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Artificial Intelligence-Driven Forecasting Practices and Supply Chain Performance: Toward a Conceptual Framework

Abdellatif El Hanaoui*
Cadi Ayyad University, Marrakech, Morocco
(a.elhanaoui.ced@uca.ac.ma)

Sarra Mrani Zentar*
Cadi Ayyad University, Marrakech, Morocco
(mranizentar.sarra2@gmail.com)

Abstract:
In an economic environment characterized by increasing demand volatility, conventional forecasting methods are revealing their limitations, prompting growing interest in demand sensing. While artificial intelligence (AI) is widely regarded as a catalyst for this transition, the precise mechanisms through which it transforms practices and impacts supply chain performance remain inadequately elucidated in the academic literature. To address this gap, this article develops the "AI–Demand Sensing–Performance (ADPsc)" conceptual model, which explicates the relationships between AI capabilities, demand sensing implementation, and supply chain performance. This study is purely conceptual and does not involve primary data collection. It is based on a structured literature review conducted using major scientific databases, with predefined keywords related to artificial intelligence, demand sensing, demand forecasting, and supply chain performance. Grounded in a deductive methodology rooted in contingency theory, this research constructs a theoretical framework articulated around three interdependent pillars: (1) real-time, multi-source data integration, (2) processing through AI algorithms, and (3) operational activation, all driven by a continuous learning loop. The ADPsc model highlights the moderating role of AI in the impact of demand sensing on performance. It demonstrates that AI serves not merely as an optimization tool, but as the foundation for a continuous adaptive capability, thereby enabling unprecedented responsiveness to demand fluctuations

Keywords: Supply Chain Performance, Artificial Intelligence, Demand Sensing, Forecasting, ADPsc Conceptual Model

1 Introduction

In an economic landscape characterized by the globalization of trade and the acceleration of production cycles, the pursuit of operational excellence in supply chain management has become a major strategic imperative for corporations. Supply chain performance a complex and multidimensional concept is now measured by its ability to reconcile operational efficiency with adaptability in an increasingly unpredictable environment. This tension between optimization and flexibility is particularly evident in the crucial domain of demand forecasting, where traditional methods reveal their limitations in the face of contemporary market volatility.

The recent emergence of demand sensing, an approach aimed at capturing very short-term demand signals, represents a promising evolution to address these challenges. Concurrently, dramatic advances in artificial intelligence (AI) offer new prospects for transforming supply chain management. However, while the literature agrees on the theoretical potential of these two fields, their interrelationships and their combined impact on performance remain underexplored. Numerous studies address AI-driven demand sensing, yet they fail to provide an integrative framework for understanding their synergies on supply chain performance.

This research aims precisely to fill this gap by proposing a conceptual model: the "AI-Demand Sensing-Performance" (ADPsc) model. Our approach is structured around three fundamental pillars. First, we will conduct a comprehensive analysis of the literature concerning supply chain performance and the limitations of traditional forecasting approaches. Subsequently, we will examine how AI is transforming demand management practices, shedding light on both its contributions and its implementation challenges. Finally, we will present our conceptual ADPsc model, which formalizes the relationships between AI capabilities, the implementation of demand sensing, and performance enhancement.

The significance of this work lies in its ambition to transcend a fragmented perspective and propose a unified analytical framework. The ADPsc model does not merely describe technologies or concepts; rather, it establishes the logical connections that elucidate how AI-powered demand sensing significantly contributes to the improvement of supply chain performance.

2 Literature Review and Theoretical Foundations

2.1 Supply Chain Performance: A Conceptual Definition

The supply chain encompasses the integrated management of all activities from sourcing and production to storage, logistics, distribution, and returns/recycling, with the ultimate objective of delivering the right product to the correct location at the optimal time and minimal cost. Given this extensive scope, its performance must be conceptualized as a multidimensional construct. It inherently combines financial and operational criteria, encompassing metrics such as profitability and return on investment, alongside delivery timeliness, reliability (Mehmeti et al., 2016), inventory levels, and perceived customer quality (Tan et al., 1999). Beyond this economic dimension, performance also incorporates qualitative indicators related to partner satisfaction, environmental sustainability (Ivanov & Dolgui, 2020), and innovation capacity (Piotrowicz & Cuthbertson, 2015).

This multifaceted performance is influenced by a confluence of factors. From a strategic standpoint, the alignment between corporate strategy and supply chain objectives is paramount for ensuring coherent and efficient flows, as is the configuration of the logistics network and its governance models. Organizational resources and capabilities also play a central role; for instance, Hofmann and Reiner (2006) emphasize that integrated information systems and digital technologies significantly contribute to achieving performance goals. Operational flexibility and the commitment of top management are equally critical. Furthermore, the collaborative dimension is a key determinant. Trust, information sharing, and sustainable partnerships with stakeholders foster activity synchronization and joint innovation (Rana & Bin Osman, 2018). Conversely, purely transactional relationships tend to undermine overall performance.

However, the increasing complexity of networks and demand uncertainty expose supply chains to significant risks of disruption, delays, and additional costs (Chand et al., 2022). High-performing companies are those that develop resilience strategies by diversifying their sources, establishing safety stock, and investing in forecasting tools.

