



## **AI-Driven Demand Forecasting and Inventory Optimization for Resilient U.S. Manufacturing Supply Chains: A Data-Driven Framework**

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**Doi:** [10.63125/sywk8963](https://doi.org/10.63125/sywk8963)

**Received:** 15 September 2024; **Revised:** 21 October 2024; **Accepted:** 15 November 2024; **Published:** 26 December 2024

### **Abstract**

*This quantitative study examined how AI-driven demand forecasting and inventory optimization strengthened resilience across U.S. manufacturing supply chains. A longitudinal quasi-experimental design combined survey responses from 602 professionals with operational data obtained from 50 manufacturers, 4,860 product–location series, 758,160 weekly demand observations, more than six million inventory transactions, and 417 verified disruption episodes over 36 months. The measurement model demonstrated satisfactory reliability and validity, with Cronbach’s alpha values ranging from .842 to .931 and composite reliability values ranging from .887 to .944. Weighted absolute percentage error declined from 18.7% to 13.6% among AI-integrated manufacturers, compared with a reduction from 18.9% to 18.2% in the matched comparison group. Stockouts decreased by 34.5%, material shortages declined by 31.8%, and order fill rate increased from 91.8% to 96.1%. Inventory turnover rose from 6.2 to 7.4 annual cycles, while average inventory value, shortage costs, obsolescence expenses, and emergency transportation costs declined. Disruption-detection time decreased from 18.6 to 9.8 hours, response time fell from 31.4 to 18.2 hours, and recovery time declined from 12.8 to 8.1 days. Structural analysis explained 53.1% of forecast quality, 64.2% of inventory optimization, and 68.7% of supply-chain resilience. Forecast quality and inventory optimization significantly mediated the relationship between AI capability and resilience. Data quality, digital maturity, analytical competence, supplier integration, and environmental uncertainty produced significant moderating effects. The findings established that integrated AI forecasting improved inventory performance, operational continuity, and disruption recovery across heterogeneous manufacturing environments.*

### **Keywords**

Artificial Intelligence, Demand Forecasting, Inventory Optimization, Supply-Chain Resilience, Manufacturing.

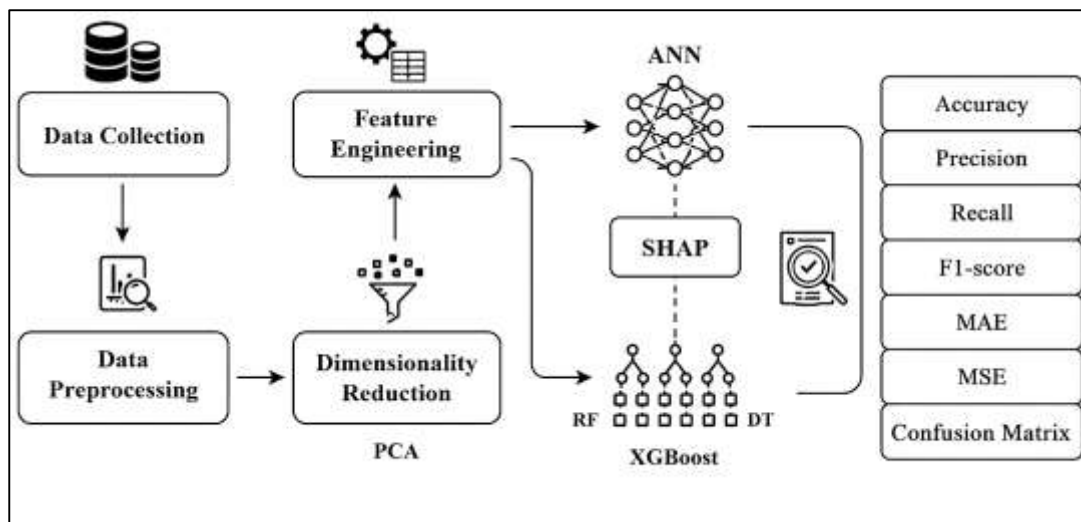
## INTRODUCTION

Artificial intelligence–driven demand forecasting refers to the systematic use of machine learning, deep learning, predictive analytics, natural language processing, and other computational techniques to estimate future demand by identifying complex relationships within historical and real-time data. Unlike conventional forecasting approaches that generally depend on stable time-series patterns, predefined statistical assumptions, and a limited number of explanatory variables, artificial intelligence–driven forecasting can process extensive combinations of sales records, production orders, customer behavior, market prices, promotional activity, economic indicators, weather conditions, supplier performance, transportation activity, and external risk signals (Seyedan & Mafakheri, 2020). Inventory optimization refers to the coordinated determination of order quantities, replenishment timing, safety-stock levels, production lot sizes, material allocations, and storage policies that balance product availability against purchasing, holding, shortage, obsolescence, and logistics costs. Supply-chain resilience describes the capacity of an interconnected production and distribution system to anticipate disruptive events, absorb operational shocks, maintain essential functions, restore acceptable performance, and adapt its processes to altered market or operating conditions. Within manufacturing environments, resilience is closely associated with demand visibility, supplier flexibility, production capacity, inventory positioning, information sharing, and decision responsiveness. A data-driven framework integrates these elements by transforming operational information into forecasts, optimization recommendations, risk alerts, and replenishment decisions. Forecasting research has established that model performance depends on demand characteristics, forecast horizons, data quality, product heterogeneity, and error-selection criteria rather than the universal superiority of a single forecasting technique (Zhu et al., 2019). Machine-learning systems have expanded this analytical foundation by capturing nonlinear relationships among large numbers of demand drivers while accommodating complex seasonality, product interactions, regional differences, and changing customer behavior. Deep-learning architectures have further strengthened forecasting capacity by automatically extracting temporal structures from high-dimensional sequential data. AI-driven demand forecasting and inventory optimization therefore represent interdependent organizational capabilities. Forecasting estimates the magnitude, timing, location, and uncertainty of demand, while optimization translates those estimates into coordinated purchasing, production, storage, and distribution decisions. Their integration is particularly important in manufacturing because inaccurate demand estimates can propagate through material requirements planning, supplier orders, capacity scheduling, workforce deployment, warehouse operations, transportation arrangements, and customer delivery performance. A forecasting error affecting one component can interrupt the production of several finished products, while excessive inventory can increase working-capital requirements and exposure to obsolescence (Johansson et al., 2017). An integrated data-driven framework consequently connects demand intelligence with inventory policies, manufacturing constraints, supplier conditions, and resilience objectives.

Demand forecasting possesses substantial international significance because modern manufacturing supply chains operate across geographically dispersed supplier networks, production facilities, logistics corridors, distribution centers, and consumer markets. A product assembled in the United States may incorporate raw materials, electronic components, machinery, packaging, and specialized services obtained from several countries. Changes in regional demand or interruptions at a single upstream location can consequently affect production availability across multiple national markets (Zhou & Zheng, 2020). Global supply networks have generated specialization, production scale, sourcing diversity, and cost efficiencies, while their structural complexity has increased exposure to natural disasters, public-health emergencies, geopolitical conflict, port congestion, transportation shortages, cyberattacks, energy-price volatility, labor interruptions, and sudden regulatory changes. International manufacturing organizations must therefore coordinate demand information across different currencies, consumer preferences, regulatory systems, lead times, transportation modes, and levels of supplier reliability. AI-driven forecasting supports this coordination by incorporating demand signals from multiple markets, detecting regional pattern changes, estimating disruption-related shifts, and generating probabilistic forecasts rather than relying exclusively on fixed-point predictions. Global manufacturers can combine enterprise resource planning records with supplier information, customs

activity, shipping data, commodity prices, exchange rates, macroeconomic indicators, online behavior, and digital market signals to obtain a more current representation of demand conditions. These information sources enable forecasting systems to distinguish localized fluctuations from broader market changes and to identify whether a demand increase is temporary, seasonal, promotional, or structural (Nti et al., 2020). International production networks also require forecasts at different levels of aggregation. Corporate planners may need global demand projections, regional managers may require market-level forecasts, and factory planners may need product- and component-level estimates for short operational periods. Artificial intelligence can reconcile these hierarchical forecasting requirements by identifying shared patterns across related products, regions, and production facilities. Inventory optimization then determines how materials and finished goods should be distributed across geographically separated nodes. Strategic inventory may be positioned near vulnerable markets, critical factories, transportation bottlenecks, or suppliers with uncertain lead times. Such decisions require simultaneous consideration of demand volatility, customs delays, storage capacity, product value, substitution options, and recovery time. International significance therefore arises not only from improved forecast accuracy but also from the ability to coordinate production and inventory decisions across complex global networks (Peres et al., 2020). A data-driven forecasting and optimization framework establishes a common analytical structure through which distributed operations can evaluate demand uncertainty, inventory exposure, production constraints, and alternative responses using synchronized information and consistent performance measures.

**Figure 1: AI-Driven Manufacturing Forecasting Framework**



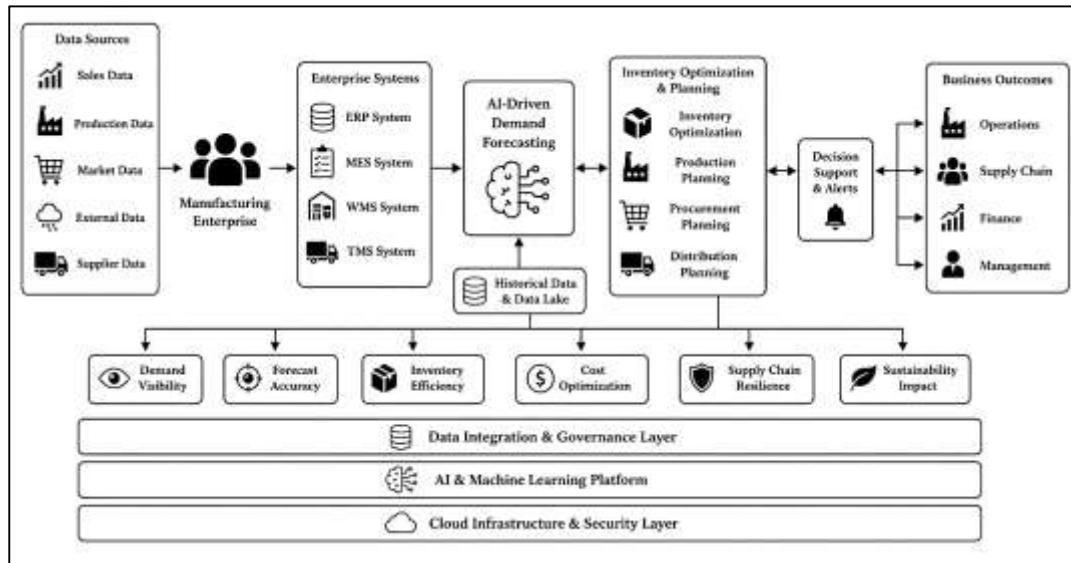
The United States manufacturing sector provides a particularly important setting for examining AI-driven demand forecasting because it encompasses industries with markedly different product structures, demand cycles, supplier configurations, and inventory requirements. Automotive, aerospace, electronics, pharmaceutical, chemical, food-processing, machinery, fabricated-metal, medical-device, textile, and consumer-goods manufacturers manage extensive combinations of raw materials, work-in-process inventory, maintenance supplies, replacement components, packaging materials, and finished products (Woschank et al., 2020). Demand uncertainty within these industries is generated by economic cycles, technological changes, customer-specific orders, seasonal purchasing, promotional activity, product introductions, regulatory approvals, government procurement, and disruptions affecting downstream distributors. Traditional planning methods may become less reliable when demand relationships change rapidly or when planners must forecast thousands of stock-keeping units across multiple factories, warehouses, customers, and time horizons. Small variations in customer demand can become amplified as orders move upstream, particularly when organizations depend on delayed information, batch ordering, promotional purchasing, shortage gaming, or poorly coordinated forecasting procedures. Information sharing and collaborative forecasting can reduce this

distortion by aligning replenishment decisions more closely with actual market consumption. Artificial intelligence extends these practices by identifying nonlinear demand drivers, automatically updating forecasts as new observations become available, segmenting products according to behavioral patterns, and producing estimates at detailed product-location-customer levels. In U.S. manufacturing, this analytical capacity is connected to operational requirements such as material planning, supplier scheduling, production sequencing, labor allocation, distribution capacity, and service-level management. Modern manufacturing systems generate substantial volumes of information through machines, industrial sensors, quality inspections, warehouse transactions, transport systems, digital customer platforms, and connected products (Ni et al., 2020). These sources provide a more detailed forecasting foundation than historical shipment records alone. Point-of-sale or customer-consumption data can distinguish genuine market demand from temporary order fluctuations, while supplier and transportation data can reveal whether projected inventory will be physically available when required. Macroeconomic indicators, housing activity, consumer confidence, energy prices, and regional employment levels can provide additional explanatory information for industries influenced by broader economic conditions. AI-driven forecasting in this environment represents an integrated decision capability rather than an isolated statistical exercise. Forecast outputs must be understandable, timely, appropriately aggregated, and connected with existing enterprise systems. Forecast performance must also be evaluated alongside service levels, shortage frequency, schedule stability, inventory turnover, production utilization, expedited transportation, and working-capital requirements because numerical accuracy alone does not ensure strong manufacturing performance (Lu, 2019).

