**Review of Applied Science and Technology**

***Volume:*** *13;* ***Issue:*** *2*
***Pages:*** *42–75*

# Machine Learning for Demand Forecasting in U.S. Third-Party Logistics: A Systematic Review and Meta-Analysis of Predictive Performance

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***Received:*** *07 November 2022;* ***Revised:*** *10 December 2022;* ***Accepted:*** *13 January 2023;* ***Published:*** *03 February 2023;*

## Abstract

*Demand forecasting in United States third-party logistics (3PL) remains difficult because volatile shipment volumes, intermittent orders, fragmented information, and inconsistent evaluation metrics complicate model selection. This study examines how machine learning approaches compare with traditional statistical methods and identifies the data and operating conditions shaping predictive performance. Guided by Organizational Information Processing Theory, the review considers whether access to integrated demand information matches uncertainty and service coordination requirements across logistics environments. It uses a cross-sectional, case-based systematic literature review guided by PRISMA 2020, with quantitative comparisons of published forecasting results and meta-analysis conditional on comparability. The review targets 100 studies published during 2005–2023, covering U.S. 3PL operations and distinguishable supporting freight, warehousing, distribution, and supply-chain cases; final eligibility counts remain pending. Variables include forecasting architecture, historical demand, external predictors, forecast horizon, demand volatility, operational complexity, and errors measured using root mean squared error and related indicators. The analysis classifies studies, assesses methodological comparability, synthesizes themes, and compares model performance against aligned benchmarks. In a published 3PL shipment case, hybrid CNN–LSTM attained RMSE 59.12 versus 62.32 for ARIMA, 59.96 for standalone CNN, 66.88 for LSTM, and 72.64 for a regression tree. Another transportation study covering 54 Brazilian distribution centers found LSTM better than statistical alternatives in approximately 94% of dispatching units. In an adjacent U.S. retail benchmark comprising 42,840 hierarchical series, the leading approach improved accuracy by 22.4% relative to its strongest comparator. Evidence indicates context-specific advantages for hybrid models, but standalone machine learning does not consistently outperform statistical baselines. Published cases also associate forecasting with capacity planning and warehouse staffing without proving downstream cost reductions. A pooled meta-analytic effect could not be estimated from the available comparable evidence. The findings underscore transparent error metrics, matched horizons, reliable data integration, and decision-oriented model selection for future U.S. 3PL implementation and evaluation.*

***KEYWORDS***

*Machine Learning; Demand Forecasting; Third-Party Logistics; Predictive Accuracy; Systematic Literature Review.*

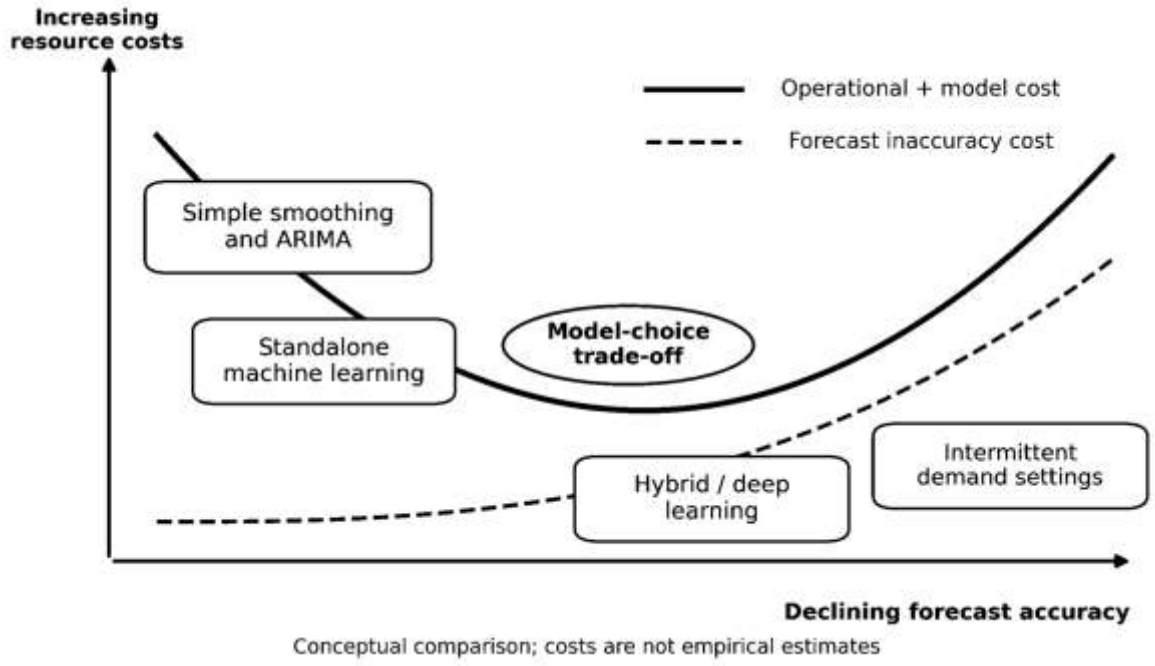
## INTRODUCTION AND REVIEW SCOPE

Demand forecasting refers to the systematic estimation of future requirements for products, transportation services, warehouse capacity, and distribution activities through the examination of historical observations and relevant explanatory information. Third-party logistics (3PL) represents an outsourcing arrangement in which specialized service providers perform transportation, warehousing, distribution, order fulfillment, and related supply chain activities on behalf of client organizations. In Third party logistics: A literature review and research agenda (pp. 125–150), the organizational and relational characteristics of logistics outsourcing were examined through an extensive classification of existing research, establishing the multidimensional nature of logistics service provision (Selviaridis & Spring, 2007). The international significance of third-party logistics has also been documented through research covering contractual arrangements, service integration, logistics networks, and relationships between logistics providers and their customers (Marasco, 2008). Within this operational environment, demand forecasting involves estimating shipment volumes, customer orders, freight movements, warehouse workloads, and transportation capacity requirements across interconnected logistics activities. Machine learning constitutes a computational approach through which algorithms identify relationships within historical observations and explanatory variables to generate predictions without relying exclusively on predetermined statistical equations. Early investigations of machine learning-based supply chain forecasting examined neural networks, support vector machines, and other predictive approaches in environments characterized by incomplete demand visibility and information distortion (Carbonneau et al., 2008; Carbonneau et al., 2007). The direct relevance of these techniques to third-party logistics has been demonstrated through research on near-real-time order arrivals at distribution centers, where forecasting models have been applied to short-interval e-commerce demand (Leung et al., 2020). In the United States, freight demand forecasting has been examined through container shipment records from an intermodal transportation company, illustrating the relationship between prediction accuracy and logistics operational planning (Hassan et al., 2020). International studies involving third-party forwarding logistics have similarly addressed uncertain order arrivals and service-capacity requirements through integrated deep learning approaches (Ren et al., 2020). Research involving urban delivery platforms has expanded the operational context of demand forecasting to geographically distributed delivery requests and short-term transportation requirements (Hess et al., 2021). The broader relationship between machine learning and freight transportation has been documented across logistics applications involving demand prediction, traffic characteristics, and transportation operations (Tsolaki et al., 2023). Information-sharing research involving third-party logistics providers has additionally identified the importance of accessible operational information for coordination between logistics organizations and their customers (Valashiya & Luke, 2023). These studies establish demand forecasting as an information-intensive activity spanning transportation, distribution, warehousing, and interorganizational logistics operations.

The scientific foundations of logistics demand forecasting have been developed through statistical time-series analysis, regression modelling, exponential smoothing, autoregressive integrated moving average models, and forecasting procedures designed for irregular demand patterns. In The accuracy of intermittent demand estimates (pp. 303–314), different statistical forecasting methods were evaluated using automotive demand series containing periods without recorded demand, demonstrating the methodological difficulties associated with intermittent observations (Syntetos & Boylan, 2005). Forecast evaluation has also been recognized as a distinct methodological concern because common accuracy measurements behave differently across continuous, intermittent, and heterogeneous demand series. In Another look at measures of forecast accuracy (pp. 679–688), limitations associated with several conventional forecasting-error measures were examined, with particular attention to the difficulties created by zero observations and comparisons across different time series (Hyndman & Koehler, 2006). Traditional demand forecasting approaches have remained relevant to supply chain research because their performance depends on the statistical properties of individual demand series and the characteristics of the forecasting environment. Comparative investigations involving individual statistical models, neural networks, and combined forecasting procedures have demonstrated variations in predictive performance across retail demand categories (Aras et al., 2017). Large-scale comparisons between machine learning and conventional statistical forecasting methods have similarly reported that algorithmic complexity does not necessarily produce higher forecasting accuracy across all evaluated time series (Makridakis et al., 2018). Research involving daily stock-keeping-unit demand has further examined differences between statistical and

machine learning approaches under comparable forecasting conditions (Spiliotis et al., 2022). Intermittent and irregular demand has received additional methodological attention through comparisons involving statistical forecasting, machine learning, and deep learning methods, particularly where demand occurrence and inventory-related evaluation criteria are relevant (Kiefer et al., 2021). Forecasting performance is also influenced by explanatory variables, historical demand structures, seasonal characteristics, and changes in purchasing behaviour. Research examining high-dimensional retail demand demonstrated the relevance of promotional information across related product categories for forecasting individual stock-keeping units (Ma et al., 2016). Daily forecasting investigations have identified the importance of explicitly representing calendar events and special days when demand patterns exhibit irregular temporal changes (Huber & Stuckenschmidt, 2020). Similarly, empirical investigations of demand volatility have evaluated statistical and machine learning models across series with different levels of promotional variation and uncertainty (Abolghasemi et al., 2020). Comparative assessments of seasonal autoregressive models and long short-term memory networks have also reported differences in forecasting performance according to demand characteristics and promotional conditions (Falatouri et al., 2022). The extensive literature on retail forecasting has consequently documented substantial variation in forecasting requirements across products, organizational environments, prediction horizons, and information structures (Fildes et al., 2022).

**Figure 1: Overview of Forecasting Model Selection and Cost–Accuracy Trade-offs in Third-Party Logistics**




Machine learning-based demand forecasting encompasses supervised learning, artificial neural networks, recurrent neural networks, ensemble learning, and hybrid architectures developed to represent nonlinear relationships within complex operational information. These approaches differ in their treatment of historical observations, explanatory variables, temporal dependence, and interactions between multiple demand characteristics. Research concerning deep neural networks in fashion retail has examined their forecasting capabilities in comparison with alternative machine learning approaches, particularly where product attributes and limited sales histories influence demand estimation (Loureiro et al., 2018). Deep learning has also been integrated with random forest algorithms to examine forecasting performance across online and offline retail channels, demonstrating the relevance of combining complementary modelling techniques within multichannel demand environments (Punia et al., 2020). In Retail sales forecasting with meta-learning (pp. 111–128), the combination of forecasting models through a learning-based selection and weighting procedure was examined using large collections of related retail demand series (Ma & Fildes, 2021). Additional research has applied deep learning to apparel demand forecasting, examining how

historical sales information and product characteristics contribute to predictive modelling (Giri & Chen, 2022). Hybrid neural architectures combining convolutional networks and bidirectional long short-term memory have also been investigated for store-item demand prediction, reflecting the integration of local feature extraction with sequential learning (Joseph et al., 2022). Comparative investigations of multichannel retail forecasting have evaluated random forest, gradient boosting, artificial neural networks, and hybrid methods under multiple forecasting criteria (Mitra et al., 2022). Other studies have examined hybrid extreme learning machines and optimization algorithms for estimating product demand from historical observations (Chaudhuri & Alkan, 2022). The importance of computational efficiency and model selection has been considered in research involving data-intensive cross-border e-commerce inventory forecasting, where alternative artificial intelligence algorithms were evaluated using forecasting accuracy and processing requirements (Tang et al., 2023). Transformer-based forecasting architectures have been examined in electronic commerce settings involving substantial sales fluctuations and complex temporal relationships (Li & Yu, 2023). At the broader supply chain level, systematic research has classified neural networks, regression techniques, support vector machines, decision trees, and other machine learning methods according to their applications in demand prediction (Seyedan & Mafakheri, 2020). Reviews of machine learning applications have similarly documented differences in forecasting algorithms, datasets, operational contexts, and methodological approaches across supply chain industries (Aamer et al., 2021). An extensive review of artificial intelligence in supply chain management has also examined the organizational and technical diversity of predictive analytics applications, including demand forecasting and related planning activities (Toorajipour et al., 2021). These investigations collectively describe a heterogeneous body of forecasting evidence in which predictive performance is examined through different model architectures, data structures, comparative benchmarks, and operational settings.