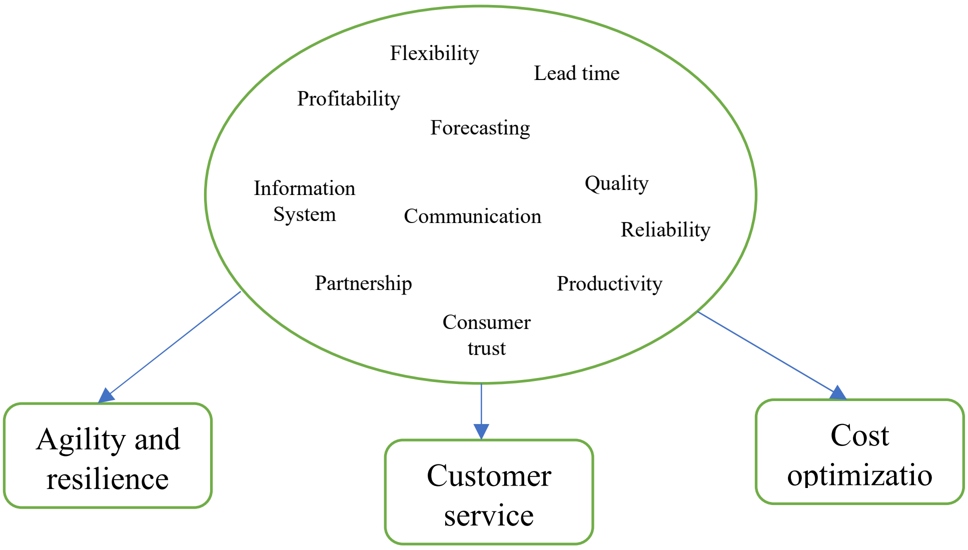
Supply chain performance now constitutes a major strategic lever for corporate competitiveness. Indeed, in an environment characterized by the globalization of trade and demand volatility, the ability to design and manage an efficient supply chain directly determines value creation. It is no longer confined to a cost-optimization logic but now encompasses responsiveness, flexibility, service quality, and resilience in the face of various disruptions.

Consequently, supply chain performance is measured through both quantitative and qualitative indicators, notably:

- Service Level ("OTIF" - On-Time In-Full)
- Stockout Rate
- Inventory Turnover
- Logistics Cost as a Percentage of Revenue
- Lead Time (the period between order and delivery)

In essence, an effective supply chain materializes through cost optimization, satisfactory customer service, and sustained operational agility. The following diagram illustrates these three core dimensions

Figure 1: Supply Chain Performance



Source: Author's own elaboration

2.2 Supply Chain and Demand Forecasting: The Age of Limitations

Undoubtedly, the modern supply chain operates in an environment of unprecedented complexity. In an environment where demand has become increasingly uncertain and difficult to anticipate, product hyper-personalization, and the rapid growth of e-commerce are reshaping competitive dynamics, the traditional supply chain, built upon a linear and reactive logic, is reaching the limits of its effectiveness (Remko, 2020). The Achilles' heel of this ostensibly traditional structure remains demand forecasting. Indeed, every erroneous forecast triggers a devastating bullwhip effect[1] (Michna et all, 2002), generating either costly stockouts or surplus inventory that erodes profitability.

In the face of this challenge, traditional statistical approaches, while useful, are no longer sufficient. It is within this context that artificial intelligence (AI) is emerging not merely as a technological option, but as a fundamental paradigm for building an agile, resilient, and predictive supply chain (Bednarski et al., 2025; Riad et al., 2024).

2.2.1 Demand Sensing and Traditional Approaches

Demand forecasting is a managerial and analytical process that involves estimating the future quantity of goods or services a market will acquire over a given period and under specific commercial conditions. It is a discipline at the confluence of marketing, operations research, and supply chain management.

Its primary objective is to reduce the uncertainty surrounding procurement, production, distribution, and inventory management decisions. Forecasts can be qualitative (relying on intuition and expertise) or quantitative (relying on mathematical models and historical data). The accuracy of a forecast is typically measured by the error between the predicted value and the actual value, using metrics such as the Mean Absolute Error, Mean Squared Error, among others. In essence, demand forecasting is the art and science of estimating future customer needs for a product or service. Historically, demand forecasting has relied on so-called classical methods, notably Time-Series Forecasting. These models aim to extrapolate future outcomes based exclusively on historical sales data. The most prevalent among these include:

- Moving Average: Smooths out fluctuations by averaging data from the most recent *n* periods.
- Exponential Smoothing: Assigns greater weight to more recent observations than to older ones.
- ARIMA[2] (AutoRegressive Integrated Moving Average): A sophisticated model designed to capture underlying trends, seasonality, and autocorrelations within historical data.

In contrast, Demand Sensing represents a significant evolution in supply chain demand management. It is fundamentally distinct from these classical approaches, which are

[1] The bullwhip effect is a supply chain dynamic wherein small variations in end-consumer demand become amplified into significant swings in order quantities and inventory levels at upstream echelons, such as distributors, wholesalers, and producers.
[2] ARIMA (Autoregressive Integrated Moving Average) is a statistical model employed for forecasting time series data. It synthesizes three distinct components: an autoregressive (AR) component, an integration (I) component, and a moving average (MA) component.

primarily anchored in historical sales data. Rather than merely looking in the rearview mirror, Demand Sensing is defined as the capability to capture, integrate, and interpret near real-time data. It leverages advanced demand analytics to adjust short-term forecasts (ranging from a few hours to a few weeks) (Garg et al., 2024). While traditional forecasting addresses the question, "What will we sell next month?", Demand Sensing seeks to answer, "What will we sell tomorrow, or next week, based on current prevailing conditions?"

This methodology aims to minimize the latency between forecasts and actual market realities. It utilizes a diverse array of data sources including daily transactions, distributor signals, consumption trends, weather data, and even social media interactions to detect fluctuations in demand at the earliest possible stage.

For corporations, the value proposition is twofold. Firstly, Demand Sensing enhances the precision of operational decisions, such as inventory adjustments, production plan adaptations, and the optimization of transport and distribution. Secondly, it bolsters supply chain proactivity by enabling firms to anticipate variations rather than merely react to them. From a strategic perspective, this anticipatory capacity confers a decisive competitive advantage. It fosters superior customer satisfaction, mitigates financial losses associated with stockouts or excess inventory, and strengthens overall resilience in increasingly volatile markets.

2.2.2 Limitations of Classical Methods in the Face of Volatility

Traditional forecasting models, such as “ARIMA”, remain effective in stable and predictable environments. However, within the current context of uncertainty and volatility, their limitations become evident.

A primary shortcoming is their inability to integrate external signals. A viral social media post, an aggressive competitor promotion, or an unforeseen event fall entirely outside their scope. By failing to account for the broader marketing context, these models isolate themselves from decisive variables required to understand true demand. Furthermore, they lack agility. Implementations are typically executed on a weekly or monthly basis, and consequently, they react too slowly to sudden market fluctuations. This lag deprives organizations of the necessary responsiveness in a perpetually shifting marketplace.