Inventory optimization constitutes the operational bridge between predicted demand and resilient supply-chain performance. Manufacturing inventory performs several essential functions: it protects production from supplier variability, supports customer service, separates dependent operational stages, accommodates transportation economies, and provides materials for uncertain demand. Inventory simultaneously consumes working capital, occupies storage capacity, generates insurance and handling expenses, and creates exposure to deterioration, expiration, damage, technological obsolescence, and product redesign (Cioffi et al., 2020). Effective inventory management therefore requires a deliberate balance between operational protection and total economic cost. Classical inventory systems establish systematic relationships among order quantities, replenishment expenses, holding costs, lead times, service targets, and shortage risks. Contemporary manufacturing conditions require these relationships to account for uncertain demand, multi-level distribution networks, capacity restrictions, supplier reliability, material substitution, product criticality, and disruption exposure. AI-driven inventory optimization expands traditional inventory control by estimating demand distributions dynamically, learning product-specific replenishment behavior, and adjusting decision parameters as market and supply conditions change. Rather than assigning the same safety-stock rule to every item, machine-learning systems can classify materials according to demand volatility, operational criticality, lead-time uncertainty, supplier risk, unit value, substitutability, shelf life, and production dependence. Optimization algorithms can then recommend differentiated policies for strategic raw materials, inexpensive consumables, intermittent-demand components, high-value finished goods, and products with limited storage lives (Zhang et al., 2019). Intermittent demand is especially relevant to replacement parts and specialized manufacturing components because long periods of zero consumption may be followed by irregular and substantial orders. Conventional averages may misrepresent such patterns and produce either unnecessary stock or repeated shortages. Artificial intelligence can learn relationships across comparable parts, product families, equipment categories, and customer segments, allowing information from items with richer histories to strengthen predictions for items with limited observations. Inventory optimization must also incorporate forecast uncertainty explicitly. Point estimates alone may encourage overconfident replenishment decisions, whereas prediction intervals and probabilistic demand distributions allow planners to evaluate alternative cost and service outcomes. Within a resilient manufacturing system, optimized inventory does not necessarily mean minimum inventory. Strategic buffers may be positioned at vulnerable suppliers, critical production stages, regional distribution centers, or high-priority customer segments. The relevant analytical objective is to identify where inventory provides the greatest operational

protection relative to its total cost. This approach replaces uniform inventory reduction with differentiated allocation based on demand, risk, and production importance (Manzoor et al., 2021).

**Figure 2: AI-Driven Inventory Optimization Framework**



Artificial intelligence provides several methodological pathways for improving demand estimation and translating forecasts into inventory decisions. Supervised-learning techniques such as random forests, support-vector regression, gradient boosting, and artificial neural networks can model relationships between historical demand and explanatory variables without requiring a strictly linear functional form (Khanagar et al., 2021). Random forests aggregate numerous decision trees to improve predictive stability and accommodate interactions among variables, while gradient-boosting techniques sequentially reduce prediction errors and perform effectively with structured operational data. Recurrent neural networks and long short-term memory models are designed for sequential information and can retain temporal relationships across multiple periods, making them suitable for demand series characterized by seasonality, delayed effects, and changing patterns. Transformer-based models can process long sequences, combine static and time-varying information, and identify which variables or periods contribute most strongly to particular forecasts. Probabilistic deep-learning models can generate entire demand distributions across related time series, enabling information to be shared among products with limited individual histories. Increased computational complexity, however, does not automatically produce superior accuracy for every dataset. Algorithm selection must reflect demand frequency, product hierarchy, forecasting horizon, information volume, explanatory-variable availability, computational requirements, and the operational cost of different errors (Bernert et al., 2020). A model that performs well for frequently purchased consumer goods may not be suitable for aerospace components or industrial replacement parts characterized by intermittent consumption. Ensemble methods can combine statistical, machine-learning, and judgmental forecasts to capture complementary strengths and reduce dependence on a single model. Forecasting systems must also recognize hierarchical relationships because total company demand is composed of regional, customer, product-family, and item-level requirements. Inconsistent forecasts across these levels can create conflicting production and inventory plans. Forecast reconciliation provides a structured method for aligning detailed predictions with aggregate organizational targets. Inventory optimization can be connected to forecasts through mathematical programming, simulation, reinforcement learning, heuristics, or multi-objective algorithms. Reinforcement-learning systems can learn replenishment policies by observing the rewards and penalties associated with ordering decisions under changing inventory states, while simulation allows manufacturers to test service, cost, and resilience outcomes without altering live operations. This transition from predictive to prescriptive analytics enables data to support recommended decisions rather than merely describe possible demand. In manufacturing

supply chains, such integration must incorporate production capacity, supplier lead times, minimum order quantities, transportation schedules, warehouse limitations, material dependencies, and customer-service priorities (Andronie et al., 2021). The resulting architecture links each forecast directly with the operational decisions it is intended to support.

Supply-chain resilience introduces a broader performance perspective because forecasting and inventory decisions must remain reliable during routine operations and disruptive conditions. Resilience incorporates preparedness, resistance, response, recovery, and adaptation capabilities. Preparedness involves identifying vulnerabilities, establishing alternative resources, maintaining appropriate buffers, and developing response procedures before disruptions occur (Chien et al., 2020). Resistance concerns the ability to preserve essential functions when an adverse event begins, while response capacity reflects the speed and effectiveness with which resources and decisions are mobilized. Recovery represents the restoration of acceptable production and delivery performance, and adaptation involves adjusting operating practices according to knowledge gained from previous disruptions. AI-driven forecasting contributes to these dimensions by detecting demand changes earlier, identifying unusual orders, measuring forecast deterioration, and distinguishing temporary interruptions from structural market shifts. Inventory optimization contributes by allocating buffers according to product criticality, recovery time, supplier concentration, material availability, and alternative-source capacity. The interaction between forecasting and optimization is essential because highly accurate demand projections cannot prevent shortages when inbound materials fail to arrive, while large inventories cannot guarantee resilience when stock is positioned at the wrong location or consists of unsuitable components. Real-time data, advanced analytics, digital twins, and simulation can strengthen disruption management by representing suppliers, factories, inventories, capacities, transport links, and customer demand within a continuously updated virtual environment (Schroeder & Lodemann, 2021). Forecast scenarios can then be assessed against possible supplier failures, port closures, demand surges, quality problems, cyber incidents, capacity losses, or transportation delays. Scenario analysis allows managers to compare inventory repositioning, alternative sourcing, production rescheduling, product substitution, and customer prioritization strategies before selecting a response. AI-driven resilience also depends on governance because automated systems may reproduce weaknesses contained in historical information, react excessively to unusual observations, or recommend decisions that planners cannot interpret. Human oversight, data validation, model monitoring, explainability, cybersecurity, and escalation procedures are therefore central elements of an operational framework. Forecasting models must be assessed for stability when market relationships change, while optimization recommendations must be checked against contractual, safety, quality, ethical, and regulatory constraints that may not be completely represented in historical datasets (Kibria et al., 2018). Resilience consequently emerges from the coordinated interaction of analytical intelligence, inventory positioning, production flexibility, supplier collaboration, employee expertise, and managerial judgment.

A quantitative data-driven framework for resilient U.S. manufacturing supply chains requires measurable relationships among AI forecasting capability, forecast quality, inventory optimization, operational responsiveness, and resilience performance. AI forecasting capability can be operationalized through data integration, analytical sophistication, automation, model adaptability, real-time processing, external-data utilization, system accessibility, and human-AI collaboration (Alexopoulos et al., 2020). Forecast quality can be measured through weighted absolute percentage error, mean absolute scaled error, root mean squared error, forecast bias, prediction-interval coverage, forecast stability, and planner acceptance. Inventory optimization can be assessed through inventory turnover, days of inventory, safety-stock adequacy, stockout frequency, order fill rate, carrying cost, obsolete inventory, emergency orders, and material availability. Resilience performance can include disruption-detection time, response time, recovery duration, order-fulfillment continuity, production schedule adherence, supplier recovery, backlog growth, and service-level preservation. Organizational characteristics such as firm size, manufacturing subsector, supply-chain complexity, digital maturity, product variety, supplier concentration, and disruption exposure can be incorporated as control variables. A resource-based perspective explains how proprietary operational information, analytical infrastructure, and specialized employee knowledge can form valuable organizational capabilities. A

dynamic-capabilities perspective focuses on how manufacturers recognize environmental changes, mobilize appropriate responses, and reconfigure operational resources under shifting conditions. An information-processing perspective establishes that higher uncertainty increases the amount and quality of information required for effective coordination. These theoretical perspectives support empirical examination of direct, mediated, and moderated relationships within a unified quantitative model (Ahmad & Chen, 2018). Forecast quality can be tested as a mediating mechanism connecting AI capability with inventory performance, while inventory optimization can be examined as a mediator between forecasting quality and supply-chain resilience. Data quality, environmental uncertainty, employee analytical competence, supplier integration, and organizational digital maturity may alter the strength of these relationships. Quantitative assessment can combine survey measurements with archival operational records to reduce dependence on a single information source. Structural equation modelling can evaluate relationships among latent organizational capabilities, while regression analysis, multi-group comparisons, forecasting experiments, and inventory simulations can examine objective performance differences (Verma et al., 2021). This framework centers on empirically observable forecasting, inventory, and disruption measures while recognizing that AI-related performance is produced through coordinated technology, data, processes, employee expertise, supplier participation, and managerial control. Such a structure provides the analytical foundation for evaluating how forecasting intelligence and inventory decisions function together across heterogeneous U.S. manufacturing supply chains.