The information requirements of machine learning-based demand forecasting are particularly relevant to third-party logistics because service providers operate across multiple customer organizations, transportation networks, warehouse facilities, and order-processing systems. Historical shipment volumes, customer transaction records, delivery schedules, inventory movements, and service-capacity observations represent distinct sources of forecasting information that may differ considerably in frequency, completeness, and statistical distribution. Research involving electronics distribution has examined an integrated forecasting framework for intermittent demand, combining data-driven techniques with temporal aggregation to address operational planning requirements (Fu & Chien, 2019). Multivariate forecasting research in automotive supply chains has investigated the contribution of leading indicators and historical observations to multi-step component-demand prediction (Gonçalves et al., 2021). The relationship between machine learning and logistics-related demand estimation has also been examined through business-to-business spare-parts sales forecasting at an after-sales service provider, where customer quotations and historical commercial records were incorporated into predictive models (Rohaan et al., 2022). Intermittent demand forecasting in industrial environments has received additional attention through hybrid procedures developed for irregular spare-parts requirements and limited demand observations (Rosienkiewicz et al., 2017). Research comparing random forest and nearest-neighbour algorithms has examined the influence of multiple predictors on intermittent retail demand forecasting, emphasizing the importance of variable selection and model characteristics (Güven et al., 2021). Distributional forecasting studies have further considered the representation of uncertainty in demand estimates and the distinction between predicting expected demand and modelling its possible distribution (Ulrich et al., 2021). In commercial forecasting environments, gradient-boosted methods have been applied to promotional demand estimation while incorporating explanations concerning the relationships between forecasting inputs and predicted outcomes (Aguilar-Palacios et al., 2020). Information integration has also been examined through federated learning approaches that allow organizations to develop demand forecasting models using distributed information resources (Li et al., 2021). Research on automobile demand has investigated the combined explanatory role of enterprise-level observations and broader economic variables in machine learning forecasting systems (Kim, 2023). From an organizational perspective, information availability and analytical capabilities have been examined through Organizational Information Processing Theory, particularly regarding the relationships among demand visibility, supply visibility, operational uncertainty, and analytical information processing (Srinivasan & Swink, 2018). In Demand planning for the digital supply chain (pp. 965–982), the integration of human judgment and predictive algorithms was investigated through experimental and field-based evidence concerning

alternative forecasting procedures (Brau et al., 2023). Together, these studies identify demand information, analytical methods, contextual variables, and organizational information-processing arrangements as distinct dimensions of the forecasting process.

The available research on machine learning-based demand forecasting has developed across several related but methodologically distinct fields, including retail sales prediction, manufacturing demand estimation, freight transportation, e-commerce distribution, inventory forecasting, and logistics service planning. The relationship between forecasting accuracy and supply chain performance has been examined through machine learning approaches combining time-series observations with explanatory information, including comparative evaluations against established forecasting methods (Feizabadi, 2022). Studies involving third-party logistics operations have investigated near-real-time distribution-centre demand, international forwarding-service capacity requirements, and freight shipment prediction using different modelling architectures and operational datasets (Leung et al., 2020; Ren et al., 2020). Research involving a U.S. intermodal transportation company has provided geographically relevant evidence concerning machine learning-based freight demand forecasting across different prediction horizons, although this operational setting does not represent the entire third-party logistics industry (Hassan et al., 2020). The broader international literature has examined applications using retail transactions, product attributes, industrial demand records, customer information, and distribution-related observations, creating substantial variation in the empirical conditions under which predictive performance has been assessed (Aamer et al., 2021; Toorajipour et al., 2021). Differences also exist in the selection of reference models, forecasting horizons, dataset dimensions, validation procedures, and evaluation measures. Studies comparing conventional forecasting with machine learning approaches have reported context-dependent performance patterns, including circumstances in which relatively simple statistical methods remain competitive with more computationally intensive alternatives (Makridakis et al., 2018; Spiliotis et al., 2022). Research involving intermittent and volatile demand has identified additional distinctions between general forecasting-error measures and inventory-oriented assessments of predictive performance (Abolghasemi et al., 2020; Kiefer et al., 2021). Evidence concerning forecast integration has further demonstrated that prediction quality can depend on how algorithmic outputs and contextual information are combined within demand-planning procedures (Brau et al., 2023). These differences create a defined research problem concerning the comparability, consistency, and contextual relevance of reported predictive performance within U.S. third-party logistics. The present research is structured as a qualitative, cross-sectional, case-study-based systematic literature review with a conditional meta-analytic component, targeting 100 valid published studies from the 2005–2023 literature period. The review examines machine learning model classifications, comparisons with conventional statistical forecasting, deep learning and hybrid architectures, explanatory demand variables, forecasting horizons, logistics operational complexity, and reported predictive accuracy. Quantitative synthesis is restricted to comparable results extracted from published investigations, while heterogeneous findings are examined through qualitative thematic synthesis and structured case-study comparisons (Fildes et al., 2022; Seyedan & Mafakheri, 2020).

**Background and Motivation**

Demand forecasting has become an essential component of third-party logistics operations, particularly in the United States, where transportation networks, warehousing systems, distribution services, and customer fulfillment activities require continuous coordination. Traditional statistical forecasting approaches have been widely employed to estimate shipment volumes and logistics service requirements. However, increasing demand variability, complex supply chain relationships, and expanding operational information have introduced additional challenges to forecasting accuracy. Machine learning techniques have provided alternative approaches for identifying nonlinear demand patterns, incorporating historical and external information, and generating predictive estimates. The growing application of artificial intelligence in logistics has also increased academic interest in comparing forecasting algorithms, evaluating predictive accuracy, and understanding their relationships with operational planning. These developments have established the research context for systematically examining machine learning-based demand forecasting within U.S. third-party logistics operations.

**Research Problem**

Demand forecasting in U.S. third-party logistics operations has remained challenging because of fluctuating shipment volumes, irregular customer orders, demand volatility, changing transportation requirements, and fragmented operational information. Although numerous studies have investigated machine learning

techniques for forecasting demand across logistics and supply chain environments, their findings have differed regarding predictive accuracy, algorithm selection, forecasting horizons, and operational applicability. Existing research has frequently examined individual forecasting techniques or specific industrial applications, making systematic comparisons across different machine learning approaches difficult. Furthermore, variations in forecasting accuracy measurements, validation procedures, and data characteristics have complicated the interpretation of published results. A research gap therefore exists concerning the consolidated evaluation of machine learning predictive performance specifically relevant to U.S. third-party logistics, particularly regarding comparative forecasting effectiveness, influential predictive variables, operational conditions, and the consistency of available empirical evidence.

**Purpose and Review Objectives**

The primary objective of this research is to systematically examine and synthesize published evidence concerning the predictive performance of machine learning-based demand forecasting models in U.S. third-party logistics operations. Specifically, the study aims to identify frequently investigated machine learning techniques, compare their forecasting accuracy with conventional statistical approaches, and evaluate the reported effectiveness of deep learning, ensemble learning, and hybrid forecasting models. Additionally, the research seeks to investigate the influence of historical demand information, external predictive variables, forecasting horizons, demand volatility, and logistics operational complexity on forecasting performance. Through a systematic review targeting 100 valid published studies, the research aims to classify existing evidence, evaluate the proposed research hypotheses, and identify relationships between forecasting capabilities and logistics operational planning. Qualitative thematic synthesis, case-study comparisons, and limited meta-analysis of compatible published results will constitute the principal analytical approaches.

**Research Questions**

RQ1: How do machine learning-based demand forecasting models compare with traditional statistical forecasting approaches in terms of predictive performance within U.S. third-party logistics operations? RQ2: How do forecasting model characteristics, historical demand information, external predictive variables, and operational conditions influence the reported predictive performance of machine learning-based forecasting approaches? RQ3: What operational benefits, implementation challenges, and research gaps have been identified concerning machine learning-based demand forecasting in U.S. third-party logistics?

**Propositions and Hypotheses**

The research has developed five hypotheses addressing the relationships between machine learning forecasting techniques, predictive performance, information characteristics, and logistics operational conditions. These hypotheses have been formulated to guide the systematic evaluation of published evidence rather than to establish relationships using newly collected quantitative observations. The first two hypotheses concern comparative forecasting accuracy, while the third examines the contribution of historical demand information and external predictive variables. The fourth considers variations in predictive performance across forecasting horizons and operational environments, whereas the fifth addresses the relationship between machine learning forecasting and logistics decision-making. The hypotheses will be evaluated through qualitative evidence synthesis, comparative case-study findings, and limited quantitative aggregation of compatible results extracted from the reviewed studies.

H1: Machine learning-based demand forecasting models demonstrate superior predictive accuracy compared with conventional statistical forecasting approaches in comparable third-party logistics applications. H2: Deep learning, ensemble learning, and hybrid forecasting models demonstrate superior predictive performance compared with standalone conventional machine learning models under comparable forecasting conditions. H3: The integration of historical demand patterns and relevant external predictive variables is associated with improved machine learning forecasting performance in third-party logistics operations. H4: Forecasting horizons, demand volatility, and logistics operational complexity influence the reported predictive performance of machine learning-based demand forecasting models. H5: Machine learning-based demand forecasting contributes to improved operational planning, resource allocation, and decision-making efficiency within third-party logistics operations.

**Research Contributions**

The significance of this research is associated with its systematic examination of machine learning applications, predictive forecasting performance, and operational decision-making within U.S. third-party logistics. The study addresses several dimensions of academic and practical relevance through the following contributions.

i. Theoretical Significance: The research applies Organizational Information Processing Theory to examine relationships among forecasting information, machine learning capabilities, operational uncertainty, and predictive performance within third-party logistics environments. ii. Methodological Significance: The study establishes a structured approach for reviewing forecasting research through PRISMA-guided study selection, methodological quality assessment, qualitative thematic synthesis, case-study classification, and limited meta-analysis of comparable published results. iii. Practical Significance: The research consolidates evidence relevant to logistics service providers concerning machine learning model selection, forecasting accuracy, transportation capacity planning, warehouse resource allocation, and operational decision-making. iv. Technological Significance: The study examines the predictive characteristics of conventional machine learning, deep learning, ensemble learning, and hybrid forecasting approaches across different demand conditions and logistics applications. v. Academic and Research Significance: The research systematically organizes existing literature, identifies methodological inconsistencies, evaluates the strength of evidence supporting the proposed hypotheses, and documents research gaps concerning machine learning-based demand forecasting in U.S. third-party logistics.

**Original Manuscript Roadmap**

The paper has been arranged into nine sections. Following the introduction, Section 2 has developed the literature review, theoretical foundation, and conceptual framework. Section 3 has described the review methodology; Section 4 has presented the literature-based findings and comparative tables. Section 5 has discussed interpretations, practical and theoretical issues, and future research. Sections 6–8 have provided the conclusion, recommendations, and limitations, followed by the references in Section 9.

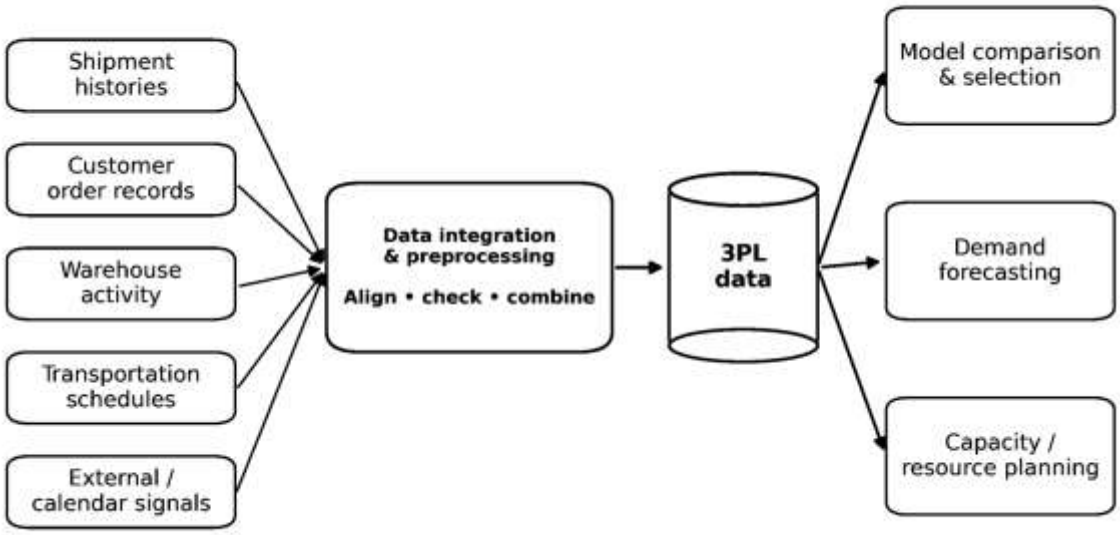
## LOGISTICS DEMAND AND DATA ENVIRONMENT

The literature review examines the theoretical, methodological, and technological foundations of machine learning-based demand forecasting in U.S. third-party logistics operations. It synthesizes published research concerning logistics demand characteristics, conventional statistical forecasting approaches, machine learning algorithms, and comparative predictive performance. Particular attention is given to deep learning, ensemble learning, hybrid forecasting methods, historical demand information, external predictive variables, forecasting horizons, and operational uncertainty. Organizational Information Processing Theory provides the theoretical foundation for interpreting relationships between information-processing capabilities and forecasting effectiveness. The review also develops a conceptual framework connecting machine learning capabilities, predictive accuracy, operational conditions, and logistics decision-making within third-party logistics environments.

**Demand Characteristics and Third-Party Logistics Operations**

Third-party logistics (3PL) refers to the provision of transportation, warehousing, distribution, fulfillment, and related services by external organizations managing activities for commercial clients. Demand forecasting within these arrangements estimates future shipment volumes, warehouse throughput, delivery requests, and resource requirements across interconnected commercial customer accounts. In the United States, providers regularly coordinate domestic freight movements with international sourcing networks, retail replenishment, manufacturing schedules, and electronic commerce orders. These operations involve multiple service contracts, distinct product categories, geographic markets, and planning horizons, making demand patterns particularly difficult to interpret through a single operational perspective. In Integration between manufacturers and third party logistics providers? (pp. 331–359), the examination of manufacturer-provider relationships illustrated how operational cooperation depends on shared processes and communication technologies (Mortensen & Lemoine, 2008). Coordination also extends beyond physical freight handling to performance evaluation, provider selection, and the exchange of operational information. In Supply chain integration with third-party logistics providers (pp. 262–271), relationships between information integration, collaboration practices, and organizational performance were investigated within supply chain management arrangements (Jayaram & Tan, 2010). For forecasting purposes, demand observed by a logistics provider may reflect aggregated activity from several customers rather than direct consumer purchases, introducing differences between shipment requirements and underlying market demand. Capacity commitments create additional complications when transport resources must be reserved before customers confirm actual shipment quantities. In A dual-response strategy for global logistics under uncertainty (pp. 397–419), a third-party logistics case illustrated how short shipment notices and advance vehicle commitments complicate logistics planning under uncertain demand (Wu, 2012).