These models are also prone to historical bias, effectively perpetuating past errors. A pertinent example is a product that experienced a stock-out last year; the model will mechanically project lower demand in the current year, thereby reinforcing the shortage and creating a self-fulfilling prophecy. Moreover, they prove ineffective in the face of novelty. For new product introductions, which lack historical data, these models become virtually unusable. In such scenarios, companies are left with no alternative but to rely on intuition and often arbitrary decisions that are disconnected from market reality.

This inherent rigidity in the face of volatility, complex and unstructured data, and the required speed of analysis creates a strategic imperative to adopt a new approach.

Consequently, companies face several major repercussions. The risk of stock-outs poses a direct threat, as the inability to meet demand leads to immediate revenue loss and a lasting deterioration of customer relationships. Conversely, the risk of overstock exerts significant pressure on cash flow. Surplus inventory immobilizes critical financial resources and increases exposure to product obsolescence, particularly in fast-paced, innovative sectors. Similarly, financial volatility is accentuated. The erosion of profit margins, coupled with unpredictable fluctuations in the costs of raw materials, transport, and energy, complicates budgetary planning and places sustained strain on the overall corporate performance.

2.3 Artificial Intelligence: A Toolkit for Enhanced Supply Chain Performance

Artificial intelligence is no longer an obscure or inaccessible domain, but rather a suite of algorithms that learn from data to identify patterns, make predictions, or automate decisions without being explicitly programmed for every specific scenario.

2.3.1 AI Models and Their Supply Chain Applications

Supervised Machine Learning (SML) serves as the cornerstone of modern demand sensing (Douaioui et al., 2024). Algorithms such as regression, random forests[3], and gradient boosting[4] are trained on labeled historical data. They learn the complex relationships between explanatory variables including price, promotions, weather, social trends, holidays, and syndicated distributor data and the target variable, sales. Once trained, the model can forecast future demand based on new inputs for these explanatory variables (Kagalwala et al., 2025).

[3] A machine learning method that builds many decision trees on subsets of data and then combines their results to improve accuracy and reduce overfitting.
[4] A machine learning method that builds a series of successive decision trees, where each new tree corrects the errors of the previous ones.

In a similar vein, Deep Learning, a subset of machine learning, utilizes deep neural networks. It is particularly powerful for processing highly complex and unstructured data (Babai et al., 2022). A prime application is the analysis of in-store shelf images to estimate stock levels in real-time. Likewise, Natural Language Processing (NLP) is used to analyze and decipher sentiment from social media, product reviews, and news articles to capture emerging trends. Reinforcement Learning offers another avenue, optimizing logistical decisions such as determining optimal stock levels or routing by learning through trial and error within a simulated environment.

Furthermore, AI systems are deployed to implement advanced time series models like Long Short-Term Memory networks (LSTMs)[5]. These are specifically designed to capture long-term, complex dependencies within sequential data, frequently surpassing the performance of traditional ARIMA models. This ecosystem is supported by a range of sophisticated software platforms, including *Blue Yonder* (formerly JDA), *o9 Solutions*, and *ToolsGroup*.

Indeed, artificial intelligence is fundamentally transforming supply chain management by providing powerful levers for optimization at every stage. In the domain of inventory management, predictive models enable demand to be anticipated at the most granular level by product, by point of sale, and even by day. When coupled with optimization algorithms, these models determine ideal order quantities and dynamic safety stock levels, thereby reducing tied-up capital while simultaneously strengthening service levels (Chopra & Meindl, 2016; Ivanov et al., 2017).

This predictive capability extends directly into production planning. Enhanced visibility into demand trends allows for more precise adjustments to manufacturing schedules, raw material procurement, and workforce allocation. Consequently, manufacturing facilities are able to minimize downtime and waste, leading to significant gains in operational efficiency (Christopher, 2011; Kouvelis et al., 2011).

Furthermore, AI paves the way for predictive logistics. By synthesizing multifaceted data streams such as weather conditions, traffic patterns, and social events these systems can anticipate transit delays, identify potential disruption risks, and propose corrective actions in real-time. They also optimize load planning for logistics assets and route selection,

[5] Long Short-Term Memory (LSTM) networks are a type of recurrent neural network (RNN) specifically designed to learn long-term dependencies in sequential data through an internal memory mechanism, making them particularly effective for time-series forecasting tasks such as demand prediction.

concurrently reducing both transportation costs and the carbon footprint (Hazen et al., 2018; Waller & Fawcett, 2013). Ultimately, this convergence of capabilities equips companies with a more agile, reliable, and sustainable supply chain, positioning it as a cornerstone for superior economic performance (Ivanov, 2021).

2.3.2 The Emergence of AI-Driven Demand Sensing: Identified Advantages and Shortcomings

Academic literature consistently reveals the tangible benefits associated with integrating artificial intelligence and machine learning into demand sensing. A major contribution is enhanced accuracy. Numerous studies indicate a reduction in forecasting errors of approximately 20% to 50% compared to traditional approaches, particularly for short-term horizons (Chopra & Meindl, 2016; Waller & Fawcett, 2013). This precision is coupled with unparalleled reactivity, as models can update forecasts on a daily or even hourly basis to adapt to sudden demand fluctuations (Hazen et al., 2018).

It is well-established that the use of AI contributes to a significant reduction of the bullwhip effect. By leveraging real-time consumption signals, firms can mitigate the successive distortions and amplifications of orders that destabilize the supply chain (Disney & Lambrecht, 2008). This dynamic fosters a simultaneous improvement in service levels and a reduction in stock-outs, enabling the achievement of the sought-after equilibrium between product availability and minimized capital tie-up, resulting in measurable financial gains in margin points (Christopher, 2011; Ivanov et al., 2016).

Furthermore, the integration of risk signals whether related to geopolitical, economic, or climatic disruptions enables companies to anticipate potential breakdowns and proactively implement contingency plans (Ivanov & Dolgui, 2020; Kouvelis et al., 2011). On this foundation, AI significantly strengthens organizational resilience. In essence, the application of AI to demand forecasting does not represent a mere technological upgrade, but a veritable paradigm shift in the management of supply chains. Its successful deployment necessitates a fundamental re-engineering of processes and an evolution of skill sets. Teams are transitioning from a role centered on generating forecasts to one increasingly focused on validating and analyzing the insights produced by AI (Chopra & Meindl, 2016).

