operators where supply chain managers have higher analytical capability. Testing this prediction requires a moderation design that compares adoption-performance relationships across high and low analytical capability groups, providing the most direct test of the Human Capital Theory prediction about training investment and technology return on investment in this specific operational context.

8. PROPOSED EMPIRICAL VALIDATION METHODOLOGY

The five hypotheses require empirical validation using primary operational data from car rental supply chain managers and fleet performance records. Table 6 presents the variable definitions and measurement approaches.

Table 6. Variable Definitions and Measurement Approaches

Variable	Operationalization	Data Source	Benchmark
IV: AI demand forecasting adoption	Composite index: AI forecasting tools deployed, data integration quality, active use rate in procurement decisions, model retraining frequency (10-item scale)	Operator survey; technology vendor audit; reservation system configuration records	Adoption stage model adapted from Nikopoulou et al. (2023) digital maturity framework
DV1: Fleet inventory accuracy	Vehicle availability by class versus forecasted demand by class; stockout rate by vehicle class; excess inventory rate by class	Reservation and fleet management system records by location	Grand View Research (2024) industry utilization benchmarks
DV2: Fleet utilization rate	Revenue-generating vehicle days as percentage of total available vehicle days; idle vehicle days per month	Fleet management system records	Euromonitor International (2024) industry average benchmarks
DV3: Supply chain cost efficiency	Vehicle procurement cost per revenue-generating rental day; repositioning cost per vehicle; emergency procurement premium as percentage of planned procurement cost	Fleet financial records; procurement transaction records	CBRE Hotels Research (2024) cost efficiency benchmarks adapted for car rental context
Moderator: Supply chain manager analytical capability	Manager self-assessment score on supply chain analytics literacy; AI forecasting governance training hours; prior analytics tool experience (adapted from Trenerry et al., 2021)	Survey instrument; HR training records	AACSB (2020) analytics competency standards
Moderator: Operator scale	Fleet size by location; number of active locations; chain vs. independent classification	Operator records; Euromonitor International (2024) fleet data	Grand View Research (2024) fleet size stratification
Control variables	Market segment (airport vs. off-airport); geographic region; seasonal demand pattern; competitive intensity	Operator records; Mordor Intelligence (2025) market data	Stratified sampling framework

Sources: Barney (1991); Raj et al. (2025); Becker (1964); Tornatzky and Fleischer (1990); Trenerry et al. (2021); AACSB (2020); Grand View Research (2024); Euromonitor International (2024); Nikopoulou et al. (2023).

The proposed empirical design uses a two-phase mixed-methods approach. Phase 1 deploys a cross-sectional survey of supply chain managers and fleet directors at a minimum of 100 U.S. car rental operating locations, stratified by operator type (major chain versus regional independent) and fleet size, measuring AI demand forecasting adoption, supply chain manager analytical capability, and self-reported fleet performance outcomes. Phase 2 uses operational fleet records from participating operators to calculate verified fleet inventory accuracy, utilization rates, and cost efficiency metrics, enabling direct comparison of supply chain performance across high and low AI adoption operators.

The use of supply chain manager analytical capability as a moderating variable in H4 requires a design that separates the effect of technology deployment from the effect of human capability on supply chain performance outcomes. This is achieved by identifying operators at similar AI adoption stages but with measured differences in supply chain manager analytical capability, then comparing their fleet inventory accuracy and cost efficiency outcomes. This design provides the most direct test of the Human Capital Theory prediction that technology investment generates higher returns when complementary capability investment is present.

9. DISCUSSION

Four findings from this systematic analysis carry implications for car rental operators, technology vendors, industry associations, and future researchers.

First, the Resource-Based View analysis establishes that AI demand forecasting capability in car rental supply chain operations is not merely an operational efficiency tool but a strategic resource that can generate sustained competitive advantage when the VRIN conditions are met. The majority of car rental operators below the major chain tier have not yet deployed AI demand forecasting with the data integration quality and governance capability required to generate its theoretical accuracy improvements. This creates a window of strategic opportunity for operators who invest systematically in AI forecasting capability, supply chain manager analytics training, and data integration infrastructure before their competitors close this gap.