The primary objective of this quantitative study is to develop and empirically evaluate a data-driven framework explaining how artificial intelligence-driven demand forecasting and inventory optimization strengthen the resilience of U.S. manufacturing supply chains. The study specifically seeks to measure the extent to which AI forecasting capabilities, including integrated data processing, automated demand-pattern recognition, predictive accuracy, real-time updating, external-data utilization, model adaptability, and human–AI collaboration, improve the quality of demand forecasts across manufacturing organizations. It also aims to determine how forecast quality, represented by accuracy, timeliness, consistency, granularity, uncertainty estimation, and managerial usefulness, influences inventory optimization practices. Inventory optimization will be assessed through safety-stock adequacy, replenishment efficiency, inventory turnover, material availability, stockout reduction, carrying-cost control, obsolete-inventory reduction, and emergency-order frequency. A further objective is to examine the direct effect of AI-driven demand forecasting on supply-chain resilience and evaluate whether forecast quality and inventory optimization mediate this relationship individually and sequentially. Supply-chain resilience will be measured through disruption-detection speed, operational responsiveness, production continuity, order-fulfillment stability, recovery time, supplier-related adaptability, backlog control, and service-level preservation. The study additionally intends to investigate whether data quality, digital maturity, supplier integration, environmental uncertainty, and employee analytical competence strengthen or weaken the relationships among AI forecasting capability, inventory optimization, and resilience performance. Comparative analyses will assess whether these relationships vary according to manufacturing subsector, organizational size, product complexity, supply-chain structure, AI adoption intensity, and disruption exposure. The research will collect quantitative information from professionals involved in demand planning, procurement, inventory management, production, logistics, data analytics, and supply-chain risk management across U.S. manufacturing enterprises. Survey measurements will be integrated with available operational performance indicators to provide a comprehensive assessment of technological capability and observable supply-chain outcomes. Statistical analysis will include descriptive assessment, reliability and validity testing, correlation analysis, multiple regression, structural equation modelling, mediation analysis, moderation testing, and subgroup comparisons. Through these objectives, the study will establish an empirically testable framework connecting artificial intelligence, forecasting performance, inventory decisions, and supply-chain resilience within heterogeneous U.S. manufacturing environments.

## **LITERATURE REVIEW**

This literature review critically examines the theoretical, technological, operational, and empirical foundations of AI-driven demand forecasting and inventory optimization within resilient U.S.

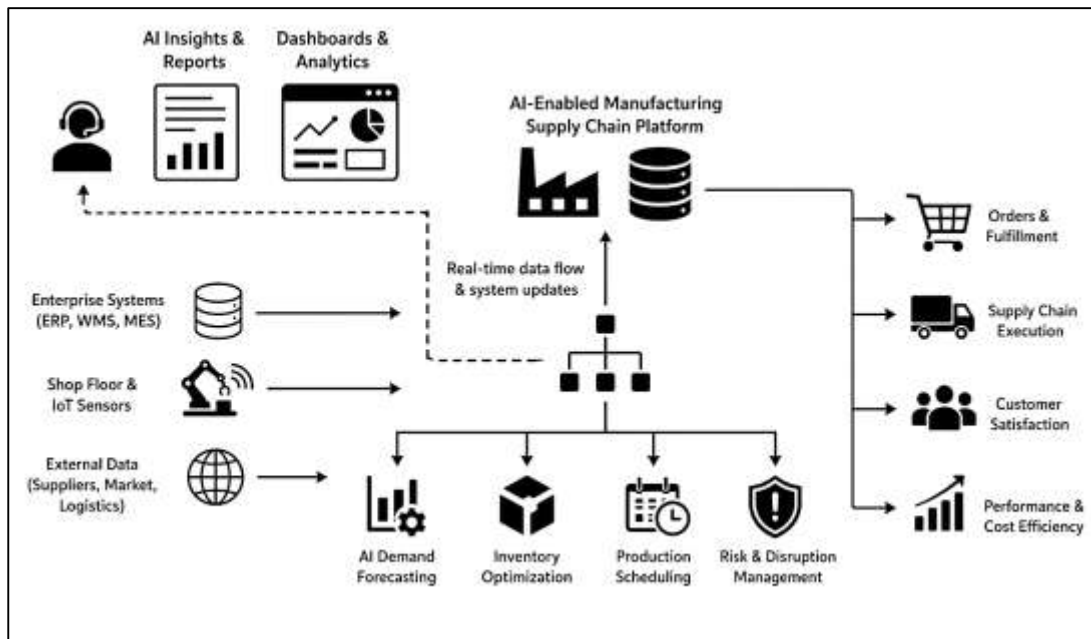
manufacturing supply chains. The review considers artificial intelligence not merely as a forecasting tool but as an integrated analytical capability through which manufacturing organizations collect, process, interpret, and convert diverse operational data into demand predictions, replenishment recommendations, inventory allocations, and disruption-response decisions (Hahn, 2020; Kanti, 2020). Particular attention is given to machine learning, deep learning, predictive analytics, probabilistic forecasting, automated model updating, external-data integration, and human-AI collaboration. The review also evaluates inventory optimization as a multidimensional capability involving safety-stock determination, order-quantity planning, reorder-point adjustment, multi-echelon allocation, material prioritization, stockout prevention, carrying-cost control, and inventory repositioning. These capabilities are examined in relation to supply-chain resilience, represented by disruption detection, response speed, production continuity, order-fulfillment stability, recovery time, sourcing adaptability, backlog control, and service-level preservation (Debasish, 2021; Nitsche et al., 2021). The literature is organized to identify the direct and indirect relationships among AI forecasting capability, forecast quality, inventory optimization, and resilience performance. It further considers data quality, digital maturity, analytical competence, supplier integration, and environmental uncertainty as contextual factors that may alter the magnitude of these relationships. The review emphasizes quantitative evidence from manufacturing, supply-chain, operations-management, forecasting, and information-systems research while distinguishing general supply-chain findings from evidence directly applicable to U.S. manufacturers. It evaluates the measurement scales, datasets, analytical techniques, effect estimates, predictive metrics, and model limitations reported in previous studies. The review also considers differences associated with manufacturing subsector, organizational size, product complexity, demand variability, supplier concentration, AI adoption intensity, and disruption exposure (Huang et al., 2021; Abdur & Iftekhhar, 2021). The resulting synthesis establishes a structured basis for developing measurable constructs, specifying hypotheses, selecting control variables, and constructing a quantitative model in which forecast quality and inventory optimization operate as potential mediating mechanisms between AI capability and supply-chain resilience.

### **Conceptual Foundations of AI-Driven Manufacturing Supply Chains**

Artificial intelligence within manufacturing supply-chain management refers to a collection of computational capabilities that enable information systems to recognize patterns, learn from operational data, generate predictions, evaluate alternatives, and recommend or execute decisions under defined conditions (Ivanov & Dolgui, 2021; Hossan, 2021). Its scope includes demand forecasting, inventory classification, production scheduling, supplier evaluation, transportation planning, predictive maintenance, quality inspection, disruption detection, and resource allocation. Artificial intelligence is broader than machine learning because it includes rule-based reasoning, expert systems, intelligent agents, natural language processing, computer vision, search procedures, and adaptive optimization. Machine learning represents a subset of artificial intelligence in which algorithms learn relationships from data instead of depending entirely on manually programmed instructions. Deep learning is a more specialized subset of machine learning that uses multilayer neural networks to identify complex representations within large, sequential, and unstructured datasets. Predictive analytics uses historical and current information to estimate probable outcomes, while automation executes predefined activities with limited human involvement (Chowdhury & Tonay, 2022; Wan et al., 2020). Optimization evaluates feasible alternatives and selects decisions that satisfy established operational objectives and constraints. These distinctions are important because manufacturing organizations frequently describe any automated or statistically generated output as artificial intelligence, even when the underlying system performs only rule-based processing or conventional analysis. Artificial intelligence may operate as both a technological resource and an organizational capability. Its technological resources include algorithms, computing infrastructure, connected equipment, industrial sensors, databases, cloud platforms, analytical applications, and integration interfaces. Its organizational capability consists of the coordinated routines through which employees acquire data, validate inputs, interpret forecasts, assess uncertainty, approve recommendations, monitor system performance, and incorporate analytical outputs into operational decisions. The presence of an advanced algorithm alone does not establish a mature AI capability. Effective implementation also requires reliable information, compatible systems, trained personnel,

clear governance, managerial support, and integration with production and supply-chain processes. Within demand planning, AI can identify nonlinear relationships among sales, customer behavior, economic conditions, promotions, supplier performance, and logistical activity. Within inventory management, it can classify materials, estimate shortage risks, revise safety stocks, and recommend replenishment quantities. Within production, it can assist capacity planning, scheduling, maintenance, and quality control (Zahidul & Begum, 2022; Trakadas et al., 2020). Artificial intelligence therefore represents an integrated decision-support capability whose operational value depends on the alignment of technology, information, employees, policies, and manufacturing objectives.

**Figure 3: AI-Enabled Manufacturing Service Framework**



The scope of artificial intelligence can be further clarified by distinguishing descriptive, diagnostic, predictive, and prescriptive analytics. Descriptive analytics summarizes what has occurred through reports, dashboards, inventory balances, sales histories, production records, and performance indicators. It allows managers to observe demand volumes, stock levels, supplier deliveries, machine utilization, order completion, and service performance (Mesbaul, 2023; Sony, 2020). Diagnostic analytics examines why an outcome occurred by identifying relationships among demand changes, supplier delays, capacity restrictions, pricing decisions, promotional activity, quality failures, and operational disruptions. Predictive analytics estimates what is likely to occur by generating demand forecasts, lead-time projections, stockout probabilities, supplier-risk assessments, maintenance requirements, and capacity expectations. Prescriptive analytics evaluates what actions should be taken by recommending replenishment quantities, inventory allocations, production schedules, sourcing alternatives, or transportation decisions. These levels are analytically related but operationally distinct. A dashboard showing declining component inventory is descriptive, an analysis connecting the decline to late supplier deliveries is diagnostic, an estimate of the expected stockout date is predictive, and a recommendation to expedite an order or activate an alternative supplier is prescriptive. Artificial intelligence can support each analytical level, although the appropriate degree of automation varies according to decision complexity, information quality, operational risk, and managerial responsibility. AI-supported decision-making occurs when the system generates forecasts, alerts, scenarios, or recommendations that employees evaluate before implementation (Chavez et al., 2017; Badrul & Mominul, 2023). Fully automated decision-making occurs when the system directly issues replenishment orders, changes production schedules, reallocates inventory, or adjusts distribution priorities without routine human approval. Repetitive, structured, and low-risk decisions may be suitable for extensive automation because decision rules and acceptable outcomes can be defined

clearly. Strategic sourcing, customer prioritization, safety-critical production, and disruption-response decisions normally require stronger managerial review because they involve uncertain consequences, ethical concerns, contractual conditions, and competing organizational objectives. Human involvement is also necessary when models encounter unusual events, incomplete data, regulatory restrictions, or conditions that differ substantially from their training information (Ebinger & Omondi, 2020; Shurovi, 2024). The operational boundaries of AI are consequently determined by data availability, forecast horizon, decision reversibility, process standardization, model transparency, cybersecurity, and the cost of incorrect action. A responsible manufacturing architecture establishes clear thresholds for automatic execution, human approval, exception escalation, and emergency suspension of algorithmic decisions.

Manufacturing demand planning developed from experience-based judgment and simple historical averages into an integrated process involving statistical forecasting, enterprise systems, cross-functional coordination, and real-time analytical intelligence. Early planning practices depended heavily on managers, sales representatives, production supervisors, and purchasing personnel who interpreted previous orders, customer relationships, seasonal experience, and market knowledge (Ivanov, 2021; Zahidul, 2024). Judgment remains valuable when organizations manage new products, extraordinary orders, regulatory changes, or disruptions for which limited historical information exists. Its reliability can nevertheless vary according to individual experience, cognitive bias, organizational incentives, departmental priorities, and access to relevant information. Statistical forecasting introduced more standardized procedures through moving averages, exponential smoothing, regression, decomposition, and time-series analysis. These methods allowed manufacturers to estimate trends, seasonality, cycles, and random variation systematically, although early applications were frequently separated from purchasing, production, and inventory decisions. The expansion of personal computing moved many forecasting activities into spreadsheets, increasing accessibility while also creating fragmented files, inconsistent assumptions, version-control problems, manual errors, and restricted organizational visibility. Material requirements planning introduced greater integration by connecting production schedules with bills of materials, inventory records, order quantities, and component lead times. Manufacturing resource planning expanded this coordination to capacity, labor, equipment, and financial resources. Enterprise resource planning subsequently integrated procurement, production, inventory, finance, sales, customer orders, and distribution information within shared organizational databases (Han et al., 2018; Kanti, 2024). These systems improved data availability and process standardization, although their planning outputs remained dependent on record accuracy, configuration quality, and employee discipline. Sales and operations planning further connected demand projections with production capacity, inventory targets, procurement requirements, workforce availability, and financial objectives. Integrated business planning broadened this coordination by aligning operational plans with revenue, profitability, working capital, risk exposure, and strategic priorities. Demand planning therefore changed from an isolated forecasting activity into a recurring organizational process through which commercial, operational, procurement, logistics, financial, and analytical functions reconcile different expectations and constraints. This transformation increased the importance of common data definitions, shared performance measures, forecast ownership, exception-management procedures, and formal decision rights (Nayak & Dhaigude, 2019; Ali et al., 2024). It also created a stronger foundation for artificial intelligence because integrated enterprise systems provide the historical and operational information required to train forecasting models, evaluate their outputs, and connect predictions with inventory and production decisions.