**Figure 2: Third-Party Logistics Demand Information Integration and Forecasting Applications**




Demand uncertainty in third-party logistics involves changes in order frequency, shipment size, destination mix, cargo characteristics, and service timing. Such fluctuations affect warehouse labor, vehicle utilization, inventory movement, and coordination between customer organizations and external carriers. Forecasting therefore depends not only on historical volumes but also on the availability and consistency of information received from several independent partners. In The information technology capability of third-party logistics providers (pp. 22–38), empirical evidence linked technology-oriented capabilities with service quality, cost control, and customized logistics services, emphasizing the organizational importance of information systems (Lai et al., 2008). Internal coordination must also accommodate differences between customer requirements, distribution partners, and service delivery processes. Research examining integration and resilience among logistics providers associated internal, customer, and collaborator integration with organizational responses and service performance (Liu & Lee, 2018). Data exchange is additionally influenced in practice by contractual relationships, technology investments, and the willingness of customers to disclose operational details. In Economic or relational first? (Article 108869), operational and strategic information sharing was examined through relationships involving asset commitments and mutual trust between third-party logistics organizations and their partners (Wang et al., 2023). These characteristics can restrict the timeliness, granularity, and reliability of demand information accessible for predictive modelling. Unexpected disruptions further alter typical shipping cycles and complicate estimates derived from previously observed demand. A study of logistics service providers during the COVID-19 pandemic identified demand changes, forecast horizons, delivery delays, regulatory measures, and supply disruptions among interrelated sources of operational uncertainty (Gultekin et al., 2022).

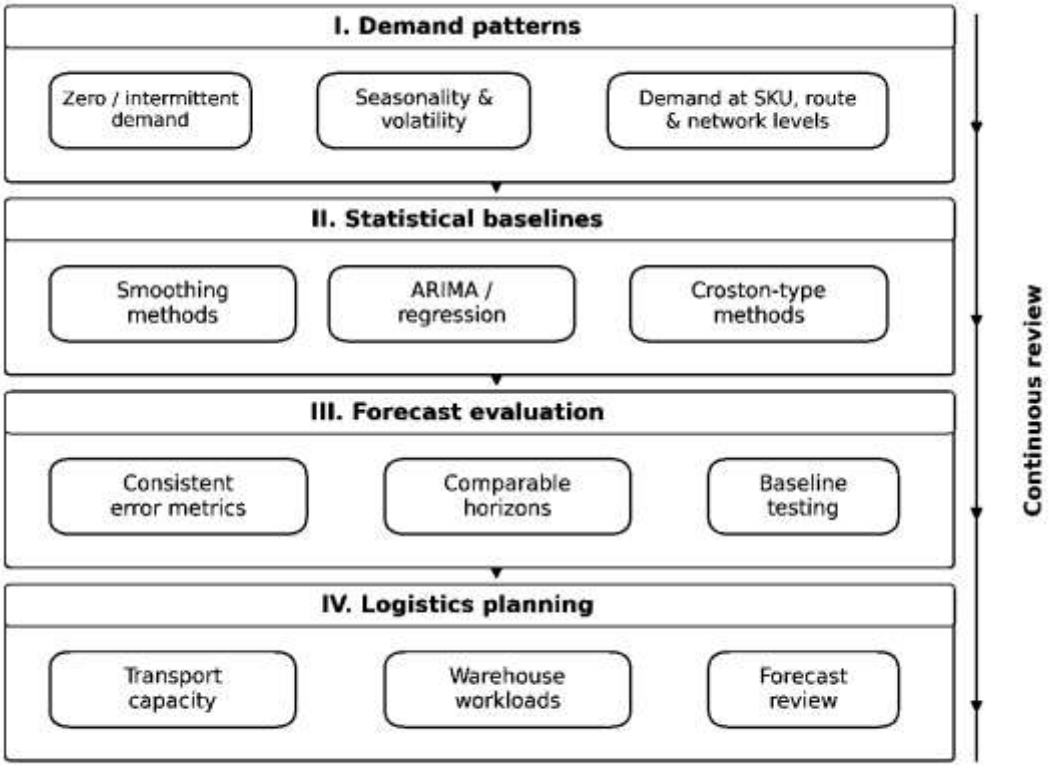
Logistics demand forecasting connects estimates of future activity with operational decisions, although forecasting requirements vary across freight modes, distribution facilities, and customer portfolios. Air cargo operations illustrate how uncertain consignment arrivals influence staffing requirements, processing schedules, and the use of handling resources. In Improving demand forecasting in the air cargo handling industry (pp. 359–380), a case study examined forecasting inaccuracies and operational factors affecting workforce management within a cargo handling company (Magaña et al., 2017). Warehousing and distribution networks present related challenges because forecasts may be required for individual stock-keeping units, customer destinations, or aggregated shipment flows. In Logistics coordination based on inventory management and transportation planning by third-party logistics (Article 8134), forecasting approaches incorporating statistical models and neural-network methods were evaluated across distribution networks to support inventory and transportation decisions (Kmiecik, 2022). Such evidence distinguishes forecasts intended for daily execution from estimates used to coordinate network-level resources. Machine learning applications also address hierarchical relationships between individual demand series and aggregated operational requirements. In A novel multi-phase hierarchical forecasting

approach with machine learning (Article 100032), information from a logistics solutions provider supported comparisons of hierarchical forecasting approaches using demand series (Taghiyeh et al., 2023). Across U.S. third-party logistics contexts, these operational distinctions are relevant because customer diversity, service specialization, and geographic dispersion influence the structure of forecasting inputs. Published cases therefore provide units of observation, predictive targets, error measures, and validation conditions, requiring careful separation of direct third-party logistics evidence from findings originating in adjacent transportation and supply chain settings.

## FORECASTING PERFORMANCE AND ORGANIZATIONAL FIT

Traditional statistical forecasting has provided the principal analytical foundation for estimating shipment volumes, warehouse activity, replenishment requirements, and transportation capacity in logistics planning. Common approaches include moving averages, simple exponential smoothing, Holt's trend adjustment, seasonal smoothing, autoregressive integrated moving average models, and regression using selected explanatory factors. Their usefulness depends on the stability, periodicity, and observational detail of the underlying demand series. In Exponential smoothing: The state of the art, Part II (pp. 637–666), the statistical foundations of smoothing procedures were reviewed, including state-space formulations and techniques for representing changing trends (Aditya & Ahmed, 2022; Gardner, 2006). These methods offer transparent specifications and relatively modest computational requirements, which are relevant when third-party logistics providers must produce forecasts across numerous client accounts. However, models calibrated to aggregate shipment history may overlook customer-specific ordering cycles, abrupt shifts in distribution schedules, and interactions among service locations. In Stochastic models underlying Croston's method (pp. 389–402), the consistency of statistical assumptions for intermittent observations was investigated, identifying limitations in established procedures for demand series containing prolonged zero-demand intervals (Asheke & Maksudul, 2022; Shenstone & Hyndman, 2005).

**Figure 3: Traditional Forecasting Workflow and Operational Evaluation Requirements**




Forecast aggregation presents a separate challenge because estimates for individual warehouses, routes, and customer groups may not sum to corresponding network totals. In Optimal forecast reconciliation for hierarchical and grouped time series (pp. 804–819), statistical reconciliation was developed to align forecasts across related aggregation levels, illustrating the importance of coherent estimates for connected operational

categories (Asheke & Badrul, 2022; Wickramasuriya et al., 2019). Such considerations distinguish mathematically convenient demand models from the complex forecasting requirements of multiparty logistics environments and contracts.

Intermittent logistics demand is especially problematic for conventional methods because infrequent orders and irregular shipment quantities generate extended sequences of zero observations. Croston-type procedures address this pattern by estimating nonzero demand size separately from the intervals between demand occurrences. However, forecasts can remain unchanged during prolonged inactivity, even when an item or service is becoming obsolete. In Intermittent demand: Linking forecasting to inventory obsolescence (pp. 606–615), an alternative probability-updating method was developed to respond to declining demand and reduce estimation bias (Khalid & Sadmeen, 2022; Teunter et al., 2011).

Forecasting performance also differs across demand categories, indicating that one statistical method should not automatically be assigned to every inventory or shipment series. In Forecasting-based SKU classification (pp. 455–462), classification rules based on demand variability and inter-demand intervals were examined using observations from several industries (Heinecke et al., 2013; Akter & Sumaiya, 2022). Empirical evaluation has additionally demonstrated that smoothing parameter choices and treatment of declining demand affect forecast accuracy and inventory outcomes, rather than constituting merely technical settings (Babai et al., 2014). Demand generation itself may reflect operational activities that are not visible in aggregated historical totals. In A two-step method for forecasting spare parts demand (pp. 386–393), information on repair events and component requirements was incorporated into estimation, showing how operational drivers can be distinguished from recorded demand quantities (Romeijnders et al., 2012). These limitations are relevant to third-party logistics contracts involving infrequent specialized shipments, heterogeneous customers, and irregular replenishment requests. They also complicate comparisons between providers whose service volumes vary by customer, location, and reporting interval.

Conventional forecasting methods also face difficulties when historical patterns change abruptly, demand observations are sparse, or operational requirements differ across service categories. Their apparent performance can depend substantially on which error measure is used and whether assessment reflects forecasting accuracy or inventory consequences. In Forecasting intermittent demand by hyperbolic-exponential smoothing (pp. 928–933), an alternative smoothing procedure was examined to address bias and declining demand through a hybrid statistical formulation (Mashiat & Morshedul, 2022; Prestwich et al., 2014). Parameter calibration presents another challenge, particularly when zero-demand periods distort the conventional error functions used to optimize forecasts. In On intermittent demand model optimisation and selection (pp. 180–190), alternative error criteria were evaluated for parameter tuning and model choice, establishing that routine accuracy measures can yield unsuitable settings for intermittent observations (Kourentzes, 2014). Comparisons of forecasting procedures must therefore consider the timing of forecast generation, prediction horizons, benchmark models, and operational evaluation criteria. In Expert systems in intermittent demand forecasting (pp. 3598–3606), forecasting approaches based on smoothing were compared with a simulation-oriented expert system across thousands of product series, using measures tailored to intermittent patterns (Doszyń, 2021; Imran & Jannatul, 2022). Within U.S. third-party logistics, these concerns arise when providers estimate fluctuating order arrivals, capacity needs, and distributions of customer demand from incomplete records. Statistical baselines remain essential because they establish interpretable reference performance against which machine learning results can be assessed. A systematic comparison consequently requires attention to data frequency, aggregation, nonstationarity, error measures, and the distinct operational contexts represented by published logistics studies and their different reported accuracy benchmarks.

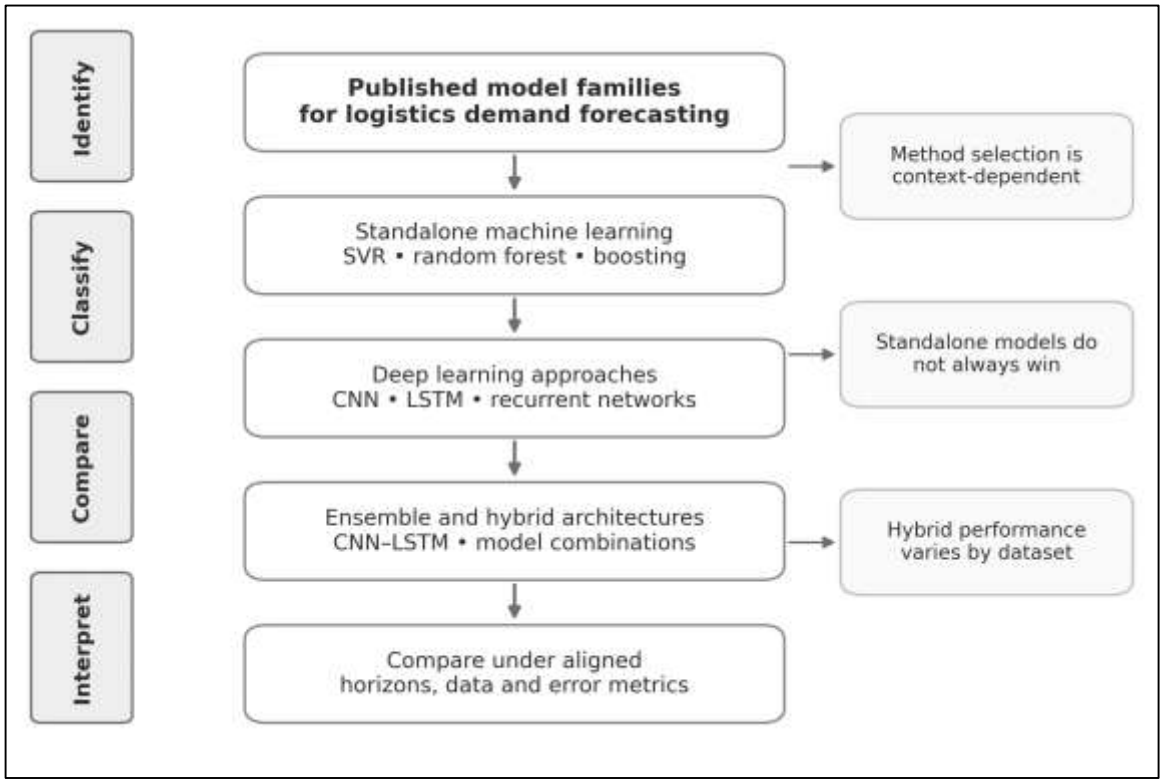
**Machine Learning, Deep Learning, Ensemble and Hybrid Models**

Machine learning approaches to logistics demand forecasting estimate future service requirements by learning associations between previous demand observations and operational predictors. Supervised regression models, including support vector regression, random forests, and gradient boosting, can represent nonlinear relationships without requiring a fixed seasonal specification for every customer or shipment series. Their relevance to third-party logistics lies in the variability of consignments, order frequencies, route requirements, and commercial activity across clients. In Support vector machines under promotions (pp. 309–325), two retail case studies examined support vector machines against established statistical methods when promotions produced irregular sales behaviour, demonstrating the importance of nonlinear forecasting relationships (Pillo et al., 2016; Maksudul & Islam, 2022). In Demand forecasting in

construction machinery (pp. 1587–1604), artificial neural networks and support vector regression were compared with regression approaches using spare-parts sales and contextual indicators; support vector regression performed well in that setting (Aktepe et al., 2021). Such evidence concerns industrial and retail supply chains rather than direct measurements of American logistics providers, making operational transferability an important consideration. In Three-stage XGBoost sales forecasting (Article 8503252), clustering, autoregressive modelling, and gradient boosting were combined for cross-border electronic commerce, with the proposed approach evaluated against component models using transaction histories (Ji et al., 2019; Morshedul & Islam, 2022). These studies distinguish conventional machine learning estimators from hybrid configurations that combine segmentation, time-series structure, and nonlinear prediction. For U.S. third-party logistics demand forecasting, the comparable prediction targets include booked shipments, incoming orders, distribution volume, and transport capacity needs, each requiring explicit alignment between forecast variables and measurable operations.