Despite its considerable potential, the adoption of AI is not without significant challenges. Foremost among these is the critical constraint of data quality and availability. The predictive accuracy and value of any model are directly contingent upon the reliability and accessibility of the underlying data a principle often summarized as "garbage in, garbage out." Consequently, the integration of heterogeneous data sources remains a major technical and organizational obstacle (Hazen et al., 2018; Waller & Fawcett, 2013).

Compounding these issues are the inherent complexity and cost associated with developing, deploying, and maintaining such solutions. Implementing an AI platform requires distinctive competencies, including data scientists and specialized AI engineers, whose recruitment and retention represent a significant investment (Davenport & Ronanki, 2018).

A further impediment lies in the "black box" perception of advanced models, such as those in deep learning. Their opacity can engender a lack of trust among supply chain planners who are accustomed to transparent tools like Excel-based models. In this context, the rise of Explainable AI[6] (XAI) methodologies appears crucial for fostering user confidence and facilitating organizational acceptance (Barredo Arrieta et al., 2019).

Finally, the methodological challenge of overfitting[7] must not be overlooked. In essence, AI-based forecasting models can become excessively tailored to historical data, thereby losing their ability to generalize to new and unforeseen data, which compromises their operational robustness (Goodfellow et al., 2016). For these reasons, their successful deployment necessitates rigorous data management, adapted organizational governance, and, above all, sustained vigilance against both technical and human-factor risks.

2.4 Synthesis and Identification of Constructs

The literature underscores a necessary evolution from forecasting to demand sensing, yet one whose underlying mechanisms remain inadequately defined. The prevailing focus is on the contribution of AI-driven demand sensing to supply chain performance. To model this transition, it is imperative to first identify and define the key conceptual foundations.

From the analysis of the three explored theoretical fields classical forecasting, demand sensing, and artificial intelligence four fundamental constructs emerge as pivotal for enhancing supply chain performance.

[6] Explainable AI refers to the set of methods, techniques, and artificial intelligence models that make the outcomes produced by algorithms transparent and understandable, both for experts and for non-technical users.

[7] The risk of over-optimization arises when one seeks to excessively optimize a part of a system or process without considering the whole. This can lead to negative effects elsewhere or reduce overall efficiency. In data science and machine learning, it occurs when a model learns the training data too well, to the point of memorizing noise or specific peculiarities of the data rather than capturing the general trend.

First, the concept of Data Accuracy and Velocity stands out as a pivotal variable. Traditional forecasting relies predominantly on aggregated internal data (e.g., monthly sales by product family). In contrast, demand sensing, as described in the literature, necessitates the integration of data that is both granular (point-of-sale data, individual consumption data) and high-velocity, even real-time (data streams, in-store scans, geolocation data). This construct represents the system's capacity to capture a precise and immediate picture of the demand environment.

Second, Analytical and Predictive Capability constitutes the core of this transformation. While robust, classical statistical models possess an inherent rigidity that renders them ill-suited for processing this new mass of complex and unstructured data. The literature on AI in SCM identifies the capacity of Machine Learning and Deep Learning algorithms to learn complex patterns, model non-linear relationships, and process diverse data types (e.g., weather, social media sentiment) as a paradigm shift. This construct reflects the analytical power that transforms raw data into an actionable vision.

Third, we identify the principle of Adaptability and Continuous Learning. A traditional forecasting model is typically re-estimated on a periodic basis. In contrast, demand sensing, as conceptualized through AI, introduces the notion of a dynamic system. The model continuously adjusts and retrains itself as new data flows in, thereby enhancing its accuracy and robustness in the face of disruptions. This capacity for self-optimization represents a distinctive characteristic.

Finally, the ultimate objective of this transition is captured by the construct of Supply Chain Performance. This construct is multidimensional, manifesting through the key variables previously identified and defined in the first section, namely: customer service, cost optimization, and agility & resilience.

From this perspective, the transition from forecasting to demand sensing is operationalized through the interaction of these four constructs. Artificial intelligence acts as the catalyst that enables the processing of vast datasets with superior diligence and speed, thanks to its enhanced analytical and predictive capability. AI itself is powered by a process of adaptability and continuous learning, ultimately generating a significant improvement in supply chain performance. This network of conceptual relationships forms the foundation upon which the integrated "AI-Demand Sensing-Supply Chain Performance" (ADPsc) model will be elaborated in the subsequent section.

3 Model Development Methodology

This study adopts a purely conceptual research design and does not involve the collection of primary data. Its primary objective is to develop a theoretical framework that explains the mechanisms through which Artificial Intelligence (AI) enhances demand sensing capabilities and, consequently, improves supply chain performance. To achieve this objective, the study follows a deductive approach, drawing upon established theoretical knowledge to develop a conceptual model and formulate research propositions that can be empirically tested in future studies.

The conceptual model was developed through a structured literature review, following the methodological guidelines proposed by Snyder (2019). The review was designed to systematically identify, analyze, and synthesize the existing body of knowledge on Artificial Intelligence, demand sensing, demand forecasting, and supply chain performance.

The review process was conducted in several stages. First, a comprehensive literature search was conducted using major international bibliographic databases, including Scopus and Web of Science. A combination of keywords was employed, including *Artificial Intelligence*, *Machine Learning*, *Demand Sensing*, *Demand Forecasting*, *Supply Chain Performance*, *Predictive Analytics*, and *Supply Chain Management*. Subsequently, explicit inclusion and exclusion criteria were applied to ensure the scientific rigor and relevance of the literature corpus. Only peer-reviewed journal articles published in English and providing a direct theoretical or empirical contribution to the research topic were retained. Conversely, conference proceedings, professional reports, and non-peer-reviewed documents were excluded from the analysis.

The selected publications were then subjected to an in-depth content analysis aimed at identifying the key concepts, recurring theoretical relationships, frequently investigated variables, and existing research gaps. This synthesis revealed the absence of an integrative conceptual framework that simultaneously explains the role of Artificial Intelligence capabilities, demand sensing processes, and their combined effects on supply chain performance.