Cloud computing, connected devices, advanced analytics, and integrated digital platforms have transformed manufacturing demand planning from periodic forecasting into continuous demand sensing and adaptive decision support. Periodic planning commonly produced monthly or quarterly forecasts from historical shipments and scheduled review meetings (Batista et al., 2018; Tonay et al., 2024). Such intervals can become inadequate when customer behavior, supplier availability, transportation conditions, market prices, or production capacity change within days or hours. Contemporary analytical environments can capture transactions, customer orders, distributor inventory, supplier status, equipment activity, logistics events, online behavior, weather information, and economic signals as they occur. Demand-sensing systems use these recent signals to update short-

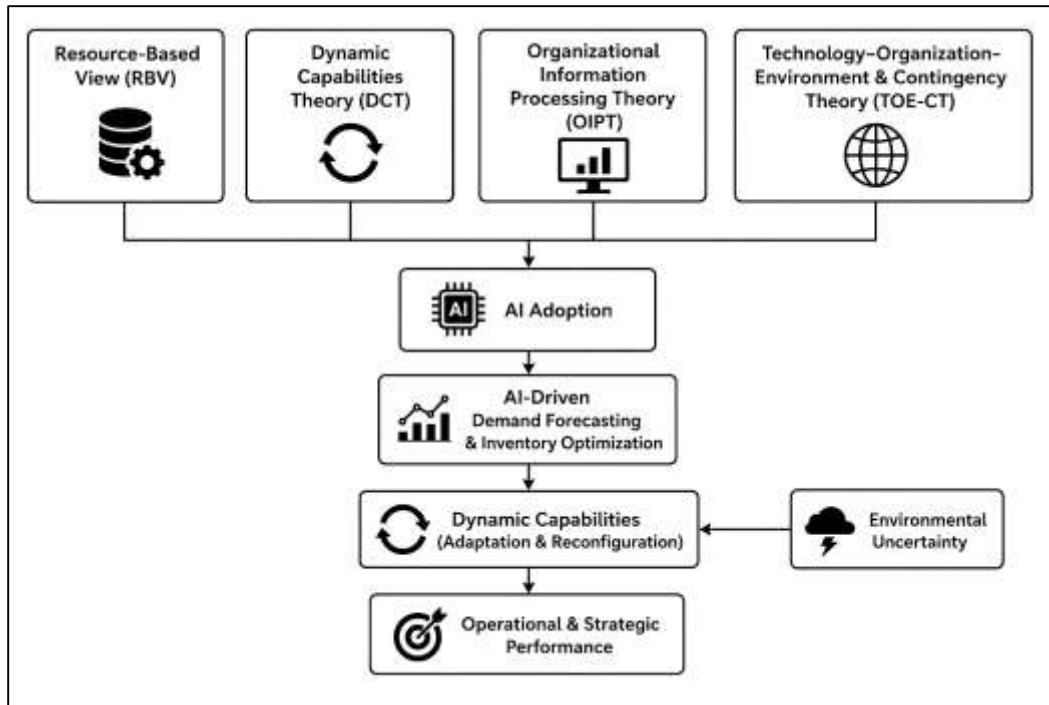
term forecasts and identify deviations from expected demand patterns. The architecture supporting this capability begins with a data-acquisition and integration layer that connects enterprise resource planning, customer relationship management, warehouse management, manufacturing execution, supplier, logistics, and external-information systems. A subsequent preparation layer cleans incomplete records, removes duplicates, reconciles inconsistent product identifiers, addresses outliers, transforms variables, and creates features representing seasonality, promotions, lead times, disruptions, customer behavior, and market conditions (Ivanov et al., 2019). Data preparation is essential because inaccurate, delayed, fragmented, or improperly classified information can weaken technically advanced forecasting systems. The forecasting and uncertainty-estimation layer then applies statistical, machine-learning, deep-learning, or combined approaches to estimate demand and represent uncertainty through ranges, distributions, or scenario categories. The inventory optimization layer translates forecast outputs into safety-stock, replenishment, allocation, sourcing, and production recommendations while considering service targets, capacity limitations, supplier lead times, minimum order quantities, storage constraints, and material dependencies. A visualization and managerial-review layer present forecasts, assumptions, uncertainty levels, exceptions, and recommended actions in forms that planners can understand and assess. Approved decisions are transmitted to operational systems, after which a monitoring layer compares predictions and recommendations with observed demand, inventory movements, service outcomes, and production performance (Huo et al., 2018). Feedback loops are central to this architecture because actual outcomes become new learning information, enabling models to be recalibrated when forecast errors increase or demand relationships change. The complete architecture consequently operates as a connected organizational system in which data integration, preparation, forecasting, optimization, visualization, human review, performance monitoring, and model retraining support continuous manufacturing decision-making.

### **Theoretical Foundations**

The resource-based view provides a suitable theoretical foundation for explaining why AI-driven demand forecasting and inventory optimization can generate differences in operational performance among U.S. manufacturing organizations (Commons, 2017). This perspective considers organizations to be heterogeneous collections of physical, technological, informational, human, and organizational resources rather than entities possessing identical capabilities. AI infrastructure represents a potentially valuable technological resource because it enables manufacturers to process large volumes of demand, production, inventory, supplier, customer, and logistics information more rapidly and consistently than conventional planning systems. The infrastructure may include cloud-computing capacity, machine-learning platforms, industrial sensors, enterprise-system interfaces, analytical dashboards, data warehouses, and automated decision-support applications. Its strategic value depends on how effectively these resources are combined with proprietary demand information. Historical sales transactions, customer order patterns, production records, promotional responses, component consumption, supplier lead times, and disruption experiences form organization-specific datasets that competitors cannot easily reproduce (Kagan, 2018). The usefulness of such information increases when it is accurate, sufficiently detailed, historically extensive, and connected across functional areas. Analytical expertise represents another critical resource because data and algorithms do not independently produce reliable manufacturing decisions. Data scientists, demand planners, procurement professionals, production managers, inventory specialists, and information-technology personnel must jointly select appropriate variables, interpret forecasts, identify unusual results, and translate predictions into feasible operational actions. Human-AI collaboration becomes an organizational capability when these activities are embedded in repeatable routines involving forecast review, exception management, inventory approval, model monitoring, and performance evaluation (Krath et al., 2021). Integrated forecasting capability is difficult to replicate because it develops through accumulated organizational learning, customized data structures, cross-functional relationships, specialized knowledge, and experience with particular products and suppliers. Competitors may purchase comparable software, yet they may not possess equivalent datasets, employee expertise, governance procedures, or system integration. The resource-based view therefore distinguishes the possession of AI technology from the organizational capacity to use it productively. Manufacturers

achieve stronger operational performance when analytical resources are coordinated with production requirements, inventory policies, supplier relationships, and managerial decision processes. This theoretical perspective supports the treatment of AI-driven forecasting as a multidimensional organizational capability whose performance effects arise through the combined use of technological infrastructure, proprietary information, analytical expertise, human judgment, and embedded operational routines ([Wisbauer, 2018](#)).

**Figure 4: AI-Driven Manufacturing Capability Framework**



Dynamic capabilities theory extends the resource-based explanation by focusing on how manufacturing organizations use AI resources to recognize changes, make timely decisions, and reconfigure operations under uncertain conditions. Manufacturing supply chains operate in environments characterized by changing customer requirements, fluctuating material prices, supplier instability, transportation delays, product transitions, regulatory constraints, and unexpected disruptions ([Marchau et al., 2019](#)). Resources that support stable operations may become inadequate when demand or supply conditions change substantially. Dynamic capabilities describe the organizational capacity to sense environmental developments, seize appropriate opportunities or responses, and transform available resources and processes. Demand sensing represents the first component of this process. Real-time analytical systems collect recent customer orders, distributor withdrawals, market signals, inventory movements, transportation events, and supplier updates to identify deviations from established patterns. AI-based models can evaluate these signals continuously and distinguish ordinary variation from changes that require managerial attention. The second component involves seizing opportunities or responding to threats through rapid inventory and production decisions. When a forecasting system detects increasing demand, managers may revise replenishment quantities, reserve supplier capacity, reposition finished goods, or adjust production schedules. When declining demand is detected, the organization may reduce orders, delay production, redirect materials, or modify inventory targets to control excess stock and obsolescence. The third component involves reconfiguring suppliers, capacity, inventory, and distribution arrangements during disruptions. A manufacturer experiencing supplier failure may activate alternative sources, substitute materials, transfer production between facilities, modify customer allocations, or relocate inventory to protect essential service levels ([Newman et al., 2019](#)). AI capability supports this process by comparing alternative scenarios, estimating operational consequences, and updating

recommendations as new information becomes available. Dynamic forecasting is therefore not limited to producing a revised numerical estimate. It involves continuous coordination among information acquisition, demand interpretation, resource evaluation, and operational adjustment. Inventory policies must also be dynamic because fixed safety stocks and reorder points may become unsuitable when demand volatility, lead times, supplier reliability, or service priorities change. The theory explains why adaptive manufacturing performance depends on the ability to modify decisions rather than merely possess advanced analytical resources. AI-driven forecasting supports operational adaptation when it is connected with flexible sourcing, responsive production planning, inventory mobility, and clear decision authority (Maier et al., 2019). Dynamic capabilities consequently provide a theoretical explanation for the relationships among real-time demand sensing, rapid inventory action, resource reconfiguration, operational continuity, and recovery from supply-chain disturbances.

Organizational information-processing theory explains AI-driven demand forecasting and inventory optimization by relating environmental uncertainty to the quantity, quality, and speed of information required for effective decision-making. Manufacturing organizations experience demand uncertainty when customer volumes, product preferences, order timing, promotional responses, or market conditions cannot be predicted reliably (Leung et al., 2017). Supply uncertainty arises from variable supplier lead times, material shortages, quality failures, capacity constraints, transportation disruptions, and geopolitical or regulatory conditions. As uncertainty increases, decision-makers require timelier, detailed, integrated, and relevant information to coordinate procurement, production, inventory, and distribution activities. Traditional reporting systems may be insufficient when information remains fragmented across departments or becomes available only after important operational changes have occurred. Data integration reduces these information gaps by connecting sales records, customer orders, inventory balances, production schedules, supplier performance, warehouse transactions, and logistical events within a shared analytical environment. Integrated information allows planners to compare expected demand with available inventory, scheduled production, committed supply, and transportation capacity. Forecast quality can consequently be understood as an information-processing outcome (Miller & Wyborn, 2020). Accurate, timely, consistent, and sufficiently granular forecasts indicate that the organization has effectively converted diverse data into decision-relevant knowledge. Weak forecasts may reflect missing information, delayed updates, incompatible data definitions, limited analytical capability, or inadequate communication among functions. Cross-functional information sharing is therefore central to the theory because demand forecasting affects multiple organizational units. Sales teams possess market and customer knowledge, procurement personnel understand supplier limitations, production managers control capacity, inventory specialists monitor material availability, and financial managers evaluate working-capital consequences. Forecasting quality improves when these perspectives are coordinated through shared data, common assumptions, structured review processes, and clearly defined decision responsibilities. Information-processing capacity must also correspond with the level of environmental uncertainty (Zhou, 2020). A manufacturer operating with stable demand, standardized products, short lead times, and reliable local suppliers may function effectively with relatively simple forecasting procedures. A manufacturer managing volatile demand, complex products, international suppliers, and long replenishment cycles requires more advanced data integration, predictive analysis, scenario evaluation, and exception monitoring. Excessively sophisticated systems may add cost and complexity when uncertainty is limited, while inadequate analytical capacity may create shortages, excess inventory, or delayed responses when uncertainty is high. Organizational information-processing theory therefore provides a structured explanation for the alignment among demand and supply uncertainty, data integration, analytical capability, forecast quality, cross-functional coordination, and manufacturing performance.