Second, the TOE barrier analysis identifies data fragmentation as the most immediately addressable technological barrier. Operators whose reservation, fleet management, maintenance, and financial records are held in separate, disconnected systems cannot generate the integrated demand signal that AI forecasting models require. Investing in data integration infrastructure, before selecting or configuring any AI forecasting platform, is the prerequisite action that determines whether subsequent technology investment generates its intended return. The Hasan, Islam, and Rahman (2025) finding that data quality is the primary determinant of AI forecasting performance, regardless of model architecture, makes this sequencing particularly important.

Third, the Human Capital Theory moderation prediction generates a specific practical implication for operator investment decisions. The Raj et al. (2025) meta-analytic finding that analytics capability improves supply chain performance through integration, flexibility, and resilience as mediating mechanisms identifies the specific operational capabilities that supply chain manager training programs should develop. Training that builds the ability to interpret AI demand forecasts, evaluate model performance, approve or override procurement recommendations with documented rationale, and identify when forecasting models are producing anomalous outputs will generate the complementary human capability that the H4 moderation hypothesis predicts will strengthen the adoption-performance relationship.

Fourth, the industry association coordination argument applies to AI supply chain analytics adoption with the same force documented in other domains of the service operations management literature. The Becker (1964) mobility problem, where operators underinvest in general analytics capability training because trained managers are likely to move to other employers, represents a coordination failure that individual operators cannot solve in isolation. Industry-level solutions including shared training standards, group platform procurement, and industry-wide supply chain analytics competency benchmarks would reduce per-operator adoption costs and create the external incentives for analytics capability investment that rational operators currently lack.

10. CONCLUSION

This paper examined AI-driven demand forecasting adoption as the independent variable and fleet inventory accuracy and supply chain cost efficiency as the dependent variables in United States car rental operations. Four conclusions stand out.

The Resource-Based View analysis establishes that AI demand forecasting capability meets the VRIN conditions for sustained competitive advantage in the current U.S. car rental market environment: it is valuable because it directly reduces inventory mismatch costs and improves customer satisfaction outcomes documented by Khwaja and Yang (2022) to drive retention, relatively rare because most operators have not deployed it with the integration quality required to realize its potential, imperfectly imitable because it requires data infrastructure and human capability development that accumulates over time, and lacks straightforward substitutes because traditional statistical forecasting methods produce systematically inferior performance on volatile, multi-variable car rental demand patterns.

The TOE barrier analysis identifies the organizational dimension as the binding constraint on AI demand forecasting value realization. Data integration quality, supply chain manager analytical capability, and governance processes that translate AI forecasting outputs into procurement decisions are the variables that determine whether deployed AI systems generate inventory accuracy and cost efficiency improvements or simply add technology costs without operational returns.

The meta-analytic foundation provided by Raj et al. (2025), spanning 174 prior studies and 104,296 informants, confirms that analytics capability positively and significantly improves supply chain performance through integration, flexibility, and resilience as mediating mechanisms. The five AI technique categories proposed in this paper, from interpretable machine learning forecasting through transformer-based multi-signal optimization, provide a sequenced adoption pathway calibrated to different levels of data infrastructure maturity and organizational analytical capability.

Future research should empirically validate the five hypotheses using the mixed-methods design proposed in Section 8, with particular attention to the H4 moderation test examining whether AI demand forecasting adoption generates stronger supply chain performance improvements at operators with higher supply chain manager analytical capability. Confirming this prediction would establish the most important practical implication of this paper: that the return on AI demand forecasting technology investment in car rental supply chain operations is determined not by the technology selected but by the human capability available to govern it.