Based on these findings, the AI–Demand Sensing–Performance (ADPsc) conceptual model was developed using a deductive logic grounded in Contingency Theory, which serves as the theoretical foundation of this study. According to Contingency Theory, initially formalized by Lawrence and Lorsch (1967) and Woodward (1958), organizational performance depends on the degree of fit between an organization's internal capabilities and the characteristics of its external environment. From this perspective, Artificial Intelligence is conceptualized as a strategic organizational capability that enables firms to better align their demand sensing practices with highly dynamic and uncertain demand conditions, thereby enhancing supply chain performance.

Within the framework of this research, we establish the following foundational postulates, derived from this theory:

- **Postulate 1:** The modern business environment is characterized by high turbulence and uncertainty (environmental contingency).
- **Postulate 2:** Classical forecasting methods constitute a demand management system designed for a stable and predictable environment.
- **Postulate 3:** A misalignment therefore exists between the demand management system inherited from classical forecasting and the new environmental contingencies, which explains the performance shortfalls.
- **Postulate 4:** To regain a high level of performance, the supply chain must adapt its demand management practices (its structure) to align with the new environmental reality.

Furthermore, the Resource-Based View (RBV) of the firm provides an analytical framework for conceptualizing the strategic contribution of artificial intelligence to demand sensing practices. From this perspective, superior and sustainable organizational performance stems from the possession of internal resources that meet the VRIN criteria: Valuable, Rare, Inimitable, and Non-substitutable (Barney, 1991).

Within the framework of this study, AI-enabled demand sensing capabilities can be conceptualized as a strategic resource. Their Value (the "V" in VRIN) lies in their ability to integrate and process multi-source data in real time, thereby generating highly accurate and granular demand forecasts that contribute directly to logistics cost optimization and enhanced service levels. However, the Rarity (the "R") of these capabilities should be interpreted with caution. While AI technologies and foundation models have become increasingly accessible through widely available commercial platforms, the organizational capability to effectively deploy them remains unevenly distributed across firms. Such capability depends on complementary assets, including proprietary datasets, domain-specific expertise, data governance, and cross-functional integration.

Similarly, the Inimitability (the "I") of AI-enabled demand sensing does not primarily derive from the algorithms themselves, which are increasingly commoditized, but from the firm-specific configurations through which they are developed and embedded. AI systems trained on proprietary historical data, continuously refined through organizational learning, and integrated into unique business processes generate capabilities that competitors cannot easily replicate. Finally, their Non-substitutability (the "N") resides in the inability of conventional forecasting approaches to achieve comparable levels of responsiveness, adaptability, and predictive accuracy in highly dynamic demand environments. Consequently, sustainable competitive advantage arises not from access to AI technology per se, but from the organization's distinctive ability to combine AI with proprietary resources, complementary capabilities, and accumulated learning to build superior demand sensing capabilities.

Moreover, the theory of Dynamic Capabilities provides the foundational rationale for explaining sustained performance in an unstable environment (Teece et al., 1997). Dynamic capabilities are defined as the firm's ability to integrate, build, and reconfigure its internal and external competencies to adapt to rapidly changing environments. In this context, AI is not merely a static optimization tool, but rather an adaptive system in perpetual evolution. It acts as the engine for a process of organizational learning. Consequently, the capacity to sense demand becomes intrinsically linked to the capacity to transform in response to it.

4 Construction and Operationalization of the "AI-Demand Sensing-Performance" (ADPsc) Conceptual Model

Grounded in the complementary perspectives of the Resource-Based View (RBV), Dynamic Capabilities Theory, and Contingency Theory, the ADPsc model explains how Artificial Intelligence (AI) transforms organizational resources into adaptive capabilities that enable supply chains to respond effectively to environmental uncertainty. The model assumes that superior supply chain performance does not result solely from AI adoption but from the way AI mediates the transformation of heterogeneous data into actionable operational capabilities. Consequently, AI occupies a central mediating position within the model, linking the availability of real-time, multi-source information to the deployment of effective demand sensing processes, which subsequently enhance forecasting accuracy, operational responsiveness, resilience, and overall supply chain performance.