The technology–organization–environment framework and contingency theory provide complementary explanations for variations in AI adoption and performance across manufacturing organizations. The technology–organization–environment framework identifies technological readiness, organizational conditions, and external environmental pressures as major influences on the adoption and use of advanced analytical systems (Syed et al., 2020). Technological readiness includes data availability, computing capacity, system compatibility, network reliability, cloud access,

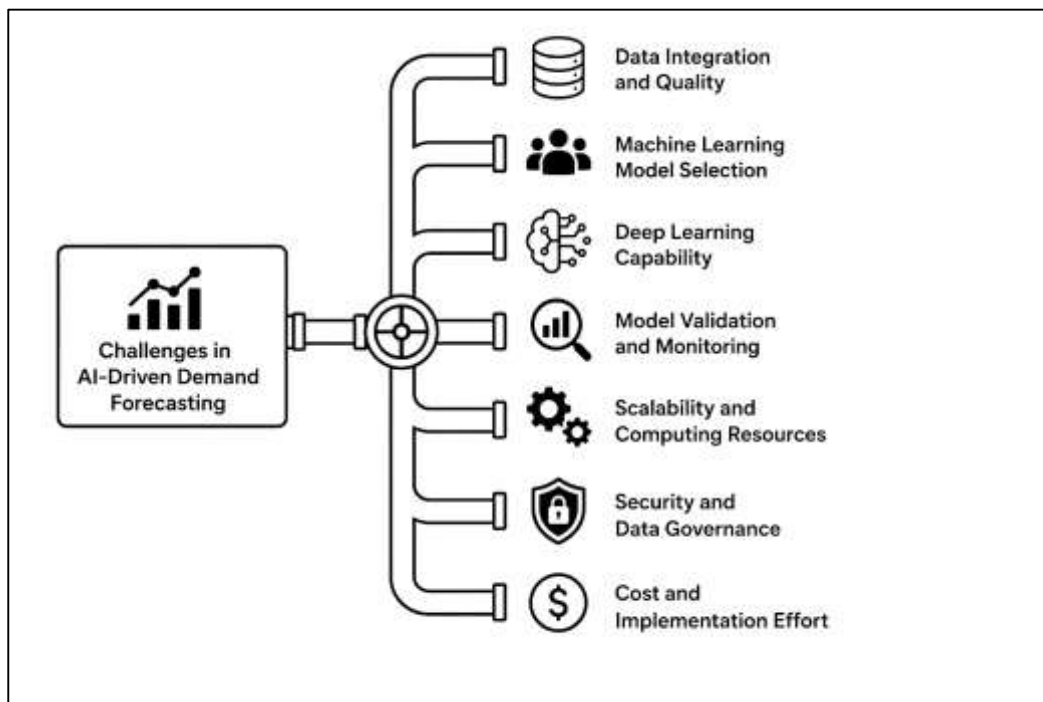
cybersecurity protection, and integration with enterprise resource planning, manufacturing execution, warehouse management, and supplier systems. An organization may possess strong interest in AI while lacking the consistent data, interoperable platforms, or technical infrastructure required for reliable implementation. Organizational conditions include financial resources, leadership support, analytical competence, employee acceptance, governance arrangements, and cross-functional cooperation. Larger manufacturers may possess specialized data-science teams and greater investment capacity, whereas smaller organizations may depend on external platforms, consultants, or standardized analytical applications. Leadership support affects whether AI initiatives receive adequate resources, whether departments share information, and whether analytical recommendations become incorporated into planning routines. Environmental conditions include competitive pressure, customer expectations, supplier digitalization, regulatory requirements, cybersecurity threats, trade uncertainty, and the availability of external technology providers. Manufacturers operating within digitally intensive sectors may face stronger pressure to introduce AI-enabled forecasting because customers and supply-chain partners expect rapid, information-based coordination ([Annamma et al., 2017](#)). Contingency theory adds that no forecasting method, inventory policy, or degree of automation is equally appropriate for every manufacturing environment. Demand variability affects whether stable statistical methods or adaptive AI models are more suitable. Product complexity influences the level of forecasting granularity and the importance of component dependencies. Organizational size shapes access to computing infrastructure, analytical professionals, and change-management resources. Supplier concentration affects the level and location of inventory buffers because dependence on a small number of suppliers can increase exposure to material interruptions. Long lead times, specialized components, limited substitution options, and high service requirements may justify larger strategic inventories, while standardized materials with multiple suppliers may require smaller protective stocks. The effectiveness of AI capability therefore depends on its fit with organizational structure, product characteristics, data maturity, demand conditions, supplier networks, and disruption exposure. Together, these perspectives explain why manufacturing organizations adopt AI at different rates and obtain different results from similar technologies ([Praetorius et al., 2018](#)). They also establish that operational performance is determined by alignment among technological capability, organizational readiness, external conditions, and the specific forecasting and inventory requirements of the manufacturing context.

#### **AI-Driven Demand Forecasting Capability**

AI-driven demand forecasting capability begins with the organizational ability to integrate diverse internal and external data into a coherent analytical environment. Manufacturing demand cannot be understood accurately through historical sales records alone because observed orders are connected with production availability, inventory constraints, purchasing decisions, transportation performance, customer behavior, and wider market conditions ([Koursiounpas et al., 2021](#)). Sales data provide information about order volumes, prices, customer segments, sales channels, promotions, and geographic demand. Production records contribute details concerning manufacturing output, capacity utilization, schedule adherence, equipment availability, quality failures, and unfinished orders. Inventory data indicate available stock, reserved quantities, materials in transit, work-in-process levels, backorders, stockouts, and obsolete items. Procurement information provides supplier order quantities, confirmed delivery dates, purchase prices, minimum order requirements, and supplier reliability. Logistics information adds transportation status, shipment duration, carrier performance, port activity, distribution capacity, and delivery exceptions. Integration with enterprise resource planning systems allows these data categories to be connected through common product, supplier, customer, facility, and time identifiers. Customer and point-of-consumption information can strengthen forecasting by distinguishing actual market consumption from orders influenced by temporary shortages, bulk purchasing, or inventory accumulation within downstream channels. Supplier and lead-time data are equally important because a demand estimate has limited operational value when planners cannot determine whether the necessary materials will arrive in time for production. External economic, weather, market, and risk information can explain variation not represented in internal transactions ([Jiang et al., 2020](#)). Interest rates, industrial production, commodity prices, employment conditions, construction activity, weather events, regulatory announcements,

public-health conditions, and geopolitical disruptions may influence demand or material availability across different manufacturing industries. The value of these sources depends on data latency, accessibility, accuracy, consistency, and interoperability. Data latency concerns the interval between an event and its availability to the forecasting system. Delayed information can cause models to react after operational conditions have already changed. Accessibility concerns whether authorized employees and analytical applications can obtain required information without excessive manual processing. Interoperability concerns whether systems exchange and interpret data consistently across departments and supply-chain partners. Effective data integration therefore requires standardized definitions, master-data governance, compatible interfaces, secure access, and continuous quality monitoring (Benzaid & Taleb, 2020). AI-driven demand forecasting capability emerges when an organization converts fragmented operational records into a timely and reliable information foundation that supports product-, customer-, location-, and period-specific predictions.

**Figure 5: AI-Driven Demand Forecasting Challenges**



Machine-learning forecasting extends this integrated information foundation by identifying relationships that conventional forecasting procedures may not capture effectively. Supervised-learning methods use historical examples in which explanatory variables and observed demand outcomes are available. The trained model learns how demand is associated with factors such as price, promotion, season, customer type, product age, economic activity, supplier performance, delivery delays, and regional conditions. Linear supervised-learning methods remain useful when relationships are relatively stable, understandable, and proportional (Huang et al., 2021). They provide clear estimates and are often suitable when datasets are limited or managerial interpretability is a central requirement. Nonlinear methods are more appropriate when demand responds differently across product categories, customer groups, price ranges, or market conditions. Random forests construct numerous decision trees from different portions of the data and combine their results to improve stability. They can process interactions among variables and accommodate nonlinear relationships without requiring planners to specify every interaction in advance. Decision-tree ensembles are also useful for identifying threshold effects, such as demand changes occurring only when prices fall below a particular level or when lead times exceed an acceptable range. Support-vector regression can model complex relationships while controlling model flexibility, making it suitable for moderate-sized datasets containing numerous demand drivers. Gradient boosting develops a sequence of models in

which each stage focuses on correcting errors produced by earlier stages. Extreme gradient boosting expands this approach through computational improvements, regularization, and procedures for handling complex structured datasets (Firouzi et al., 2020). Artificial neural networks process information through interconnected layers and can represent highly nonlinear demand relationships, although their performance depends heavily on data preparation, configuration, and validation. Model selection must be based on product and demand characteristics rather than algorithm popularity. Frequently purchased standardized goods with stable seasonality may be forecast adequately through simpler methods, while products affected by complex promotions, customer interactions, or economic conditions may benefit from nonlinear learning. Intermittent-demand components require methods capable of handling extended zero-demand periods and irregular order sizes. New products require information from comparable items because their individual histories are limited. Short-life-cycle products require models that respond quickly to recent changes, while long-life industrial products may require stronger treatment of economic cycles and customer investment patterns (Uzsoy et al., 2018). A capable forecasting system therefore maintains several candidate models, evaluates them using consistent performance measures, and assigns methods according to demand frequency, volatility, history length, forecast horizon, and operational importance. Machine learning strengthens forecasting when algorithm selection remains connected to manufacturing conditions and decision requirements.

Deep-learning forecasting offers additional capability for manufacturing environments containing large volumes of sequential, high-dimensional, or interconnected information. Recurrent neural networks are designed to process ordered observations and retain information from earlier periods while generating subsequent predictions (Mouatadid & Adamowski, 2017). This structure allows models to represent relationships involving trends, recurring seasons, delayed customer reactions, and production cycles. Long short-term memory networks extend recurrent processing through internal mechanisms that regulate which historical information should be retained, updated, or discarded. These mechanisms make them useful when important demand relationships extend across long periods or when recent activity must be interpreted in relation to earlier seasonal behavior. Gated recurrent units provide a related structure with fewer internal components and may require less computation while still representing temporal dependencies. Convolutional neural networks, commonly associated with image processing, can also be applied to temporal forecasting by identifying local patterns across consecutive observations. They may detect recurring short-term demand shapes, promotional responses, order clusters, or disruption-related sequences. Transformer-based forecasting models use attention mechanisms to evaluate the relative importance of different historical periods and explanatory variables (Marahatta et al., 2020). Their capacity to process long sequences and combine static product characteristics with changing demand drivers makes them relevant to manufacturers managing extensive product portfolios. Deep probabilistic forecasting expands the analytical output from a single predicted value to a range of possible demand outcomes. It can learn shared behavior across related products, allowing information from high-volume items to improve estimates for products with shorter or less complete histories. The suitability of deep learning depends on computational requirements and data volume. These models commonly require extensive training records, powerful computing resources, careful parameter selection, and systematic monitoring. A limited dataset may not support a complex architecture because the model can memorize historical noise rather than learn general demand relationships. Data volume thresholds vary according to the number of products, observation frequency, input variables, forecast horizon, and degree of shared structure among time series. Deep-learning models may also be difficult for planners to interpret, particularly when recommendations are generated through numerous hidden transformations. Their use therefore requires performance comparison with simpler baselines, testing across different periods, monitoring for deteriorating accuracy, and presentation of understandable evidence supporting each forecast (Punia et al., 2020). Deep learning constitutes a valuable component of AI-driven forecasting when its complexity is justified by the scale, structure, and operational value of the available manufacturing data.