REFERENCES

1) Association to Advance Collegiate Schools of Business (AACSB). (2020). 2020 guiding principles and standards for business accreditation. AACSB International.
https://www.aacsb.edu/-/media/documents/accreditation/2020-aacsb-business-accreditation-standards-june-2023.pdf
2) Barney, J. B. (1991). Firm resources and sustained competitive advantage. Journal of Management, 17(1), 99-120.
https://doi.org/10.1177/014920639101700108
3) Becker, G. S. (1964). Human capital: A theoretical and empirical analysis, with special reference to education. University of Chicago Press.

4) Brynjolfsson, E., Mitchell, T., and Rock, D. (2018). What can machines learn, and what does it mean for occupations and the economy? AEA Papers and Proceedings, 108, 43-47. https://doi.org/10.1257/pandp.20181019
5) Bureau of Labor Statistics, U.S. Department of Labor. (2024). Productivity and costs: Fourth quarter and annual averages 2023. https://www.bls.gov/news.release/prod2.nr0.htm
6) CBRE Hotels Research. (2024). New labor challenges arise in 2023. Trends in the Hotel Industry. https://www.hotel-online.com/press_releases/release/new-labor-challenges-arise-in-2023/
7) Euromonitor International. (2024). The world market for car rental. Euromonitor International. https://www.euromonitor.com/the-world-market-for-car-rental/report
8) Filani, O. M., Olajide, J. O., and Osho, G. O. (2023). Artificial intelligence in demand forecasting and inventory optimization. Journal of Applied Research in Technology and Innovation. https://doi.org/10.62225/2583049X.2023.3.6.4617
9) Grand View Research. (2024). U.S. car rental market size, share and trends analysis report. Grand View Research. https://www.grandviewresearch.com/horizon/outlook/car-rental-market/united-states
10) Hasan, M. R., Islam, M. R., and Rahman, M. A. (2025). Developing and implementing AI-driven models for demand forecasting in US supply chains. Edelweiss Applied Science and Technology. https://doi.org/10.55214/25768484.v9i1.4308
11) Khwaja, A., and Yang, N. (2022). Quantifying the link between employee engagement, and customer satisfaction and retention in the car rental industry. Quantitative Marketing and Economics, 20, 275-292. https://doi.org/10.1007/s11129-022-09253-6
12) Mordor Intelligence. (2025). United States car rental market size and outlook. Mordor Intelligence. https://www.mordorintelligence.com/industry-reports/united-states-car-rental-market
13) Nikopoulou, M., Kourouthanassis, P., Chasapi, G., Pateli, A., and Mylonas, N. (2023). Determinants of digital transformation in the hospitality industry: Technological, organizational, and environmental drivers. Sustainability, 15(3), 2736. https://doi.org/10.3390/su15032736
14) Raj, A., Kumar, R. R., Narayanan, S., Kirca, A. H., and Jeyaraj, A. (2025). Analytics capability, supply chain capabilities, and operational performance: A meta-analytic investigation. Journal of Operations Management, 71(6), 786-805. https://doi.org/10.1002/joom.1376
15) Schultz, T. W. (1961). Investment in human capital. American Economic Review, 51(1), 1-17. https://www.jstor.org/stable/1818907
16) Soppert, M., Oliveira, B. B., Angeles, R., and Steinhardt, C. (2024). On the benefit of combining car rental and car sharing. Journal of Business Economics, 94(9), 1261-1298. https://doi.org/10.1007/s11573-024-01204-9
17) Tornatzky, L. G., and Fleischer, M. (1990). The processes of technological innovation. Lexington Books.
18) Trenerry, B., Chng, S., Wang, Y., Suhaila, Z. S., Lim, S. S., Lu, H. Y., and Oh, P. H. (2021). Preparing workplaces for digital transformation: An integrative review and framework of multi-level factors. Frontiers in Psychology, 12, 620766. https://doi.org/10.3389/fpsyg.2021.620766

Corresponding Author: Salami Abdul Mohammed