Deep learning methods extend demand forecasting by learning temporal representations from sequences of historical observations. Recurrent neural networks and long short-term memory models can represent dependencies across successive periods, while globally trained models share statistical information across related demand series. In Sales demand forecasting in e-commerce (pp. 462–474), a globally trained long short-term memory framework used related product histories and grouping procedures on Walmart.com data, demonstrating the importance of cross-series learning when forecasting many distinct items (Bandara et al., 2019; Feroz & Pervaz, 2022).

**Figure 4: Classification of Machine Learning and Hybrid Forecasting Architectures**




Such retail evidence is relevant to the upstream order patterns that eventually influence warehouse throughput and parcel requirements, although sales forecasts cannot be treated as equivalent to recorded logistics service demand. In Demand forecasting with supply-chain information (pp. 3231–3252), machine learning models incorporated cross-series training, downstream inventory information, and domain knowledge for pharmaceutical demand prediction; the findings highlighted the informational value of relationships among products and supply-chain stages (Feroz & Shabbir, 2022; Zhu et al., 2021). The usefulness of shared learning consequently depends on whether customer accounts and freight streams exhibit transferable patterns instead of unrelated fluctuations. In DeepExpress: Express delivery prediction (Article 89, pp. 1–22), a sequence-to-sequence architecture combined heterogeneous contextual features with

attention-based modelling to estimate incoming and outgoing parcel volumes (Ren et al., 2022). This application is more directly aligned with logistics demand because it predicts parcel flows rather than product purchases alone. Together, the approaches describe alternative ways of learning from distinct temporally ordered demand histories, correlated service categories, and operational contextual conditions while preserving meaningful distinctions between prediction tasks.

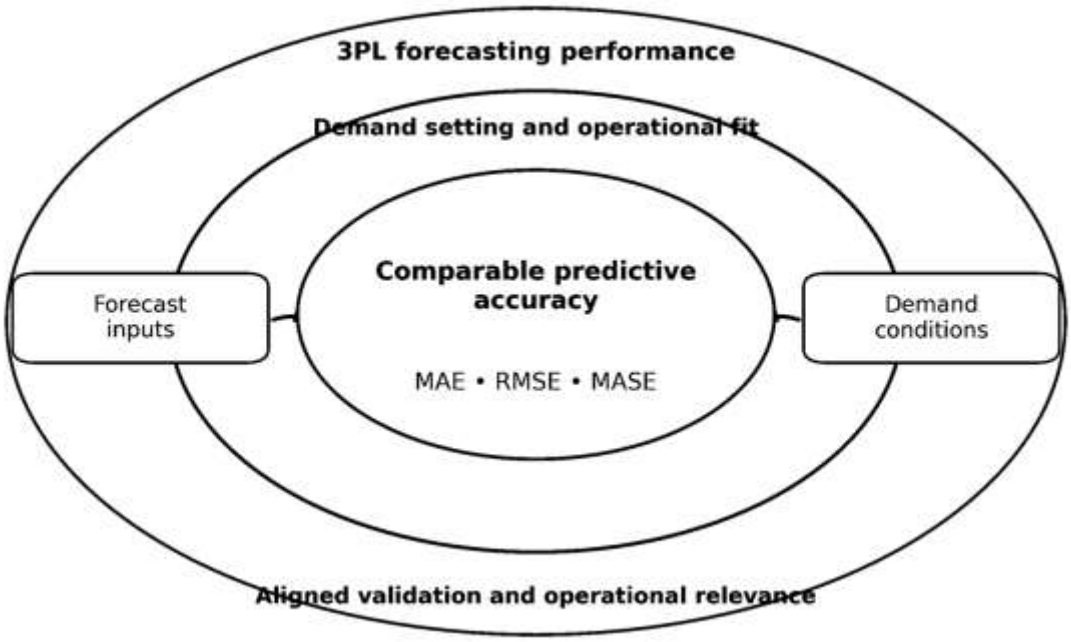
Ensemble and hybrid architectures combine different modelling mechanisms to capture complementary properties of demand series across customer accounts and dispersed service networks. Clustering can separate heterogeneous demand patterns before model estimation; ensembles can integrate predictions from multiple learners; and convolutional recurrent systems can extract localized features while retaining temporal dependencies. In Clustering and fuzzy neural networks for sales forecasting (pp. 344–355), a printed-circuit-board case combined k-means grouping with fuzzy neural networks, illustrating one approach to segmenting historical patterns before prediction (Islam & Md, 2023; Chang et al., 2009). In Cross-item learning for volatile demand (pp. 828–852), research with an electronics distributor used pooled data, feature engineering, and ensemble-based machine learning to address forecasting under substantial demand volatility (Chuang et al., 2021). Direct evidence from third-party logistics is provided by Deep learning in a 3PL company (pp. 331–339), where a hybrid convolutional neural network and long short-term memory model forecast shipment demand during the COVID-19 period and was compared with statistical and learning-based benchmarks (Peköz & İnkaya, 2023). Freight-specific evidence appears in Air cargo demand forecasting with ConvLSTM2D (Article 101009), which examined hybrid convolutional recurrent learning and socioeconomic predictors using Colombian air-cargo observations (Mostari & Kynatun, 2023; Anguita & Olariaga, 2023). Neither international case should be presented as direct evidence about U.S. 3PL performance. Their methods nevertheless clarify which predictive structures and comparison conditions require examination in an American-focused review. Accordingly, model families should be classified alongside dataset provenance, forecasting horizon, baseline selection, validation design, and reported error measures rather than ranked solely by architectural complexity.

**Accuracy Metrics and Operational Determinants**

Predictive performance evaluation in third-party logistics requires distinguishing statistical fit from the practical usefulness of shipment, order, and warehouse workload forecasts. Common indicators include mean absolute error, root mean squared error, mean absolute percentage error, and scaled measures, although their interpretation changes with demand frequency and magnitude. In Evaluation of forecasting error measurements (pp. 625–636), the authors demonstrated that different error measures capture different dimensions of intermittent demand, including accumulated shortages and periods of excess stock (Wallström & Segerstedt, 2010). This distinction matters when a forecast appears numerically accurate but generates costly capacity shortages during unexpected order surges. In On the selection of forecasting accuracy measures (pp. 937–954), a comparative analysis examined whether changing evaluation criteria altered rankings among forecasting procedures, clarifying the importance of defining a consistent assessment framework (Koutsandreas et al., 2022). Percentage errors are particularly difficult to interpret when a client generates no shipments during several observation periods. In A new metric of absolute percentage error (pp. 669–679), an arctangent-based measure was developed to address the instability of percentage calculations near zero demand (Kim & Kim, 2016). For irregular service requirements, evaluation may also separate the probability of demand occurrence from the quantity expected when demand materializes. Research on two-stage intermittent forecasting compared classification, quantity prediction, and inventory-oriented measures using automotive demand histories (Mashfiqur & Jamil, 2023; Rožanec et al., 2022). Such differences complicate comparisons across diversified customer service portfolios. Consequently, literature comparisons must document the forecast target, denominator, temporal aggregation, and baseline before interpreting reported improvements across different logistics applications.

The predictive value of machine learning models also depends on the information supplied to forecasting algorithms and the operational level at which observations are measured. Relevant variables may include historical customer orders, planned promotions, prices, calendar effects, location attributes, and changes in network activity. In A score-driven model of short-term demand forecasting (pp. 715–725), researchers used distribution-center-level retail observations and compared statistical density forecasting against neural networks and other benchmarks, highlighting the role of explanatory variables and probabilistic forecasts (Hoeltgebaum et al., 2021; Mashiat & Binte, 2023).

**Figure 5: Integrated Conditions for Evaluating Predictive Performance in Third-Party Logistics**




Although the investigation concerned Brazilian retail distribution rather than American third-party logistics, its evaluation design shows why warehouse throughput should be distinguished from store-level product sales. In Improving sales forecasting accuracy (pp. 1644–1660), a tensor-based framework combined information across products, stores, and periods to capture demand dynamics that isolated series might miss (Bi et al., 2022). Such cross-series information has potential relevance to providers handling multiple customers, but its transferability depends on the similarity of shipment patterns and on the availability of compatible records. In M5 accuracy competition (pp. 1346–1364), a large-scale comparison examined hierarchical retail sales series alongside contextual variables and common evaluation rules, making aggregation and benchmark consistency central features of predictive assessment (Makridakis et al., 2022). Forecasting horizons introduce further differences because daily staffing, weekly trailer allocation, and monthly facility planning require distinct lead times. Published accuracy comparisons therefore require explicit identification of prediction horizons, temporal train-test separation, information availability at forecast creation, input provenance, and any potential risk of leakage from future observations.

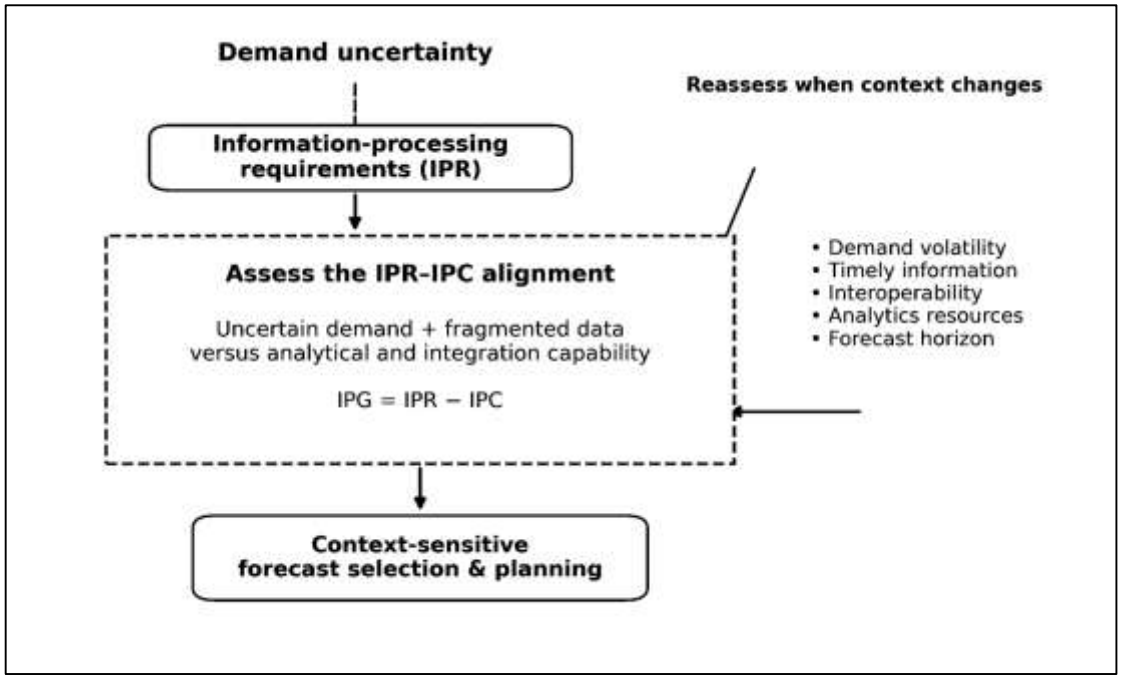
Operational determinants of forecasting accuracy extend beyond algorithm choice to demand intermittency, geographical dispersion, data processing, and the organizational ability to integrate forecasts into logistics plans. In Lumpy and intermittent retail demand forecasts (pp. 1146–1160), score-driven count models were evaluated against alternative approaches on irregular retail series, demonstrating how the assumed demand distribution affects predictive assessment (Shahid, 2023; Sarlo et al., 2023). Logistics operators encounter related distributional difficulties when individual customers generate infrequent consignments, even while total network activity remains relatively stable. In Quality of forecasts as the factor determining coordination (Article 1013), the relationship between demand forecasting and distribution-network coordination was examined through logistics-operator characteristics and an information-system-supported forecasting arrangement (Kramarz & Kmiecik, 2022; Islam & Ahmed, 2023). This evidence identifies organizational access to operational information as a relevant condition, without establishing a universal forecasting advantage for any algorithm. In Deep learning and statistical models for forecasting transportation demand (Article 86), researchers assessed shipment demand across fifty-four Brazilian distribution centers, comparing recurrent neural networks with conventional time-series models under alternative preprocessing and validation scenarios (Mamede et al., 2023). Their results also illustrated tradeoffs between predictive accuracy and model training requirements. For U.S. third-party logistics, comparable operational conditions include customer heterogeneity, uneven route volumes, disruption periods, service-level constraints, and the timeliness of booking information. Such factors should be recorded as study characteristics rather than treated as interchangeable data conditions. The evidence base accordingly requires case-specific

interpretation of error statistics, explanatory variables, time horizons, benchmark models, and operational feasibility before judging relative predictive performance across published cases.