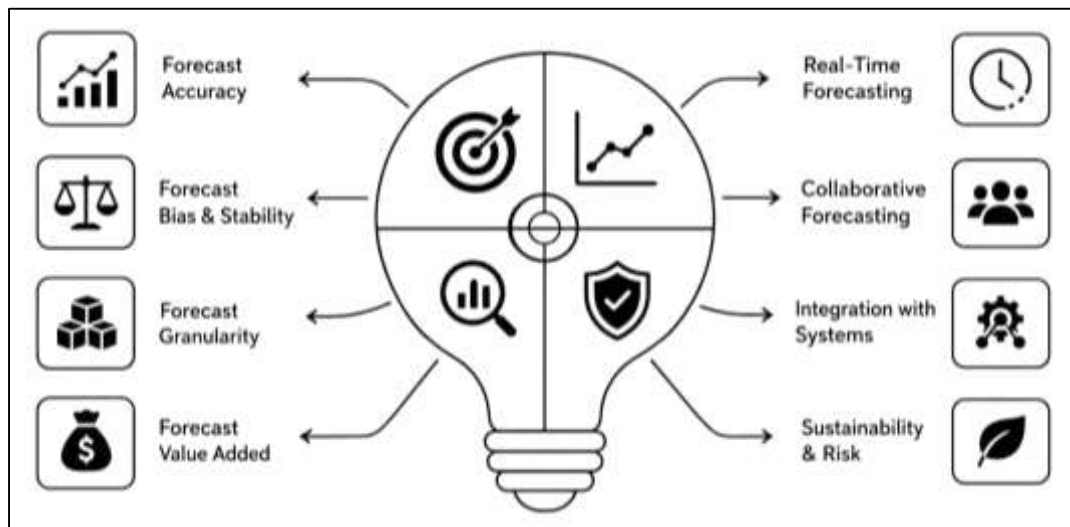
### **Measurement of Forecast Performance**

Quantitative measurement of forecast performance provides the empirical foundation for determining whether an AI-driven demand forecasting system produces reliable improvements over existing manufacturing planning methods. Forecast accuracy indicators evaluate the difference between predicted demand and observed demand, although individual indicators emphasize different characteristics of the forecast error (Buturac, 2021). Mean absolute error expresses the average size of errors in the original unit of measurement, making it understandable to planners who work with physical quantities such as units, kilograms, liters, or pallets. It is useful for evaluating a single product or a group of items with similar demand volumes, but comparisons across products can become misleading when their sales scales differ substantially. Root mean squared error also measures error in the original demand unit, while assigning greater influence to large forecasting mistakes. This feature makes it valuable when extreme errors create serious consequences such as production stoppages, urgent procurement, customer-service failures, or substantial excess inventory. Its sensitivity to unusually large errors can also cause a small number of exceptional periods to dominate the evaluation. Mean absolute percentage error expresses forecast error relative to actual demand and enables comparison among products with different sales volumes. Its interpretation is intuitive, but it becomes unstable when actual demand is very small and cannot be calculated meaningfully when actual demand is zero. These limitations are especially important for manufacturing components with intermittent consumption (Murphy & Daan, 2019). Weighted absolute percentage error evaluates total absolute error relative to total actual demand and reduces the excessive influence of low-volume observations. It is widely useful for product portfolios because high-volume items receive proportionate influence, although weak performance for strategically critical low-volume components may become hidden within the aggregate result. Mean absolute scaled error compares model errors with those generated by a simple baseline and remains applicable when demand includes zero values. It also supports comparisons across datasets measured on different scales. Symmetric mean absolute percentage error was designed to produce a more balanced percentage measure, although it can still behave unusually near zero and may treat positive and negative errors differently. No single indicator captures every aspect of forecast performance. Manufacturing organizations should therefore evaluate several complementary measures and interpret them according to product value, operational criticality, demand frequency, and error consequences (Ouyang et al., 2019). Portfolio-level averages should also be accompanied by item-level distributions because similar average errors may conceal substantially different patterns across products, locations, and time periods.

Forecast bias and stability provide additional evidence that cannot be obtained from average accuracy measures alone. Forecast bias refers to the persistent tendency of a model or planning process to predict demand above or below the values that are eventually observed. Systematic overforecasting can cause excessive purchasing, unnecessary production, elevated carrying costs, warehouse congestion, markdowns, and material obsolescence (Ittner & Michels, 2017). Systematic underforecasting can generate stockouts, production interruptions, expedited freight, emergency supplier orders, lost sales, customer dissatisfaction, and unstable production schedules. A forecasting system may produce a moderate average error while remaining strongly biased if positive and negative errors do not balance appropriately over time. Evaluation should therefore examine both the magnitude and direction of error. Forecast-error distributions provide information about central tendency, dispersion, asymmetry, and extreme values. A narrow distribution centered near zero indicates relatively consistent forecasting, whereas a wide or heavily skewed distribution indicates instability or recurring directional errors. Extreme-error analysis is particularly important in manufacturing because a small number of large mistakes can produce severe operational consequences. Tracking signals allow planners to monitor whether cumulative errors indicate persistent bias beyond accepted control limits. Such signals support exception management by identifying product, customer, or location forecasts that require investigation. Forecast stability concerns the degree to which predictions change across consecutive planning cycles (He et al., 2017). Some revisions are necessary because new information becomes available, but excessive period-to-period changes can create production nervousness, repeated schedule adjustments, unstable supplier orders, labor inefficiency, and unnecessary inventory movements. Forecast revision magnitude should therefore be measured alongside final accuracy. A

forecast that becomes accurate only after repeated large revisions may be less operationally useful than a slightly less accurate forecast that remains sufficiently stable for production planning. Accuracy must also be assessed across alternative horizons because short-, medium-, and long-range predictions support different decisions. Daily forecasts may guide order fulfillment and immediate scheduling, weekly forecasts may support replenishment and workforce planning, and monthly forecasts may influence supplier commitments, capacity allocation, and financial planning (Li et al., 2021). Models that perform strongly at short horizons may produce weak long-horizon results. Bias and stability analysis should consequently be segmented by horizon, product class, demand pattern, forecast method, and decision level to determine whether the forecasting system provides dependable information throughout the manufacturing planning process.

**Figure 6: AI-Driven Forecast Evaluation Framework**



Forecast granularity concerns the level of detail at which demand predictions are produced and evaluated. Product-level accuracy measures how well a model estimates total demand for an individual finished product, material, or stock-keeping unit. This level is essential for purchasing, production quantities, and inventory control, although aggregate product accuracy may conceal important geographical or customer-specific variation (Steenbergen & Mes, 2020). Product-location accuracy evaluates each item at a particular factory, warehouse, distribution center, or market region. It is especially important for decentralized supply networks because total demand may be estimated correctly while inventory is positioned in locations where it is not needed. Customer-level forecasts support contract planning, service prioritization, account management, and allocation decisions. Their performance may be influenced by order batching, promotional activity, customer inventory policies, and irregular purchasing behavior. Component-level forecasts translate demand for finished products into requirements for raw materials, parts, and subassemblies. Component forecasting is complicated by bills of materials, shared components, product substitution, engineering changes, yield losses, and differences between planned and actual production. A forecasting system may therefore perform well at the finished-product level while producing weak material-availability outcomes when component relationships are not represented correctly. Time granularity creates another measurement requirement. Daily forecasts are highly sensitive to order timing and calendar effects, weekly forecasts often provide a more stable basis for production and replenishment, and monthly forecasts support capacity and financial planning (Chakraborty et al., 2019). Aggregating demand usually reduces apparent error because positive and negative variations offset one another. Accuracy results should consequently identify the exact product, location, customer, component, and time level being evaluated. Hierarchical forecast reconciliation addresses inconsistencies among related forecasts. Company-level demand should correspond with the combined forecasts of divisions, regions, product families, products, and locations. Independently generated forecasts may not satisfy these

relationships, creating conflicting targets for commercial, production, and financial functions. Reconciliation aligns detailed and aggregate forecasts while retaining relevant information from each level. Evaluation should assess both accuracy and coherence before and after reconciliation. Granular measurement also requires weighted reporting because high-volume products, high-value materials, and production-critical components possess different operational importance (Adcock & Gradojevic, 2019). A comprehensive assessment therefore combines disaggregated accuracy, aggregated performance, hierarchical consistency, and operational weighting to determine whether the model supports decisions throughout the manufacturing network.

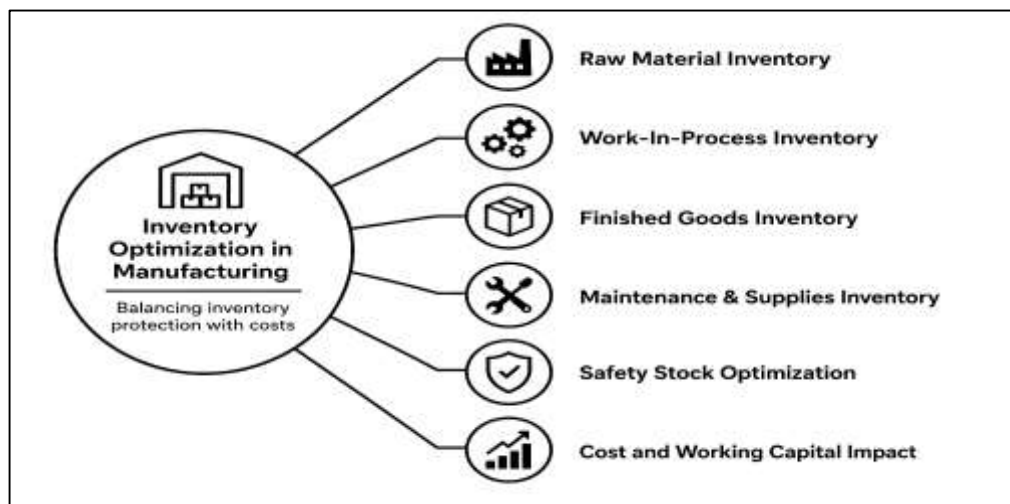
Forecast value added evaluates whether each stage of the forecasting process improves performance relative to a credible alternative. This perspective is broader than reporting the final error of an AI model because it determines whether additional data, analytical complexity, managerial intervention, and organizational resources generate measurable benefits (Lima-Junior & Carpinetti, 2017). AI forecasts should first be compared with transparent statistical baselines such as previous-period demand, seasonal repetition, moving averages, or exponential smoothing. A technically complex system produces limited analytical value when it fails to improve upon a simple method. Comparisons should use identical products, observation periods, forecast horizons, and error indicators so that apparent improvement is not produced by inconsistent evaluation conditions. AI forecasts should also be compared with managerial forecasts because planners may possess contextual knowledge unavailable to algorithms. The assessment can identify whether the model, the planner, or a combined forecast performs best across stable periods, promotions, new-product introductions, customer-specific orders, and disruptions. External information should be evaluated incrementally by comparing models trained with and without economic indicators, weather information, customer-consumption records, supplier conditions, transportation events, or market signals (Nespoli et al., 2019). This procedure determines whether the additional sources contribute genuine predictive value or merely increase complexity and processing costs. Forecast overrides require similar analysis. A managerial adjustment creates positive value when it reduces error or improves an operational decision, while an adjustment that increases error produces negative value. Override evaluation should consider frequency, direction, size, stated reason, employee role, product category, and resulting performance. Percentage reduction in forecast error provides an accessible method for communicating improvement relative to a baseline, but it should be reported with absolute error changes and operational outcomes. A small percentage improvement for a high-volume or production-critical item may have greater economic value than a large improvement for an inexpensive, low-demand product (Yin et al., 2018). Operational value should therefore be evaluated through inventory availability, fill rate, stockout frequency, safety-stock requirements, production stability, obsolete inventory, emergency orders, expedited transportation, working capital, and recovery during disruptions. Forecast accuracy represents an intermediate analytical outcome rather than the complete measure of system success. Forecast value added is established when improved predictions lead to better inventory and manufacturing decisions after accounting for software, computing, data preparation, training, governance, and monitoring costs.