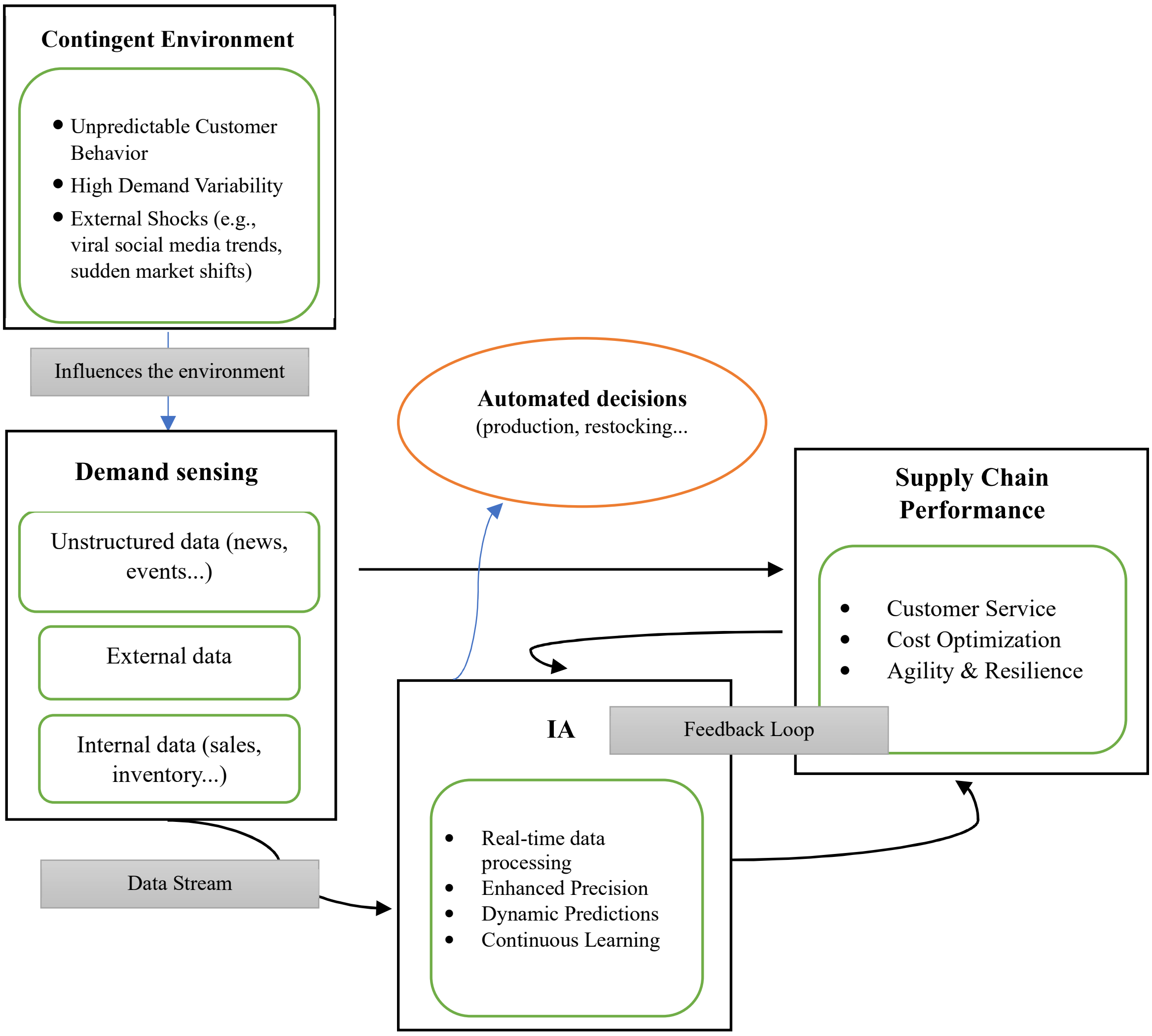
The model begins with the identification of the primary contingency affecting supply chain management: environmental uncertainty, characterized by market volatility, rapidly changing customer preferences, and highly variable demand patterns. According to Contingency Theory, these environmental conditions require organizations to develop structures and processes capable of continuously adapting to external changes. In this context, three complementary organizational capabilities emerge as essential requirements. First, organizations must develop an enhanced sensing capability that enables the continuous acquisition of weak signals originating from both internal operations and external market environments. Second, they require an advanced analytical capability capable of processing large volumes of heterogeneous data and transforming them into reliable demand forecasts. Third, organizations must possess an adaptive capability allowing operational decisions to be continuously revised as new information becomes available.

Within the ADPsc model, these capabilities are operationalized through three interdependent pillars. Pillar 1 (Multi-Source Data Integration) captures and consolidates structured and unstructured data originating from enterprise systems, customers, suppliers, social media, IoT devices, and other relevant information sources, thereby strengthening the organization's sensing capability. Pillar 2 (AI Capability) constitutes the analytical core of the model. Through machine learning, predictive analytics, pattern recognition, and anomaly detection, AI transforms raw data into actionable knowledge. In doing so, AI acts as the mediating mechanism between data availability and effective demand sensing by converting dispersed information into accurate demand predictions and operational recommendations. Pillar 3 (Operational Activation and Performance Impact) translates these predictive insights into concrete managerial actions, including inventory adjustments, production planning, procurement decisions, logistics coordination, and resource allocation. These adaptive decisions ultimately improve forecasting accuracy, operational responsiveness, supply chain resilience, and overall organizational performance.

The dynamic nature of the ADPsc model is ensured by a continuous learning loop that distinguishes it from traditional forecasting systems. Rather than operating as a linear sequence of activities, the model functions as an iterative learning system in which every operational outcome contributes to subsequent decision-making. Following implementation, actual demand, operational performance indicators, customer responses, and execution results are continuously collected and compared with the forecasts generated by the AI models. Forecasting errors, unexpected demand variations, and newly emerging market patterns are automatically identified and incorporated into the learning process. Machine learning algorithms subsequently update their parameters, recalibrate predictive models, and refine their decision rules based on these new observations. This recursive process progressively improves forecasting precision, increases the system's responsiveness to environmental changes, and strengthens its capacity to anticipate future demand fluctuations. Consequently, the feedback loop transforms AI from a static analytical tool into a self-learning adaptive capability that continuously enhances demand sensing performance over time.

Overall, the ADPsc model should therefore be understood as a dynamic capability system in which AI does not merely support forecasting activities but mediates the transformation of organizational data resources into adaptive demand sensing capabilities. Through its continuous learning mechanism, the model enables organizations to maintain strategic alignment with changing environmental conditions, thereby improving supply chain agility, resilience, and long-term performance.

Figure 2: Architecture of the AI-Demand Sensing–Performance Model (ADPsc)



Source: Author's own elaboration

To clarify the conceptual foundations of the ADPsc model and facilitate its future empirical operationalization, a summary table is provided in the Appendix (1). It synthesizes the key concepts underpinning the model, together with their conceptual definitions, principal dimensions, underlying theoretical foundations, and potential measurement indicators.

5 Research Propositions

The conceptual model developed in this study provides a theoretical explanation of the mechanisms through which artificial intelligence enhances demand sensing capabilities and ultimately improves supply chain performance. Because this article is purely conceptual, the relationships identified within the ADPsc model are expressed as research propositions rather than empirically validated hypotheses. These propositions are derived from the integration of theories with the literature on artificial intelligence, demand sensing, forecasting, and supply chain performance. They constitute a theoretical agenda for future empirical investigations.

Proposition 1: According to Contingency Theory, organizational effectiveness depends on the degree of fit between organizational capabilities and environmental conditions. As market uncertainty increases, traditional forecasting approaches become progressively less effective because they rely primarily on historical demand patterns. AI-enabled demand sensing, by integrating real-time internal and external data sources and continuously updating forecasts, provides organizations with greater responsiveness under volatile conditions. Consequently, organizations operating in highly uncertain environments are expected to derive greater benefits from adopting the ADPsc model.

P1: The greater the environmental uncertainty faced by a supply chain, the greater the need to adopt an AI-enabled demand sensing model to maintain high levels of supply chain performance.