**Organizational Information Processing Theory**

Organizational Information Processing Theory (OIPT) explains how organizations organize information acquisition, interpretation, and communication when uncertainty increases the information required for coordinated decisions. Its central proposition concerns alignment between information-processing requirements and the capabilities available to satisfy them. In U.S. third-party logistics, requirements arise from fluctuating shipment bookings, heterogeneous customer contracts, warehouse constraints, transportation schedules, and incomplete visibility across external partners. In An Empirical Test of the Information Processing Theory (pp. 45–59), a study of North American manufacturers associated environmental uncertainty with information quality, sourcing coordination, and operational design, providing a supply-chain illustration of the theory (Sadia & Mosheur, 2023; Zhou, 2011). In The Contingency Effects of Environmental Uncertainty (pp. 604–615), research involving automotive plants examined how uncertainty conditioned relationships between supply-chain integration and operational performance, distinguishing internal coordination from customer and supplier integration (Wong et al., 2011). This distinction matters because logistics providers receive information from independent clients while allocating shared resources internally. Information delays may cascade across dispatch decisions when customer bookings change unexpectedly overnight. In Understanding Responses to Supply Chain Disruptions (pp. 833–856), information-processing and resource-dependence perspectives explained differences in organizational reactions to disrupted supply relationships, emphasizing interpretation rather than data availability alone (Bode et al., 2011). In Managing Information Processing Needs in Global Supply Chains (pp. 87–113), multi-industry case evidence identified task, source, and supply-chain uncertainty as separate sources of information requirements (Busse et al., 2017; Sumaiya & Taufiqur, 2023). Together, these studies position forecasting as an organizational information-processing task whose demands depend on uncertain conditions, partner relationships, and the complexity of operating decisions.

**Figure 6: Organizational Information Processing Theory and Forecasting Capability Alignment**




Machine learning forecasting can be interpreted within OIPT as one component of information-processing capability rather than as an autonomous determinant of logistics performance. Historical order records, booking updates, route characteristics, seasonal indicators, and customer-provided schedules become useful only when they can be combined, checked, and interpreted at a suitable operational level. In Leveraging Supply Chain Integration through Planning Comprehensiveness (pp. 823–861), information-processing theory was applied to examine how integration, planning practices, and supply-chain

management systems jointly influenced operational outcomes in a multicountry sample (Srinivasan & Swink, 2015; Sadmeen & Khalid, 2023).

Planning comprehensiveness is particularly relevant to third-party logistics because the same demand estimates can inform trailer allocation, warehouse staffing, and delivery commitments. In How the Use of Big Data Analytics Affects Value Creation (pp. 4–39), evidence from U.S. companies examined analytics use as an organizational information-processing capability and considered environmental dynamism when interpreting its relationship with value creation (Chen et al., 2015). Although this analysis was not confined to third-party logistics, it distinguishes possessing data from effectively using analytical resources. In Information Sharing, Coordination and Supply Chain Performance (pp. 1046–1071), structured and unstructured customer information were associated differently with operational and strategic coordination under varying demand uncertainty (Li et al., 2019). Consequently, this review distinguishes information quantity from relevance, timeliness, interoperability, and decision accessibility when examining reported forecasting results. Algorithmic sophistication alone cannot establish information-processing adequacy without considering whether users can translate predictions into coordinated operational actions. This distinction also prevents interpreting lower reported forecasting errors as direct evidence of organizational effectiveness everywhere.

For case-study synthesis, OIPT provides a common interpretation of how demand uncertainty creates information requirements and how forecasting systems, integration routines, and analytical expertise contribute to processing capacity. In Supply Chain and External Conditions under Which Supply Chain Resilience Pays (Article 107610), organizational information-processing theory was used to explain how disruption conditions affected relationships between resilience and performance in supply chains (Wong et al., 2020). In Role of Big Data Analytics Capability in Developing Integrated Hospital Supply Chains (Article 120417), analytics capability was examined alongside organizational integration and operational flexibility, offering an adjacent sector illustration rather than direct evidence from logistics providers (Yu et al., 2021). In Procurement's Role in Resolving Demand–Supply Imbalances (pp. 68–100), buffering and collaborative bridging were evaluated as mechanisms for addressing imbalances, with different consequences for delivery continuity and cost efficiency (Laari et al., 2023). The organizing relationship for the present review is expressed conceptually in the following information-processing-gap equation, where IPG denotes the information-processing gap, IPR the information requirements, and IPC the available processing capability in study context j. A positive gap indicates unmet requirements; the expression is an interpretive device, not a published OIPT estimation formula or a value calculated from unavailable data. Across the reviewed cases, it structures comparisons of forecasting inputs, uncertainty, model capabilities, and operational coordination. A study with strong forecasting algorithms but weak information sharing can therefore remain poorly aligned with the decisions governing capacity and service commitments. Its application remains qualitative unless original publications report sufficiently comparable measurements for defensible numerical synthesis.

$$IPG_j = IPR_j - IPC_j$$

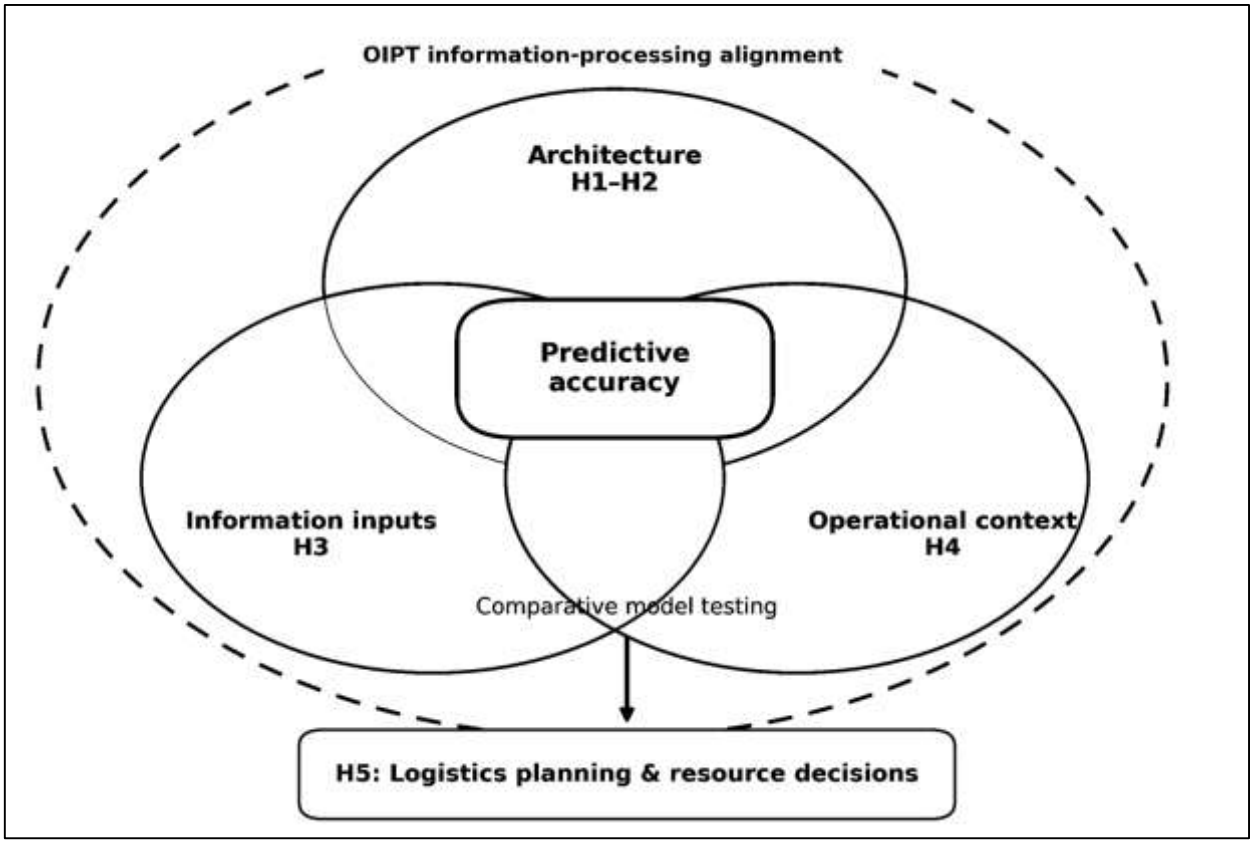
**Forecasting-to-Decision Conceptual Framework**

Organizational Information Processing Theory provides the conceptual foundation for explaining why machine learning demand forecasting varies across third-party logistics (3PL) operations. In the proposed framework, uncertain shipment arrivals, heterogeneous customer orders, changing freight routes, and uneven warehouse workloads increase information-processing requirements, while timely records, interoperable systems, and forecasting algorithms constitute processing capabilities. In How supply chain analytics enables operational supply chain transparency (pp. 47–68), analytics deployed across planning and delivery functions was associated with operational transparency, showing that technical capability must be considered alongside information flows (Zhu et al., 2018). In Analytical foundations for development of real-time supply chain capabilities (pp. 1571–1589), data quality, reporting quality, and managerial analysis were examined as conditions affecting the value of real-time visibility (Oliveira & Handfield, 2019). This distinction is relevant to U.S. 3PL providers because access to booking records does not ensure that forecasts reflect actual carrier availability or facility constraints. In Environmental scanning, supply chain integration, responsiveness, and operational performance (pp. 787–814), scanning and integration were connected to responsiveness within an information-processing framework (Yu et al., 2019). Accordingly, the conceptual sequence begins with demand uncertainty and data availability, proceeds through forecasting capability, and considers predictive accuracy as an intermediate outcome linked to operational decisions. Forecasts are

interpreted as decision inputs rather than automatic improvements in performance. The framework differentiates a provider's access to information from its ability to transform information into actionable estimates at the required planning interval. Such separation permits case studies with different data architectures to be compared more consistently.

The framework's forecasting component distinguishes model architecture, input richness, evaluation design, and operational context, allowing competing explanations of predictive performance to be examined. Traditional statistical methods form the comparison category for H1, while standalone machine learning, deep learning, ensembles, and hybrid approaches form the categories relevant to H2. In Big data analytics in supply chain management: A state-of-the-art literature review (pp. 254–264), analytical techniques were classified according to their supply chain functions and levels of analysis, supporting an application-sensitive rather than algorithm-only classification (Nguyen et al., 2018).

**Figure 7: Conceptual Framework of Forecasting Capability, Conditions, and Logistics Planning**




In Review and analysis of artificial intelligence methods for demand forecasting (pp. 1126–1131), forecasting approaches were differentiated by data dimensionality, data volume, and prediction horizon (Mediavilla et al., 2022). Accordingly, H3 concerns the availability and integration of historical shipments, calendar indicators, customer commitments, and appropriately observed external predictors. H4 treats horizon length, demand volatility, and logistics complexity as conditions that may moderate observed performance differences. In Analytics capability and firm performance in supply chain organizations (pp. 1–14), process integration and employee analytics skills were examined alongside analytical capability, indicating that information use is also organizationally conditioned (Farivar et al., 2022). A separate investigation of big data analytics identified the role of process-oriented capabilities in relating analytical resources to firm performance, reinforcing the distinction between possessing models and acting on their outputs (Wamba et al., 2017). None of these cross-industry associations is assumed to establish a forecasting advantage specifically within U.S. 3PL firms. Comparability also requires identifying whether reported covariates were available before prediction.