### **Inventory Optimization in Manufacturing Supply Chains**

Inventory optimization in manufacturing supply chains involves balancing the operational protection provided by inventory against the financial, logistical, and obsolescence costs created by holding it. Manufacturing inventory is not a single category because raw materials, work-in-process, finished goods, and maintenance supplies perform different functions and require different control policies. Raw-material inventory includes commodities, purchased components, packaging, chemicals, and other inputs required to initiate or sustain production (Praveen et al., 2019). Its appropriate level depends on supplier lead times, material availability, price variability, transportation reliability, minimum order requirements, and production consumption. Work-in-process inventory consists of materials that have entered production but have not reached finished-goods status. It helps separate dependent manufacturing stages and protects downstream activities from temporary equipment failures, quality problems, and processing-time differences. Excessive work-in-process can conceal production bottlenecks, extend throughput time, occupy floor space, and delay the detection of quality defects. Finished-goods inventory supports customer availability and allows organizations to respond rapidly when production lead times exceed customer delivery expectations. Its value depends on

demand variability, product shelf life, customization requirements, distribution structure, and expected service levels (Huang et al., 2020). Maintenance, repair, and operating supplies support equipment availability and operational continuity. These items may have low usage frequency but high criticality because the absence of an inexpensive replacement part can stop an entire production line. Inventory also performs a decoupling function by reducing direct dependence among sequential production stages. A temporary disruption in one activity does not immediately stop the next stage when an appropriate buffer is available. Strategic inventory extends this protection to broader supply-chain disruptions. Manufacturers may hold additional quantities of critical materials when suppliers are geographically concentrated, lead times are long, substitution is limited, or transportation routes are vulnerable. Strategic inventory should be differentiated from uncontrolled excess because it is positioned deliberately according to disruption exposure, material criticality, recovery time, and service requirements (Singh & Verma, 2018). The optimization objective is therefore not to minimize all inventory categories uniformly. It is to determine which materials should be held, where they should be positioned, how much protection they should provide, and how frequently their levels should be reviewed. Effective inventory optimization recognizes the different economic and operational functions of each inventory category while connecting them with production continuity, customer service, working capital, and supply-chain resilience.

**Figure 7: Manufacturing Inventory Optimization Framework**



Safety-stock optimization determines the protective inventory required to absorb uncertainty in demand, replenishment lead time, supply reliability, and production performance. Demand variability increases safety-stock requirements because actual consumption may exceed the expected forecast during the replenishment period. The relevant uncertainty is not only the size of demand variation but also its timing, persistence, and relationship with product seasonality, promotions, customer ordering, and market disruptions. Lead-time variability creates a separate source of exposure because a supplier may deliver later than the average replenishment period (Fatorachian & Kazemi, 2021). Even stable demand can produce shortages when transportation delays, supplier capacity constraints, quality failures, customs procedures, or administrative errors extend delivery time. Required service levels influence how much protection an organization maintains. Products connected with contractual obligations, safety requirements, essential services, or strategically important customers may require higher availability than standard items. Product and component criticality should therefore shape safety-stock policies. A low-value component used across numerous finished products may require substantial protection because its absence can interrupt several production lines. A high-value specialized component may require a smaller quantity but stronger monitoring because of its cost and limited substitution options. Supplier reliability further affects buffer decisions through delivery consistency, defect frequency, financial stability, capacity flexibility, communication quality, and

disruption exposure. Manufacturers that depend on a single supplier or geographic region may require different protection from organizations possessing multiple qualified sources (Tiwari et al., 2018). Static safety-stock parameters may become unsuitable when demand patterns, lead times, service priorities, or supplier conditions change. Dynamic adjustment uses recent demand errors, delivery performance, inventory consumption, and risk information to revise protective stock levels. This process can increase buffers when forecast uncertainty or supplier risk rises and reduce them when conditions stabilize. Dynamic policies require governance because frequent parameter changes can create order instability and confuse procurement or production teams. Adjustments should therefore follow defined review rules, approved data sources, and exception thresholds. Safety-stock performance should be assessed through material availability, stockout frequency, production interruptions, order fill rates, emergency purchases, excess stock, and carrying costs. Strong optimization does not eliminate shortages under every possible condition (Ivanov et al., 2021). It establishes protection that is proportionate to uncertainty, operational importance, and the consequences of unavailability while avoiding unnecessary investment across low-risk items.

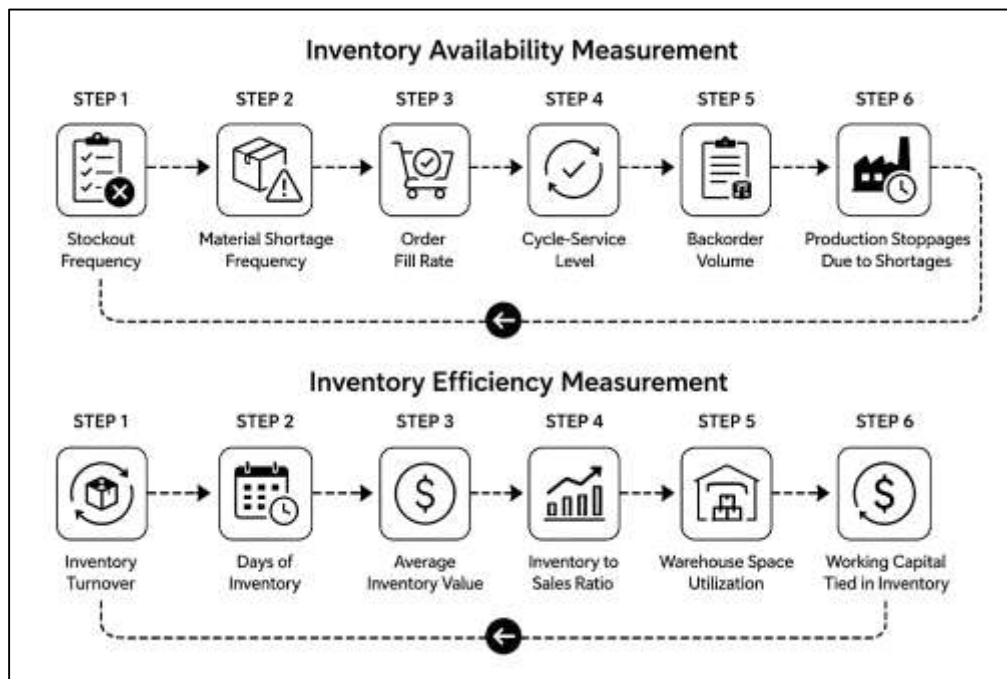
### **Quantitative Measurement of Inventory Optimization**

Inventory availability represents the extent to which required raw materials, components, work-in-process items, maintenance supplies, and finished products are accessible at the location and time of operational need (Hajek & Abedin, 2020). Its quantitative assessment requires several complementary indicators because no individual measure fully represents the availability experienced by production departments and customers. Stockout frequency records how often inventory reaches an unavailable level during a specified period. It can be calculated for individual items, product groups, warehouses, factories, or the entire manufacturing network. A low overall stockout frequency may still conceal serious exposure when shortages occur among production-critical components, making classification by material criticality essential. Material-shortage frequency concentrates specifically on inputs required for production and identifies how often planned operations cannot obtain the necessary quantity of a component. This indicator may be reported by production order, work center, supplier, component family, or manufacturing facility (Yang et al., 2017). Order fill rate evaluates the proportion of customer demand satisfied directly from available inventory and therefore reflects both product availability and inventory positioning. A high fill rate indicates that most requested quantities are supplied without delay, while a low rate suggests shortages, allocation restrictions, or stock located at unsuitable network nodes. Cycle-service level examines the proportion of replenishment cycles completed without a stockout. It is particularly useful for evaluating whether safety stocks provide the intended protection, although it does not show the size or duration of shortages occurring within unsuccessful cycles. Backorder volume measures demand that has been accepted but cannot be fulfilled immediately. It should be assessed through the number of delayed orders, units awaiting fulfillment, financial value of outstanding demand, and average backorder age. Growing backorders may indicate persistent under forecasting, insufficient replenishment, supplier unreliability, or ineffective allocation. Production stoppages caused by missing materials provide a direct measure of manufacturing consequences. Their evaluation should include the number of stoppages, affected production hours, delayed units, labor idle time, rescheduling activity, and lost output. Availability indicators should be analyzed by product importance, supplier, facility, customer priority, and disruption condition. An inventory system can appear effective when measured through aggregate availability while performing poorly for strategically significant items (Ren et al., 2020). Quantitative measurement must therefore connect stock availability with the operational consequences of unavailability. Combining frequency, quantity, duration, service, and production-impact measures provides a more accurate assessment of whether inventory policies support manufacturing continuity and customer fulfillment.

Inventory efficiency concerns how effectively a manufacturing organization uses its inventory investment to support sales, production, and service requirements. Inventory turnover indicates how frequently inventory is consumed or sold during a reporting period. Higher turnover commonly suggests that materials move through the organization efficiently, while lower turnover may indicate excess stock, slow-moving products, inaccurate forecasts, or declining demand (Maity et al., 2021). Interpretation must account for industry conditions because aerospace components, pharmaceutical materials, consumer goods, and industrial machinery possess different demand frequencies, lead times,

values, and service requirements.

**Figure 8: Manufacturing Inventory Performance Framework**



Extremely high turnover can also indicate insufficient protection when low inventory levels produce frequent shortages or emergency replenishment. Days of inventory on hand translates inventory levels into the approximate period for which available stock can support expected usage. This measure enables planners to compare inventory coverage across products, facilities, and reporting periods. It should be interpreted alongside demand variability and replenishment lead time because identical coverage may provide adequate protection for a stable local supplier but insufficient protection for a volatile imported component (Kadambala et al., 2017). Average inventory value measures the financial amount invested in raw materials, work in process, finished goods, and operating supplies over a specified period. Separating these categories helps determine whether excessive investment originates in purchasing, production flow, finished-goods planning, or maintenance policies. The inventory-to-sales ratio compares inventory investment with organizational sales activity and can indicate whether stock growth remains proportionate to business volume. An increasing ratio may signal slower demand, excess purchasing, ineffective production planning, or growing strategic buffers. Warehouse-space utilization measures the proportion of available storage capacity occupied by inventory (Hamdi et al., 2018). High utilization may appear efficient but can reduce accessibility, increase handling time, obstruct stock rotation, and limit the ability to respond to unexpected deliveries. Low utilization may indicate excess facility capacity or inefficient inventory distribution. Working capital tied to inventory captures the financial resources unavailable for other organizational purposes because they remain invested in stored materials and products. This measure is particularly important for high-value components and slow-moving finished goods. Inventory efficiency should not be evaluated as inventory reduction alone (Ribeiro & Barbosa-Povoa, 2018). Reductions that weaken production continuity, customer service, or disruption protection do not represent genuine optimization. A balanced assessment should connect turnover, coverage, financial value, sales alignment, space utilization, and working-capital requirements with fill rates, shortages, and operational resilience.