Proposition 2: The proposed model assumes that AI does not directly improve supply chain performance. Rather, its contribution operates through the enhancement of demand sensing capabilities. More specifically, AI improves the integration and processing of heterogeneous data, thereby increasing short-term forecasting accuracy and enabling faster operational responses. These intermediate capabilities ultimately translate into superior supply chain performance.

P2: The positive effect of the ADPsc model on supply chain performance is mediated by improvements in short-term forecasting accuracy and operational responsiveness.

Proposition 3: Contingency Theory emphasizes that performance results from the alignment between organizational capabilities and environmental requirements. Accordingly, the benefits of AI-enabled demand sensing should be particularly pronounced when demand uncertainty is high. Under these conditions, organizations capable of rapidly sensing market changes and adapting operational decisions are expected to demonstrate greater resilience.

P3: The alignment between high demand uncertainty and the adoption of the ADPsc model is positively associated with supply chain resilience.

Table (1) summarizes the conceptual relationships proposed by the ADPsc model.

Tableau 1: Summary of Research Propositions

Proposition	Source Concept	Target Concept	Expected Relationship	Theoretical Foundation	Suggested Empirical Test
P1	Environmental uncertainty	Adoption of AI-enabled demand sensing	Positive	**Contingency Theory**: organizations achieve superior performance by aligning their capabilities with environmental uncertainty. **Dynamic Capabilities Theory**: AI-enabled demand sensing strengthens the ability to sense and respond to market changes.	Structural Equation Modeling (SEM) or PLS-SEM
P2	AI capabilities embedded in the ADPsc model	Supply chain performance	Positive indirect effect through demand sensing capabilities, forecasting accuracy, and operational responsiveness (mediation)	**Resource-Based View (RBV)**: AI represents a valuable, rare, and difficult-to-imitate organizational resource. **Dynamic Capabilities Theory**: AI transforms this strategic resource into operational capabilities that enhance performance.	Mediation analysis using SEM or PLS-SEM
P3	Alignment between environmental uncertainty and AI-enabled demand sensing	Supply chain resilience	Positive	**Contingency Theory**: performance depends on the fit between organizational capabilities and environmental conditions. **Dynamic Capabilities Theory**: continuous sensing and adaptation enhance resilience under uncertainty.	Moderated regression analysis or SEM with interaction effects

Source: Author’s own elaboration

6 Discussion

Our research transcends the instrumental view of AI, which often reduces it to a mere, albeit more powerful, algorithmic tool. The ADPsc model contributes to management science on three distinct levels.

First, it offers conceptual clarification and a unifying framework. Whereas the literature often treats demand sensing and AI in a fragmented manner, as seen in studies by Chaudhary (2025) and Xu et all (2024), our contribution lies in the synthesis of these concepts into a single integrative framework. The model specifies the three constitutive pillars and highlights their dynamic interactions via a feedback loop, thereby providing a common language and structure for comprehending the complexity of this transition.

Second, it positions AI as the foundation of a dynamic capability, drawing upon contingency theory. AI is not conceived as a one-off solution, but as the bedrock of a continuous learning capacity that enables the firm to sense, seize, and transform its resources to adapt to a changing environment. In this way, our research builds a bridge still underexplored between the technical literature on AI and the strategic theory of dynamic capabilities.

Finally, the model explicates the underlying mechanisms through which AI operationalizes demand sensing. In contrast to a prediction-centric view, it demonstrates that the true mechanism is the establishment of a "perception-translation loop" system: the first two pillars correspond to the sensory dimension (capturing and understanding the environment), the third pillar to the motor dimension (acting and adapting), while the feedback loop acts as the nervous system, ensuring learning and coordination.

Beyond its academic contribution, the ADPsc model provides practitioners with a tangible, actionable roadmap. It guides investment and priorities by emphasizing that efforts must not be limited to algorithms. Instead, resources must be allocated in a balanced manner across technology (data platforms, models), data (access, quality, governance), and processes/skills (reorganizing roles, training, fostering a data-driven culture). An imbalance in any of these areas jeopardizes the entire system. Ultimately, the model helps shift mindsets, assisting organizations in moving from a logic of forecasting to a logic of sensing and adapting. The goal is no longer to produce a perfect forecast, but to build a system capable of continuously adjusting to a shifting reality.

That being said, our model, like all conceptual models, has its limitations. This research presents several, which constitute opportunities for future work. The primary limitation is conceptual:

the ADPsc model remains a theoretical construct whose validity requires empirical confirmation. Future research could test its propositions through multiple case studies across different sectors to refine and contextualize the model, or quantitatively validate the causal relationships by operationalizing its components into measurable variables and employing statistical methods such as Structural Equation Modeling (SEM).

Furthermore, broadening the research scope opens several promising avenues. Investigating adoption barriers is a central area for exploration, whether they are organizational and cultural resistances, data privacy issues, or skill deficits. The integration of AI ethics and governance concerns is also indispensable and warrants dedicated investigation.

7 Limitations and Future Research Directions

This study contributes to the literature by proposing the "AI–Demand Sensing–Performance (ADPsc)" conceptual model, which integrates insights from the Resource-Based View (RBV), Dynamic Capabilities Theory, and Contingency Theory to explain how artificial intelligence enhances demand sensing capabilities and, ultimately, supply chain performance. Despite its theoretical contribution, several limitations should be acknowledged to delineate the scope of the proposed model and identify avenues for future research.

The first limitation is conceptual in nature. The ADPsc model provides a theoretical representation of the mechanisms linking artificial intelligence, demand sensing, and supply chain performance. Although it is grounded in well-established theoretical foundations and supported by a structured literature review, the model inevitably simplifies the complexity of organizational processes. To preserve theoretical coherence and parsimony, several potentially influential variables were intentionally excluded, including digital maturity, data governance quality, analytical capabilities, organizational culture, and the degree of interorganizational collaboration. Incorporating these factors into future conceptual frameworks may provide a more comprehensive understanding of the mechanisms through which artificial intelligence creates value within supply chains.