The framework's outcome pathway connects forecasting accuracy with capacity planning, workforce assignment, routing preparation, and service coordination, while preserving a distinction between

predictive results and documented operational benefits. In Big data and predictive analytics for supply chain and organizational performance (pp. 308–317), connectivity, information sharing, and analytics assimilation were examined in relation to performance, supporting the inclusion of implementation mechanisms in H5 (Gunasekaran et al., 2017). In An analytic infrastructure for harvesting big data (pp. 559–574), integration of fragmented data was examined through a case-based decision-support approach, illustrating why isolated predictions may not be immediately usable (Zhan & Tan, 2020). In Big data-driven supply chain performance measurement (pp. 65–86), analytical capability and supply chain process outcomes were treated as separate measurement domains (Kamble & Gunasekaran, 2020). For comparable study-level forecasting errors, the review uses the descriptive relative-improvement expression shown below, where E_b represents baseline error and E_m represents machine learning error for study comparison i. A positive value indicates lower error for the machine learning model, provided both errors use the same metric, forecast horizon, target, and test observations. This expression does not itself constitute a pooled meta-analytic effect or establish statistical significance. Reported operational outcomes are assessed separately through case evidence, preserving theoretical alignment without treating qualitative associations as measured causal effects. This structure maps H1 and H2 to model comparisons, H3 to information inputs, H4 to conditional forecasting performance, and H5 to documented planning outcomes, while distinguishing U.S. logistics cases from transferable international or cross-sector evidence in reviewed publications.

$$RI_i = \frac{E_{b,i} - E_{m,i}}{E_{b,i}} \times 100\%$$

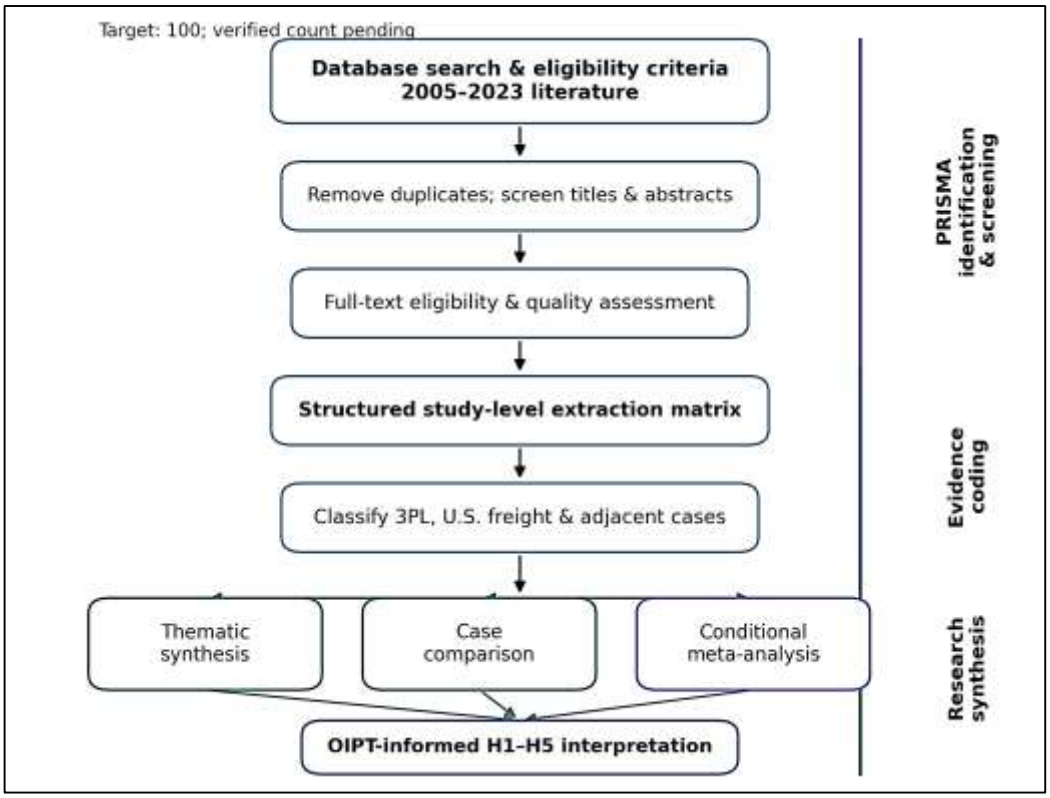
## EVIDENCE IDENTIFICATION AND REVIEW DESIGN

This research has adopted a predominantly qualitative, cross-sectional, case-study-based systematic literature review design, with a conditional meta-analysis of compatible published forecasting outcomes, to examine machine learning for demand forecasting in U.S. third-party logistics. The Case Study Context has been defined as published empirical investigations of third-party logistics operations and carefully distinguished evidence from related freight transportation, warehousing, distribution, and supply chain forecasting settings. The Population and Unit of Analysis have consisted of scholarly studies and their documented forecasting comparisons, rather than surveyed logistics employees or independently collected shipment records. A purposive eligibility-based Sampling Strategy has been developed around a target of 100 valid articles published between 2005 and 2023, with the final number dependent upon reproducible identification and eligibility screening.

The Data Collection Procedure has been specified as structured searches of Scopus, Web of Science, IEEE Xplore, ScienceDirect, and supplementary Google Scholar discovery, followed by duplicate elimination, title and abstract screening, full-text eligibility review, and PRISMA 2020 documentation. Instrument Design has taken the form of a standardized literature-extraction matrix containing bibliographic details, geographical setting, directness of 3PL relevance, model family, demand target, observation frequency, forecasting horizon, comparator, error metric, validation design, reported outcomes, and operational interpretations. Pilot Testing has been conceptualized as checking extraction definitions and coding consistency on a subset of eligible publications; no questionnaire pilot, respondent recruitment, or Likert survey has been conducted. Validity and Reliability have been addressed through predetermined inclusion criteria, transparent provenance, methodological-quality assessment, consistent definitions, and, where multiple reviewers are involved, independent screening and resolution of coding disagreements; Cronbach's alpha and respondent-scale validity tests have not been applicable to the present literature review. The Thematic Synthesis procedure has grouped findings according to comparative accuracy, algorithm architecture, predictive inputs, operational conditions, and documented planning applications.

The Meta-Analysis has been restricted to published numerical results with compatible targets, error definitions, forecasting horizons, benchmarks, and sufficient uncertainty information, and has not been claimed as completed without such extractable data. H1–H5 have been assessed using the direction and consistency of published evidence and their alignment with Organizational Information Processing Theory. Regarding Software and Tools, Microsoft Excel has been designated for the extraction register and descriptive comparisons, EndNote for reference management, and Microsoft Word for manuscript preparation; SPSS has been listed as an optional tool for eligible study-level statistical summaries rather than as software used to generate unreported regressions or survey outputs. The resulting method has preserved cross-sectional synthesis of available published evidence without confusing the source literature's empirical samples with a new primary dataset.

**Figure 8: PRISMA-Guided Research Design and Conditional Evidence Synthesis Workflow**




**PRISMA Screening and Eligibility Status**

**Table 1: PRISMA-Based Literature Selection and Study Inclusion Status**

| Selection variable | Result or review requirement |
|---|---|
| Literature publication period | 2005–2023 |
| Target number of eligible studies | 100 |
| Research approach | Systematic literature review and conditional meta-analysis |
| Primary geographical focus | United States |
| Primary industry | Third-party logistics |
| Reporting framework | PRISMA 2020 |

Table 1 has presented the proposed literature selection framework and has distinguished the target sample from the number of studies actually verified through systematic screening. The research has established a target of 100 eligible publications covering machine learning-based demand forecasting, predictive performance, and third-party logistics operations. The literature review has identified relevant research across freight transportation, warehouse demand, e-commerce distribution, and supply chain forecasting. However, a complete database search record, duplicate-removal register, and study-level eligibility assessment have not yet been established. Under PRISMA 2020, final inclusion numbers have required documentation of the identification, screening, and eligibility stages. From an Organizational Information Processing Theory perspective, the selection framework has emphasized the relationship between forecasting information, analytical capability, and operational uncertainty. The final review has therefore required a transparent distinction between direct U.S. 3PL evidence and supporting international or cross-industry research. This distinction has been necessary for evaluating the research objectives without overstating the geographical relevance of the literature (Page et al., 2021).

**Study Characteristics and Evidence Classification**

**Table 2: Characteristics of Selected Published Studies Relevant to Machine Learning Demand Forecasting**

| Study | Research setting | Verified study characteristic | Relevance |
|---|---|---|---|
| (Al Hajj Hassan et al., 2020) | U.S. intermodal freight transportation | Container shipment demand forecasting | Direct U.S. freight evidence |
| (Zeybel Peköz & İnkaya, 2023) | Third-party logistics company | June–December 2020 shipment data | Direct 3PL application |
| (Mamede et al., 2023) | Brazilian logistics provider | 54 distribution centers | International logistics evidence |
| (Makridakis et al., 2022) | U.S. retail forecasting | 42,840 hierarchical time series | Supporting U.S. forecasting benchmark |
| (Leung et al., 2020) | E-commerce distribution centers | Near-real-time order-arrival forecasting | 3PL-relevant application |
| (Brau et al., 2023) | Demand-planning experiment and field study | 353 experimental participants | Supporting analytical decision-making evidence |
| (Srinivasan & Swink, 2018) | Global supply chain organizations | 191 participating firms | Supporting OIPT evidence |

Table 2 has classified selected publications according to their operational settings, research characteristics, and relevance to the present investigation. The evidence has demonstrated that machine learning demand forecasting has been examined through several distinct research environments rather than one standardized logistics population. The U.S. intermodal transportation study has provided geographically relevant evidence concerning freight shipment forecasting, whereas the third-party logistics case has offered direct evidence of algorithmic comparisons within a logistics service provider. The Brazilian investigation has contributed findings from 54 distribution centers, while the M5 competition has provided a substantial U.S. retail forecasting benchmark involving 42,840 hierarchical time series. These numerical values have represented the original studies' datasets or participants, not the number of studies included in the present review. Organizational Information Processing Theory has connected these environments through their shared dependence on information availability, forecasting capability, and operational coordination. The classification has also identified important differences in geographical coverage and forecasting targets that have limited direct comparisons across studies.

**PUBLISHED MODEL EVIDENCE AND PREDICTIVE PERFORMANCE**

The results chapter has been structured around a target corpus of 100 eligible studies published between 2005 and 2023; final inclusion numbers have remained subject to documented PRISMA screening. The available, individually verifiable evidence has indicated that forecasting performance varies substantially by model family, operational context, and evaluation procedure. In a published third-party logistics case examining shipment data from June through December 2020, a hybrid CNN–LSTM achieved a root mean squared error (RMSE) of 59.12, compared with 62.32 for ARIMA, 67.84 for k-nearest neighbours, and 72.64 for a regression tree (Peköz & İnkaya, 2023). This comparison has provided case-specific evidence relevant to H1 and H2, without establishing universal machine learning superiority. In the U.S. M5 retail forecasting competition, 42,840 hierarchical series were evaluated; the winning method improved weighted forecasting accuracy by 22.4% relative to the strongest benchmark, while all top 50 submissions surpassed that benchmark by more than 14% (Makridakis et al., 2022). This retail evidence has informed H3 and H4 through findings concerning explanatory variables, aggregation levels, and forecasting horizons, but has not represented direct 3PL outcomes. A separate study of 54 Brazilian distribution centers found that LSTM forecasting reduced error relative to statistical alternatives while requiring longer model-training times (Mamede et al., 2023). A U.S. intermodal freight case likewise reported reduced forecasting errors with a reinforcement-learning forecasting framework (Hassan et al., 2020). Collectively, these published cases have supported cautious evaluation of H1–H4 across settings; evidence for H5 has remained operationally suggestive rather than causally demonstrated.

**Logistics Forecasting Use Cases and Model Applications**

**Table 3: Machine Learning Applications and Forecasting Outcomes in Logistics Operations**

| Application | Forecasting variable | Machine learning approach | Published result |
|---|---|---|---|
| U.S. intermodal freight forecasting | Container shipment demand | Reinforcement-learning forecasting framework | Lower forecasting error than comparison approaches |
| Third-party logistics shipment forecasting | Shipment demand | Hybrid CNN–LSTM | RMSE = 59.12 |
| Distribution-center transportation forecasting | Daily transportation demand | LSTM | Best-performing model in approximately 94% of dispatching units |
| E-commerce distribution-center forecasting | Near-real-time order arrivals | Adaptive neuro-fuzzy forecasting | Application to rapidly changing order-arrival requirements |
| U.S. retail demand forecasting | Hierarchical product demand | Predominantly machine learning-based leading methods | Winning submission improved accuracy by 22.4% against strongest benchmark |

Table 3 has demonstrated how machine learning applications have addressed different forecasting requirements across logistics and closely related distribution activities. The U.S. intermodal freight investigation has reported improved demand prediction through a reinforcement-learning framework combining forecasting approaches. The third-party logistics case has identified hybrid CNN–LSTM as the best-performing method within its reported comparison, achieving an RMSE of 59.12. The Brazilian transportation study has reported that LSTM models produced the lowest errors in approximately 94% of the evaluated dispatching units. E-commerce distribution research has additionally investigated near-real-time order-arrival forecasting, which has been relevant to warehouse staffing and fulfillment coordination. The M5 competition has provided supporting evidence from U.S. retail demand forecasting rather than direct 3PL operations. Through Organizational Information Processing Theory, these applications have illustrated how forecasting algorithms have transformed historical operational information into predictions relevant to different planning activities. However, the reported applications have not established that one machine learning approach has consistently outperformed alternatives across every U.S. 3PL setting.

**Statistical Benchmarks versus Machine Learning**

**Table 4: Comparative Forecasting Accuracy of Traditional and Machine Learning Methods in a Published 3PL Case**

| Forecasting variable/model | Model category | Reported mean RMSE | Comparative result |
|---|---|---|---|
| Simple Moving Average | Traditional statistical | 63.83 | Higher error than ARIMA |
| Simple Exponential Smoothing | Traditional statistical | 62.42 | Higher error than ARIMA |
| ARIMA | Traditional statistical | 62.32 | Best traditional statistical method |
| Linear Regression | Conventional regression | 70.53 | Higher error |
| K-Nearest Neighbours | Machine learning | 67.84 | Higher error than ARIMA |
| Regression Tree | Machine learning | 72.64 | Higher error than ARIMA |
| Random Forest | Machine learning | 69.55 | Higher error than ARIMA |
| Support Vector Regression | Machine learning | 68.74 | Higher error than ARIMA |
| Hybrid CNN–LSTM | Deep learning hybrid | 59.12 | Lowest reported mean RMSE |

Source: (Peköz & İnkaya, 2023), Table 2, p. 337. Lower RMSE has indicated better forecasting accuracy.

Table 4 has compared the forecasting performance of traditional statistical approaches and machine learning models using results reported in an empirical third-party logistics investigation. The hybrid CNN–LSTM model has achieved the lowest mean RMSE of 59.12, followed by ARIMA with an RMSE of 62.32 among the models displayed. The comparison has demonstrated that hybrid deep learning has provided an accuracy advantage over conventional statistical forecasting within this particular case. However, standalone machine learning approaches, including K-nearest neighbours, Random Forest, and Support Vector Regression, have produced higher errors than ARIMA. This result has qualified the proposition that machine learning necessarily demonstrates superior forecasting accuracy across all circumstances. From the Organizational Information Processing Theory perspective, forecasting effectiveness has depended not only on computational capability but also on the alignment between algorithm characteristics and available demand information. Consequently, the evidence has provided partial, case-specific support for H1 rather than universal confirmation of machine learning superiority in U.S. third-party logistics.