The second limitation concerns the methodological approach adopted in this study. As a purely conceptual investigation, this research does not involve the collection of primary data. Instead, the proposed model is developed through a deductive reasoning process supported by a structured review of the scientific literature. While this approach ensures theoretical consistency, it does not provide empirical validation of the proposed relationships. Consequently, the propositions advanced in this study should be regarded as research propositions requiring empirical verification. Future studies could employ quantitative approaches, particularly Structural Equation Modeling (SEM) or Partial Least Squares Structural Equation Modeling (PLS-SEM), to examine the direct, mediating, and moderating relationships identified in the ADPsc model. Complementary qualitative research, including multiple-case studies and longitudinal investigations, could further explore how organizations develop and institutionalize AI-enabled demand sensing capabilities over time.

Finally, this study presents contextual limitations. The ADPsc model has been developed as a generic conceptual framework intended to be applicable across a wide range of supply chain settings, without explicitly considering differences in industry sectors, organizational size, or levels of digital maturity. However, the effectiveness of AI-enabled demand sensing is likely to vary according to organizational characteristics, market dynamics, technological infrastructure, and sector-specific requirements. Likewise, the model does not explicitly incorporate institutional, regulatory, or cultural factors that may shape the adoption, implementation, and effectiveness of artificial intelligence within supply chain operations.

These limitations provide several promising directions for future research. First, empirical studies should validate the ADPsc model across different industrial and organizational contexts to assess its explanatory power and generalizability. Second, future research could extend the model by incorporating complementary variables, such as data quality, AI governance, digital competencies, trust in AI systems, and collaborative relationships among supply chain partners. Third, comparative studies across industries, organizational sizes, and levels of technological maturity could provide deeper insights into the contingency factors that strengthen or weaken the proposed relationships. Finally, longitudinal research would be particularly valuable for examining the continuous learning mechanisms embedded in the ADPsc model and assessing their contribution to the long-term development of dynamic capabilities, supply chain resilience, and sustained organizational performance in increasingly volatile environments.

8 Conclusion

This research has analyzed the structural limitations of traditional forecasting methods in the face of increasing market volatility and has demonstrated how artificial intelligence paves the way for a new approach based on demand sensing. The "AI-Demand Sensing-Performance" (ADPsc) conceptual model we have developed makes a significant contribution by formalizing the relationships between AI capabilities, the implementation of demand sensing, and the improvement of supply chain performance.

The key findings of our work reveal that AI is not confined to a mere incremental improvement of existing tools but constitutes the foundation for a profound transformation of practices. Our model highlights three major contributions: AI's capacity to process multiple data streams in real-time, its potential to identify complex patterns imperceptible to conventional methods, and its ability to create continuous learning loops enabling dynamic adaptation to market fluctuations.

The limitations of this research, primarily related to its conceptual nature, nonetheless open stimulating perspectives for future work. Empirical studies aiming to quantitatively validate the ADPsc model using advanced statistical methods, or in-depth qualitative research exploring the organizational barriers to the adoption of these new practices, would constitute natural and relevant extensions. The impact of AI on supply chain professions and the ethical questions raised by the increasing automation of decisions also warrant particular attention.

Ultimately, this research underscores that the transition from classical forecasting to AI-powered demand sensing represents much more than a technological evolution: it is a strategic paradigm shift that redefines the very nature of supply chain management. Companies that succeed in mastering this transition will develop a sustainable competitive advantage, founded on an unprecedented capacity to anticipate and adapt to changes in their environment.

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Appendix 1: Conceptual Definition and Operationalization of the ADPsc Model Constructs

Concept	Conceptual definition	Main dimensions	Theoretical foundations	Potential measurement indicators (future empirical studies)
Environmental Uncertainty	The degree to which customer demand, market conditions, and the external environment are unpredictable, volatile, and difficult to anticipate.	Demand variability; Market turbulence; Customer behavior uncertainty; Environmental dynamism	Contingency Theory	Demand volatility; Forecast error variability; Frequency of market changes; Customer demand fluctuations
Multi-Source Data Integration	The organization's capability to collect, integrate, and synchronize heterogeneous data originating from internal and external sources in real time.	Data variety; Data quality; Data integration; Real-time availability	Resource-Based View	Number of integrated data sources; Data freshness; Data quality; Real-time data accessibility
Artificial Intelligence Capability	The organizational capability to process large volumes of heterogeneous data using AI techniques in order to generate predictive insights and support managerial decision-making.	Machine learning capability; Predictive analytics; Pattern recognition; Automated decision support	Resource-Based View Dynamic Capabilities	AI adoption level; Forecasting automation; Prediction accuracy; AI analytical capability
Demand Sensing Capability	The capability to continuously detect, interpret, and anticipate short-term changes in customer demand through real-time data analysis.	Signal detection; Demand prediction; Market responsiveness; Decision agility	Dynamic Capabilities Theory; Supply Chain Agility Literature	Forecast accuracy; Response speed; Detection of demand changes; Decision responsiveness
Continuous Learning Capability	The capability of AI systems to continuously improve forecasting models through feedback derived from operational outcomes and newly available data.	Feedback integration; Model updating; Algorithm adaptation; Continuous improvement	Dynamic Capabilities Theory	Frequency of model retraining; Learning speed; Forecast improvement over time; Adaptive accuracy

Operational Responsiveness	The ability of the supply chain to rapidly adjust operational decisions in response to changing demand conditions.	Production flexibility; Inventory adjustment; Procurement responsiveness; Distribution flexibility	Dynamic Capabilities Theory; Supply Chain Responsiveness Literature	Order fulfillment speed; Inventory adjustment time; Production rescheduling capability
Supply Chain Resilience	The capability of the supply chain to anticipate, absorb, adapt to, and recover from disruptions while maintaining operational continuity.	Absorption; Adaptation; Recovery; Robustness	Dynamic Capabilities Theory; Supply Chain Resilience Literature	Recovery time; Service continuity; Disruption absorption capacity; Operational stability
Supply Chain Performance	The extent to which supply chain activities achieve operational and strategic objectives through efficiency, effectiveness, and responsiveness.	Operational performance; Financial performance; Customer service; Agility	Resource-Based View; Contingency Theory	Forecast accuracy; Inventory turnover; Service level; Order fulfillment rate; Logistics costs; Customer satisfaction

Source: Author's own elaboration