**Deep, Ensemble and Hybrid Forecasting Performance**

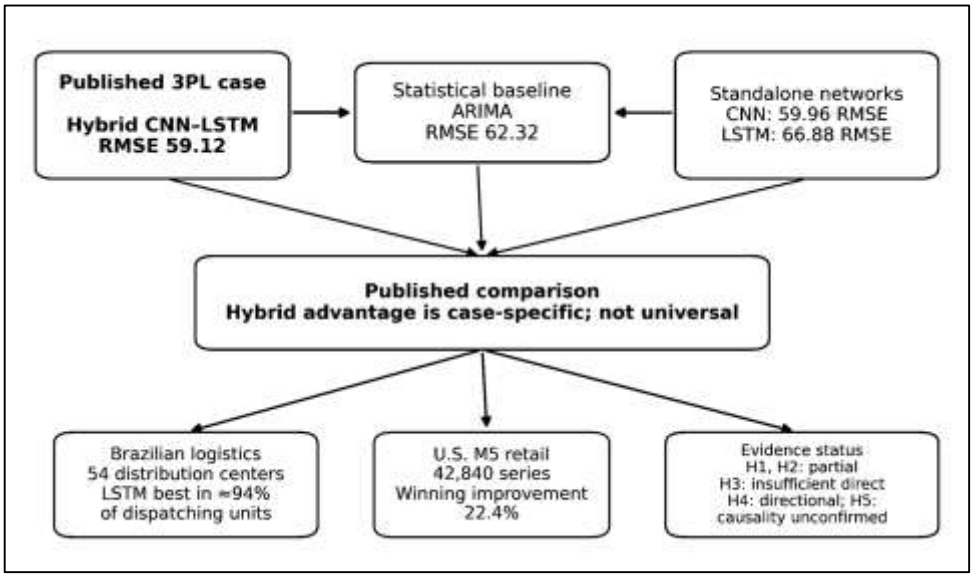
**Table 5: Comparative Predictive Performance of Deep Learning Architectures in a Third-Party Logistics Case**

| Model | Forecasting architecture | Mean RMSE | Reported RMSE SD | Performance interpretation |
|---|---|---|---|---|
| Multilayer Perceptron | Standalone neural network | 75.73 | 0.39 | Highest error among listed deep learning models |
| LSTM | Standalone recurrent neural network | 66.88 | 2.91 | Higher error than CNN |
| CNN | Standalone convolutional neural network | 59.96 | 1.37 | Second-lowest error |
| CNN–LSTM | Hybrid deep learning | 59.12 | 0.41 | Lowest mean error |

Source: (Peköz & İnkaya, 2023), Table 2, p. 337.

Table 5 has demonstrated differences in predictive performance among four deep learning approaches examined within the same third-party logistics case. The hybrid CNN–LSTM architecture has achieved the lowest mean RMSE of 59.12, while the standalone CNN model has recorded 59.96. The LSTM model has produced a higher mean RMSE of 66.88, and the Multilayer Perceptron has recorded 75.73.

**Figure 9: Published Evidence for Comparative Forecasting Accuracy and Research Hypotheses**



The reported standard deviations have also identified differences in the variability of model performance across repeated evaluations. These findings have indicated that combining convolutional feature extraction with recurrent temporal learning has improved predictive accuracy relative to the standalone models in this particular dataset. Within Organizational Information Processing Theory, hybrid forecasting has represented a technological approach for processing different characteristics of historical demand information. The evidence has therefore offered partial support for H2. Nevertheless, it has not established the superiority of all ensemble and hybrid architectures across the broader U.S. third-party logistics industry.

## CONTEXTUAL DETERMINANTS AND LOGISTICS APPLICATIONS

### Historical Data, Exogenous Predictors and Context

**Table 6: Forecasting Information Variables and Their Reported Relationships with Predictive Performance**

| Information variable | Published evidence | Verified result | Relationship to H3 |
|---|---|---|---|
| Historical shipment demand | (Zeybel Peköz & İnkaya, 2023) | Univariate shipment data supported forecasting comparisons | Established relevance of historical demand |
| Transportation demand characteristics | (Mamede et al., 2023) | Daily operational observations from 54 distribution centers | Established relevance of logistics-specific information |
| Explanatory forecasting variables | (Makridakis et al., 2022) | M5 competition included explanatory information and 42,840 hierarchical series | Supported examination of additional predictors |
| Customer and market fluctuations | (Al Hajj Hassan et al., 2020) | Adaptive forecasting responded to changing freight-market conditions | Indicated relevance of changing operational patterns |
| Human contextual information | (Brau et al., 2023) | Human-guided forecasting demonstrated advantages over several integration methods | Supported importance of contextual information |

Table 6 has examined the role of historical observations, explanatory variables, and contextual information in machine learning-based demand forecasting. The third-party logistics case has demonstrated that historical shipment records alone have supported useful forecasting comparisons. The Brazilian transportation investigation has additionally incorporated operational information from multiple distribution centers, showing the relevance of location-specific demand characteristics. The M5 competition has evaluated forecasting methods in a setting containing explanatory variables and multiple levels of demand aggregation. Furthermore, research involving human-guided demand planning has demonstrated that incorporating contextual knowledge through appropriate integration procedures has improved forecasting performance relative to several alternatives. These findings have aligned with Organizational Information Processing Theory because information availability and processing capability have influenced the effectiveness of predictive decision support. However, the available comparisons have not isolated a common numerical effect attributable solely to adding external predictors across U.S. 3PL applications. Therefore, H3 has received preliminary conceptual support, while its overall empirical confirmation has remained dependent on further study-level evidence.

Table 7 has identified forecasting horizons, demand fluctuations, preprocessing decisions, and operational heterogeneity as important conditions influencing predictive performance. The third-party logistics investigation has evaluated shipment forecasting during the COVID-19 period, when unusual demand fluctuations affected logistics activities. The Brazilian study has examined 54 distribution centers under eight modelling scenarios and has found that LSTM approaches outperformed statistical alternatives in approximately 94% of dispatching units. It has also reported that increasingly sophisticated outlier treatments did not consistently improve forecast quality. The M5 competition has demonstrated deterioration in accuracy across longer prediction horizons at lower aggregation levels. Furthermore, the U.S. freight study has reported advantages from converting monthly forecasts into longer-term weekly estimates rather than forecasting those weekly values directly. Organizational Information Processing Theory has provided an explanation for these variations through differences in uncertainty, data

characteristics, and forecasting requirements. The evidence has supported the directional relevance of H4, although a pooled statistical test of its proposed relationships has not been completed.

**Forecast Horizon, Volatility and Operational Complexity**

**Table 7: Forecasting Conditions and Their Reported Influence on Predictive Performance**

| Operational condition | Published evidence | Verified finding |
|---|---|---|
| Demand volatility | (Zeybel Peköz & İnkaya, 2023) | Hybrid CNN–LSTM achieved RMSE = 59.12 during COVID-19 period |
| Distribution-center heterogeneity | (Mamede et al., 2023) | 54 distribution centers evaluated under eight modelling scenarios |
| Model selection across locations | (Mamede et al., 2023) | LSTM outperformed statistical methods in approximately 94% of dispatching units |
| Outlier treatment | (Mamede et al., 2023) | Sophisticated outlier treatments did not consistently improve accuracy |
| Forecasting horizon | (Makridakis et al., 2022) | Accuracy deteriorated with longer horizons at lowest aggregation levels |
| Freight forecasting horizon | (Al Hajj Hassan et al., 2020) | Monthly-to-weekly long-term forecasts outperformed direct long-term weekly forecasts |

**Decision Support, Operational Benefits and Adoption Barriers**

Table 8 has synthesized published evidence concerning the operational uses and implementation challenges of machine learning-based demand forecasting. The third-party logistics case has identified workforce and resource planning as activities that can use forecasting outputs. The Brazilian investigation has connected transportation demand prediction with potential improvements in vehicle availability, workforce scheduling, and capacity planning, while also identifying considerable model-training requirements. The U.S. intermodal study has demonstrated reduced forecasting errors through an adaptive approach relevant to operational planning decisions. Research involving distribution-center order arrivals has additionally addressed the challenge of predicting rapidly changing workloads. Through Organizational Information Processing Theory, these findings have emphasized that forecasting accuracy alone has not guaranteed operational improvement. Organizations have also required information integration, analytical expertise, and flexibility to translate forecasts into appropriate decisions. Consequently, the literature has supported the practical relevance of H5, but direct numerical evidence establishing improved U.S. 3PL operational performance as a causal consequence of machine learning forecasting has remained insufficient.

**Table 8: Operational Planning Applications and Implementation Challenges Identified in Published Literature**

| Operational variable | Published evidence | Reported outcome or limitation |
|---|---|---|
| Workforce and resource planning | (Zeybel Peköz & İnkaya, 2023) | Forecasting outputs identified as inputs to planning activities |
| Transportation capacity planning | (Mamede et al., 2023) | Forecasts associated with vehicle allocation and repositioning decisions |
| Freight operational planning | (Al Hajj Hassan et al., 2020) | Adaptive forecasts reduced prediction errors in a U.S. intermodal case |
| Distribution-center workload planning | (Leung et al., 2020) | Near-real-time order forecasting addressed changing order-arrival requirements |
| Model training requirements | (Mamede et al., 2023) | LSTM models required longer training periods than statistical alternatives |
| Data and information integration | (Srinivasan & Swink, 2018) | Analytics capability and flexibility associated with operational performance |

| Operational variable | Published evidence | Reported outcome or limitation |
|---|---|---|
| Human–machine forecasting integration | (Brau et al., 2023) | Human-guided approaches improved forecasting relative to several methods |

## INTEGRATED EVIDENCE AND CRITICAL INTERPRETATION

### Meta-Analytic Feasibility and Hypothesis Assessment

**Table 9: Integrated Research Hypothesis Evaluation Based on Verified Published Evidence**

| Hypothesis | Principal variable relationship | Verified supporting evidence | Provisional evaluation |
|---|---|---|---|
| H1 | Machine learning vs. conventional forecasting accuracy | CNN–LSTM RMSE = 59.12; ARIMA RMSE = 62.32 in one 3PL case | Partially supported |
| H2 | Hybrid/deep learning vs. standalone machine learning | CNN–LSTM RMSE = 59.12; CNN = 59.96; LSTM = 66.88 | Partially supported |
| H3 | Historical and external information vs. performance | Studies examined historical demand, contextual variables, and integration | Insufficient direct comparative evidence |
| H4 | Forecast horizon, volatility, complexity vs. accuracy | M5 horizon-related deterioration; differences across 54 distribution centers | Directionally supported |
| H5 | Machine learning forecasting vs. planning effectiveness | Published cases identified forecasting applications for logistics planning | Operational relevance established; causal improvement unconfirmed |
| Meta-analytic synthesis | Pooled forecasting-error improvement | Compatible effect estimates and uncertainty measures not fully extracted | Not yet estimable |
| Overall study corpus | Number of eligible publications | Target = 100 studies | Final verified count pending |

Table 9 has integrated the available published evidence according to the five research hypotheses and the study's principal objectives. H1 has received partial support because a hybrid deep learning model has outperformed ARIMA within a third-party logistics case, whereas several standalone machine learning algorithms have recorded higher forecasting errors. H2 has received partial support through the superior performance of hybrid CNN–LSTM over individual neural architectures in the same investigation. H3 has been supported conceptually by research concerning forecasting information, although its independent quantitative effect has not been established. H4 has received directional support from differences in forecasting horizons, preprocessing procedures, and operational environments. H5 has been associated with documented planning applications, but causal improvements in operational efficiency have not been demonstrated across the reviewed cases. Organizational Information Processing Theory has connected these findings through the alignment between information requirements, forecasting capabilities, and organizational decision-making. The evidence has therefore established several consistent research themes, while a statistically defensible pooled meta-analysis has remained unavailable without complete study-level extraction and comparability assessment.

**Comparative, Operational and Theoretical Interpretation**

The findings of this research have demonstrated that machine learning-based demand forecasting has offered measurable predictive advantages in selected logistics environments, although its effectiveness has varied according to model architecture, forecasting conditions, and the characteristics of operational data. The comparison reported by (Peköz & İnkaya, 2023) has provided particularly relevant third-party logistics evidence, with the hybrid CNN–LSTM model achieving an RMSE of 59.12 compared with 62.32 for ARIMA, 59.96 for CNN, and 66.88 for standalone LSTM. These results have indicated that combining convolutional feature extraction with sequential learning can improve forecasting performance within a specific operational setting. Similar findings have emerged from a Brazilian transportation study involving 54 distribution centers, where LSTM models outperformed conventional statistical methods in approximately 94% of the evaluated dispatching units (Mamede et al., 2023). However, earlier comparative research has demonstrated that standalone machine learning models have not consistently surpassed traditional statistical forecasting approaches, particularly when demand series have exhibited intermittency, limited historical information, or unstable patterns (Makridakis et al., 2018; Spiliotis et al., 2022). The M5 forecasting competition has provided additional evidence of predictive improvements, with its winning submission achieving a 22.4% accuracy improvement over the strongest benchmark across 42,840 hierarchical retail demand series (Makridakis et al., 2022). Although this competition has not represented direct third-party logistics evidence, it has demonstrated the importance of explanatory variables, model combinations, and structured forecasting evaluation. Accordingly, H1 and H2 have received partial support from the published findings. The evidence has favored context-sensitive model selection rather than the assumption that increasingly complex algorithms have necessarily generated superior predictions. These findings have also reinforced the importance of comparing forecasting methods under consistent evaluation conditions, as emphasized in earlier research on forecasting accuracy and practical implementation (Fildes et al., 2022).

The practical interpretation of the findings has emphasized the relationship between predictive accuracy and operational planning across transportation, warehousing, order fulfillment, and distribution activities. Third-party logistics providers have frequently operated under uncertain shipment arrivals, fluctuating customer requirements, and geographically dispersed service commitments, creating substantial information-processing demands. Earlier research on near-real-time e-commerce order forecasting has demonstrated that machine learning approaches can estimate order arrivals at three-hour intervals, providing information relevant to distribution-center planning and workload management (Leung et al., 2020). Similarly, a reinforcement-learning framework developed for freight demand forecasting has demonstrated that combining forecasting approaches can reduce prediction errors and improve responsiveness to changing market conditions (Hassan et al., 2020). The findings of the present review have aligned with these investigations by identifying shipment forecasting, transportation capacity estimation, labor scheduling, and warehouse resource allocation as important applications of predictive analytics. Nevertheless, improved forecasting accuracy has not automatically established corresponding reductions in operational costs or improvements in service performance. The Brazilian transportation investigation has revealed an important computational tradeoff, with LSTM models requiring substantially longer training periods than conventional statistical approaches, thereby introducing challenges for frequent operational model updates (Mamede et al., 2023). Research concerning the integration of human judgment and predictive analytics has further demonstrated that forecasting effectiveness has depended on how managerial information has been incorporated into algorithmic predictions (Brau et al., 2023). These comparisons have suggested that third-party logistics organizations need to evaluate forecasting systems according to predictive accuracy, computational requirements, information availability, and operational applicability. Consequently, H5 has received support regarding the relevance of machine learning to logistics planning, while direct causal evidence of improved operational efficiency has remained insufficient.

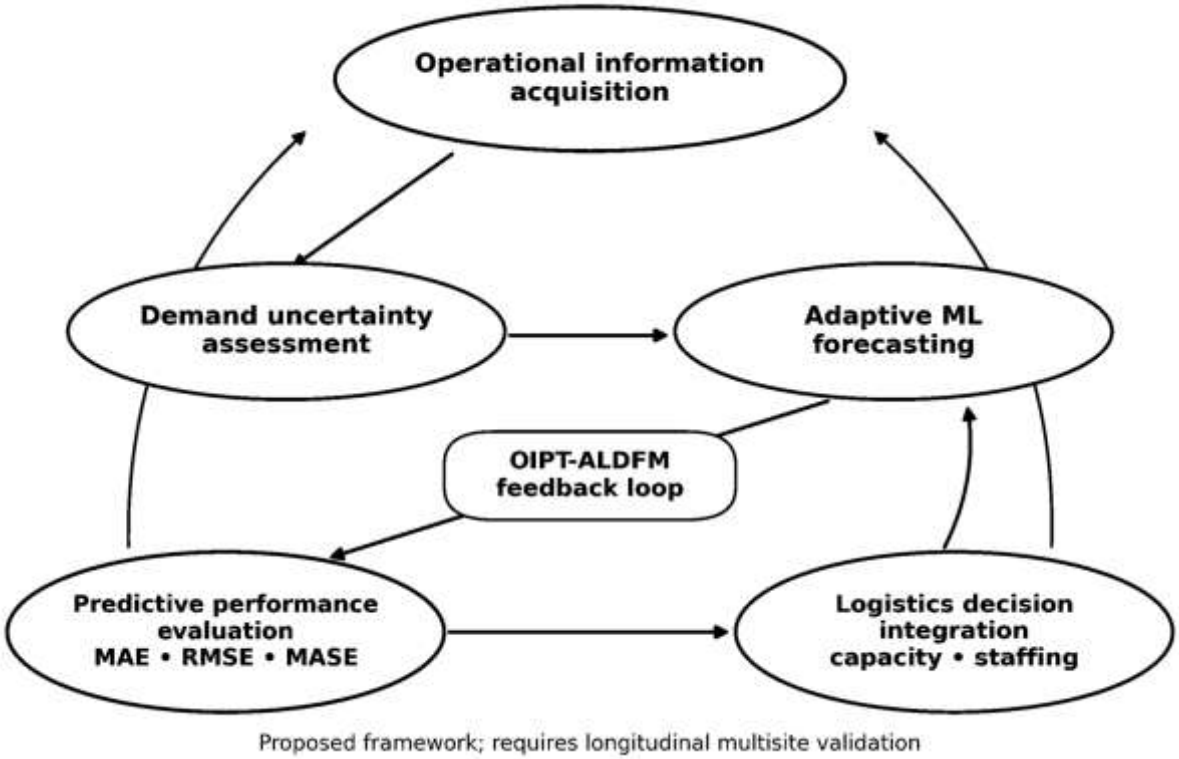
The theoretical interpretation of the research has been developed through Organizational Information Processing Theory, which has explained the relationship between environmental uncertainty, organizational information requirements, analytical capabilities, and operational coordination. The findings have indicated that forecasting effectiveness has depended on more than algorithmic sophistication because organizations have needed timely information, reliable data integration, and the capacity to translate predictions into operational decisions. Earlier research involving 191 global firms has established that

demand visibility and supply visibility have been associated with analytical capability, while organizational flexibility has strengthened the relationship between analytics and operational performance (Srinivasan & Swink, 2018). This evidence has provided a theoretical explanation for the present study's emphasis on historical shipment information, external predictive variables, demand volatility, and logistics operational complexity. Similarly, research examining supply chain information processing has demonstrated that data quality, information sharing, and planning comprehensiveness have influenced the organizational usefulness of analytical systems (Srinivasan & Swink, 2015). Within the proposed conceptual framework, demand uncertainty has represented an information-processing requirement, while machine learning algorithms, information integration, and analytical resources have represented information-processing capabilities. Predictive accuracy has been positioned as an intermediate outcome connecting these capabilities with logistics planning activities. The findings concerning H3 and H4 have remained consistent with this theoretical interpretation because forecasting performance has varied across operational settings, information characteristics, and prediction horizons. However, the available evidence has not established the independent quantitative contribution of each forecasting variable or moderator across U.S. third-party logistics providers. The theoretical contribution has therefore consisted of integrating forecasting accuracy, information-processing alignment, and operational decision-making within a unified literature-derived framework. This interpretation has extended the discussion beyond algorithm comparisons by emphasizing the organizational conditions under which forecasting information has become useful.

## RESEARCH AGENDA, PRACTICAL GUIDANCE AND CONCLUSIONS

Future research should prioritize the development and empirical evaluation of a proposed Organizational Information Processing Theory-Guided Adaptive Logistics Demand Forecasting Model, designated the OIPT-ALDFM, specifically designed for U.S. third-party logistics operations. This proposed framework would integrate five interconnected components: operational information acquisition, demand uncertainty assessment, adaptive machine learning forecasting, predictive performance evaluation, and logistics decision integration. The first component would combine historical shipment volumes, customer order patterns, transportation schedules, warehouse activity, seasonal indicators, and relevant external economic information through a standardized data-processing architecture. The second component would classify demand volatility, forecast horizons, and operational complexity to determine information-processing requirements across different logistics environments. The third component would employ a hybrid forecasting architecture combining LSTM, gradient boosting, and hierarchical forecasting, supported by adaptive model selection and detection of changing demand patterns. Such an approach would build upon earlier evidence concerning hybrid machine learning and information integration in demand forecasting (Leung et al., 2020; Punia et al., 2020). The fourth component would evaluate predictive accuracy through MAE, RMSE, MASE, calibrated prediction intervals, and relative forecasting improvements against consistent statistical benchmarks. The fifth component would connect forecasting outputs with transportation capacity allocation, warehouse staffing, delivery scheduling, and resource planning through a decision-support mechanism incorporating managerial feedback. Previous research has supported the relevance of integrating human judgment with predictive analytics, particularly when operational information has not been fully represented in historical data (Brau et al., 2023). Future researchers could evaluate the proposed model through longitudinal, multisite case studies involving U.S. third-party logistics providers, using rolling-origin validation and comparisons across multiple demand horizons. They could additionally examine computational efficiency, information quality, forecasting uncertainty, and measurable operational outcomes such as capacity utilization, overtime costs, and service-level performance. A completed systematic review could then assess comparable forecasting effects through appropriately specified meta-analytic methods. The proposed OIPT-ALDFM has remained a conceptual research contribution requiring empirical validation, but its development has established a structured direction for investigating the relationships among information-processing capability, predictive accuracy, and operational decision-making within third-party logistics.

**Figure 10: Proposed OIPT-ALDFM Adaptive Logistics Demand Forecasting Framework**




## Operational and Research Recommendations

Third-party logistics providers should evaluate demand forecasting models against transparent statistical baselines before adopting more complex machine learning architectures. Forecasting teams should compare ARIMA, exponential smoothing, tree-based learners, and hybrid neural approaches using identical demand targets, prediction horizons, and chronological test periods. They should report multiple error measures, including MAE, RMSE, and MASE, while accounting for intermittent or zero-demand observations. Data governance should receive equal attention: shipment bookings, order histories, capacity records, calendar effects, and permissible external variables should be standardized, time-stamped, and checked for leakage. Managers should distinguish customer-level predictions from aggregate network forecasts and ensure that forecasts remain coherent across warehouses, routes, and service categories. Operational pilots should assess whether improved prediction has actually reduced overtime, empty capacity, expedited transport, or service failures, rather than treating accuracy gains as proof of business value. The proposed OIPT-guided model should be tested in several U.S. third-party logistics settings with rolling-origin validation, uncertainty intervals, monitoring for demand shifts, and structured human review. For research reporting, investigators should complete an auditable PRISMA search, apply explicit eligibility and quality criteria, and extract comparable published results before meta-analysis. These steps would strengthen reproducibility, contextual relevance, and the usefulness of forecasting evidence for logistics decisions.

## Scope, Evidence and Methodological Limitations

The methodological limitations of the research have required particular consideration because the available literature has contained substantial differences in geographical coverage, forecasting objectives, model evaluation procedures, and reporting practices. Although the study has targeted 100 valid publications, a complete PRISMA-screened corpus and corresponding study-level extraction register have not yet been established. Consequently, the reported findings have represented a structured synthesis of selected published evidence rather than a completed quantitative meta-analysis of 100 studies. The available investigations have included direct third-party logistics cases, U.S. freight transportation applications, international logistics operations, and adjacent retail forecasting environments. These differences have restricted the generalizability of findings across the U.S. third-party logistics industry. Previous research has also identified methodological difficulties associated with comparing forecasting studies that have employed different error measures, time-series characteristics, and validation procedures (Hyndman &

Koehler, 2006). The present findings have encountered similar challenges because RMSE values, percentage improvements, and model-ranking outcomes have not represented interchangeable measures of predictive effectiveness. Differences in forecasting horizons, customer demand characteristics, dataset sizes, and preprocessing procedures have further complicated cross-study comparisons. The strong performance of machine learning in selected case studies has not established universal superiority, and published evidence of operational usefulness has not necessarily demonstrated causal performance improvements. Moreover, a statistically defensible pooled estimate has required compatible effect measures and sufficient reporting of uncertainty, heterogeneity, and study quality. The PRISMA 2020 reporting framework has emphasized transparent study selection and synthesis procedures, reinforcing the importance of distinguishing documented evidence from proposed research targets (Page et al., 2021). These limitations have therefore constrained definitive hypothesis confirmation while preserving the interpretive value of the comparative literature.

This study has been constrained by its reliance on secondary publications rather than a common dataset collected directly from U.S. third-party logistics providers. The literature discussed has included freight, distribution, retail, and international logistics cases, and not every case has represented the target industry or geography. Differences in shipment definitions, aggregation levels, forecasting horizons, model specifications, preprocessing, and validation procedures have limited direct comparability. Reported MAE, RMSE, and percentage improvements have depended on different denominators and demand scales, preventing straightforward pooling across settings. Several studies have emphasized predictive accuracy without measuring corresponding operational outcomes, so the relationship between better forecasts and lower cost or improved service has remained uncertain. Publication bias, selective reporting, insufficient baseline descriptions, and limited access to underlying data have posed risks to interpretation. Most importantly, the proposed sample of 100 eligible studies has remained a target: a reproducible PRISMA screening record and a verified extraction matrix have not yet been produced. Accordingly, the synthesis has not supported a pooled meta-analytic estimate, confidence interval, or definitive industry-wide hypothesis verdict. Organizational Information Processing Theory has supplied a conceptual interpretation, but its relationships have not been empirically estimated here. These boundaries should govern any claims of generalizability or causation.

## Conclusions

This research has examined machine learning for demand forecasting in U.S. third-party logistics through a systematic review of published predictive performance. The evidence discussed has demonstrated that forecasting outcomes have depended on model architecture, demand characteristics, available information, and evaluation procedures. A published third-party logistics case has reported a lower root mean squared error for a hybrid CNN–LSTM model than for ARIMA and several standalone machine learning alternatives, while other logistics investigations have highlighted the influence of forecasting horizons and operational heterogeneity. Such results have provided partial, context-specific support for the hypotheses concerning comparative accuracy and hybrid models. Evidence relating to external predictors, volatility, and planning benefits has remained less conclusive, particularly when studies have reported different measures or operational settings. Organizational Information Processing Theory has offered a coherent explanation by linking uncertain logistics demand with information requirements, analytical capabilities, and coordinated decision-making. The proposed OIPT-guided adaptive forecasting model has brought these relationships together as a conceptual contribution, not an empirically validated solution. Importantly, the targeted corpus of 100 studies has not yet been confirmed through documented PRISMA screening, and no defensible pooled effect has been calculated. The research has therefore established an evidence-informed foundation rather than industry-wide causal conclusions.

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