### **Supply-Chain Resilience in U.S. Manufacturing**

Supply-chain resilience in U.S. manufacturing refers to the capacity of manufacturers and their interconnected suppliers, production facilities, logistics providers, distributors, and customers to anticipate disruptive events, absorb operational shocks, respond effectively, recover acceptable

performance, and adapt operating practices to changed conditions (Hosseini et al., 2020). Anticipation begins with identifying vulnerable suppliers, critical materials, capacity limitations, transportation dependencies, geographic concentrations, and demand-related risks before they interrupt operations. It involves mapping supply networks, evaluating warning signals, estimating disruption probabilities, and preparing response procedures for events with significant operational consequences. Absorption concerns the ability to maintain essential production and delivery functions after a disruption has occurred. Available inventory, alternative capacity, substitute materials, flexible labor, backup systems, and contractual arrangements may allow a manufacturer to continue operating while corrective actions are organized. Response capacity reflects the speed and coordination with which the organization activates alternative suppliers, reallocates materials, revises production schedules, communicates with customers, and redirects transportation. Performance recovery refers to the restoration of production volumes, inventory availability, order fulfillment, and service levels after the initial interruption. Operational adaptation extends recovery by modifying supplier portfolios, inventory policies, digital systems, planning procedures, or facility configurations in response to knowledge obtained from disruption experience (Golan et al., 2021). Resilience differs from related concepts that are sometimes used interchangeably. Robustness describes the ability of a supply chain to resist disturbance and maintain planned performance without substantial structural change. Agility emphasizes rapid recognition of change and prompt response to shifting demand or supply conditions. Flexibility refers to the availability of alternative actions, such as changing production volumes, suppliers, routes, materials, or product mixes. Resilience incorporates elements of robustness, agility, and flexibility but also includes preparation, survival, recovery, and adaptation over the complete disruption period. A supply chain may be robust against minor demand variation but unable to recover from a prolonged supplier closure. It may possess production flexibility but lack the visibility required to activate that flexibility quickly. Resilience should therefore be conceptualized as a multidimensional capability rather than a single inventory buffer or emergency procedure (Alfarsi et al., 2019). In U.S. manufacturing, this capability connects risk awareness, information processing, resource availability, cross-functional coordination, and operational decision-making. Its assessment requires attention to what happens before, during, and after disruption because preparation, resistance, response, recovery, and adaptation represent different yet interdependent dimensions of manufacturing continuity. U.S. manufacturing supply chains face diverse disruption sources whose frequency, duration, geographic reach, and operational consequences vary substantially. Supplier failure can result from financial distress, equipment breakdown, quality problems, capacity shortages, regulatory action, cyber incidents, labor disputes, or natural hazards. Its consequences become more severe when the affected supplier provides a specialized component, possesses proprietary production knowledge, or operates as the sole approved source. Material shortages can originate from limited global capacity, scarcity of raw materials, inaccurate demand forecasts, long replenishment periods, export restrictions, or competition among industries for the same inputs (Aigbedo, 2021). Transportation interruptions include port congestion, carrier shortages, route closures, customs delays, fuel constraints, infrastructure damage, and interruptions affecting rail, road, air, or maritime movement. Natural hazards such as hurricanes, floods, wildfires, winter storms, earthquakes, and extreme temperatures can disrupt factories, warehouses, utilities, transportation corridors, and employee access. Geopolitical and trade-related events may alter tariffs, import restrictions, customs procedures, supplier access, transportation routes, and material prices. These events can affect U.S. manufacturers even when their immediate operations are domestic because upstream components or raw materials may originate from internationally connected suppliers. Cybersecurity incidents represent another critical risk because manufacturing increasingly depends on connected machinery, enterprise platforms, supplier interfaces, warehouse systems, and digital logistics networks (Davis et al., 2021). A cyberattack can interrupt production, corrupt inventory records, block communication, expose proprietary information, or prevent the execution of customer and supplier transactions. Labor shortages and industrial disputes can reduce production capacity, delay deliveries, and constrain warehouse or transportation operations. Equipment failures may interrupt an individual production stage, while capacity failures can affect an entire plant or network when alternative facilities cannot produce the same materials or products. Unexpected customer-demand changes create both upward and

downward disruption. Sudden demand growth can exhaust inventory and production capacity, whereas rapid decline can create excess stock, idle resources, and obsolescence. These disruption sources frequently interact. A natural hazard may close a supplier facility, restrict transportation, delay materials, increase market prices, and produce emergency customer orders simultaneously. Risk analysis should therefore avoid treating disruptions as isolated events (Kim & Bui, 2019). Manufacturing resilience depends on understanding interdependencies among suppliers, materials, equipment, labor, digital systems, logistics routes, and customer demand throughout the supply network.

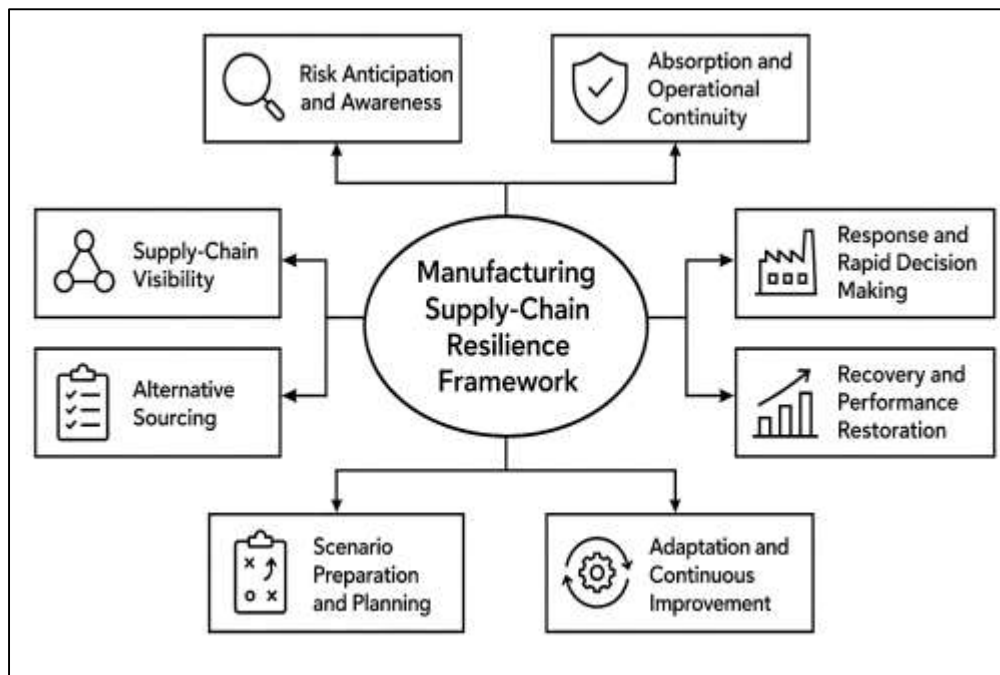
Resilience capabilities provide the organizational mechanisms through which U.S. manufacturers anticipate, absorb, respond to, and recover from supply-chain disruptions. Supply-chain visibility is the ability to obtain timely and reliable information concerning inventory positions, supplier status, production capacity, customer demand, transportation activity, and emerging risks. Visibility allows decision-makers to identify an interruption before its effects spread across production and distribution operations. Its value depends on data accuracy, system integration, supplier participation, and the ability to convert information into actionable alerts (Mancheri et al., 2019). Alternative sourcing reduces dependence on a single supplier by qualifying additional providers, developing substitute materials, or distributing purchases across geographic regions. Multiple sourcing can increase administrative and purchasing complexity, making it most valuable for components whose unavailability would cause substantial operational damage. Production flexibility enables manufacturers to change output volumes, product mixes, processing sequences, materials, equipment assignments, or factory locations. Flexible capacity is particularly useful when disruption affects one production line or facility but other resources remain available. Inventory buffers protect operations against temporary demand and supply variation. Their resilience value depends on whether the correct materials are stored at suitable locations and remain usable throughout the disruption period. Logistics flexibility includes alternative carriers, transportation modes, ports, routes, consolidation arrangements, and distribution facilities. It allows material and product flows to continue when normal channels become unavailable or excessively delayed (Ivanov & Dolgui, 2021). Collaborative planning connects manufacturers with suppliers, logistics partners, customers, and internal functions through shared forecasts, capacity information, inventory status, and disruption updates.

Collaboration reduces information gaps and limits uncoordinated decisions such as duplicate ordering, unnecessary stock accumulation, or conflicting customer commitments. Scenario preparation enables organizations to evaluate disruption possibilities before they occur and to specify responsibilities, escalation thresholds, alternative resources, and communication procedures. Scenarios may address supplier closure, material scarcity, cyberattack, capacity loss, transportation interruption, or sudden demand change. Rapid decision-making converts these capabilities into action. It requires accurate information, predefined authority, cross-functional coordination, and clear prioritization criteria. An organization may possess alternative suppliers and inventory buffers while responding slowly because approval responsibilities are unclear. Resilience therefore results from the integration of visibility, sourcing, production, inventory, logistics, collaboration, preparation, and decision speed. These capabilities should be evaluated collectively because weakness in one area can restrict the usefulness of strengths elsewhere. Strong visibility without flexible resources identifies problems but does not resolve them, while flexible resources without timely visibility may be activated too late (Ralston & Blackhurst, 2020).

Quantitative resilience indicators translate manufacturing continuity, response, and recovery into measurable performance outcomes. Disruption-detection time measures the interval between the beginning of an adverse event and its recognition by the organization. Shorter detection periods indicate stronger visibility and monitoring, although detection is valuable only when the information reaches responsible decision-makers (Bevilacqua et al., 2020). Time to respond measures the interval between disruption recognition and the activation of a corrective action, such as changing a supplier, reallocating inventory, modifying production, or rerouting transportation. It reflects decision authority, information quality, preparation, and cross-functional coordination. Time to recover measures how long the supply chain requires to restore an acceptable level of production, fulfillment, or service performance. The acceptable level should be defined clearly because recovery to minimum operating

capacity differs from restoration of normal output.

**Figure 9: Manufacturing Supply Chain Resilience Framework**



Time to survive estimates how long operations can continue before disruption causes an unacceptable loss of service or production. Available inventory, alternative capacity, customer prioritization, and material substitution influence this duration. Production continuity rate measures the proportion of planned output maintained during the disruption (Singh et al., 2019). It can be evaluated through completed units, operating hours, production orders, or utilized capacity. Schedule-adherence rate measures whether manufacturing activities occur according to revised or original plans and reveals the degree of operational instability created by disruption. Order-fulfillment continuity assesses the proportion of customer demand served throughout the disruption period. It should distinguish complete, partial, delayed, and cancelled orders because aggregate shipment volume may conceal service deterioration among particular customers or products. Backlog growth measures the accumulation of unfulfilled orders and can be reported through order counts, units, financial value, or average waiting time. Rapid backlog growth indicates that response resources are insufficient relative to disruption severity. Post-disruption service restoration measures the pace at which fill rates, delivery reliability, production schedules, and customer service return to established levels. Resilience assessment should combine these indicators because individual measures can provide incomplete interpretations. A manufacturer may recover production quickly while carrying a substantial backlog, or maintain order fulfillment by consuming inventory that leaves the organization exposed to further interruption (Chang & Lin, 2019). Quantitative measurement should compare pre-disruption, disruption, and recovery periods while accounting for event severity, product importance, facility characteristics, and customer priorities. This multidimensional approach establishes whether resilience capabilities preserve essential performance and limit the duration and magnitude of operational loss.

#### METHOD

This study employed a quantitative longitudinal quasi-experimental design to examine the effects of AI-driven demand forecasting and inventory optimization on the resilience of U.S. manufacturing supply chains. The design combined organizational survey data with historical operational records collected across a 36-month observation period. Participating manufacturers were classified into an AI-integrated group and a matched comparison group. The AI-integrated group consisted of organizations that had used machine-learning or deep-learning forecasting applications connected with inventory-

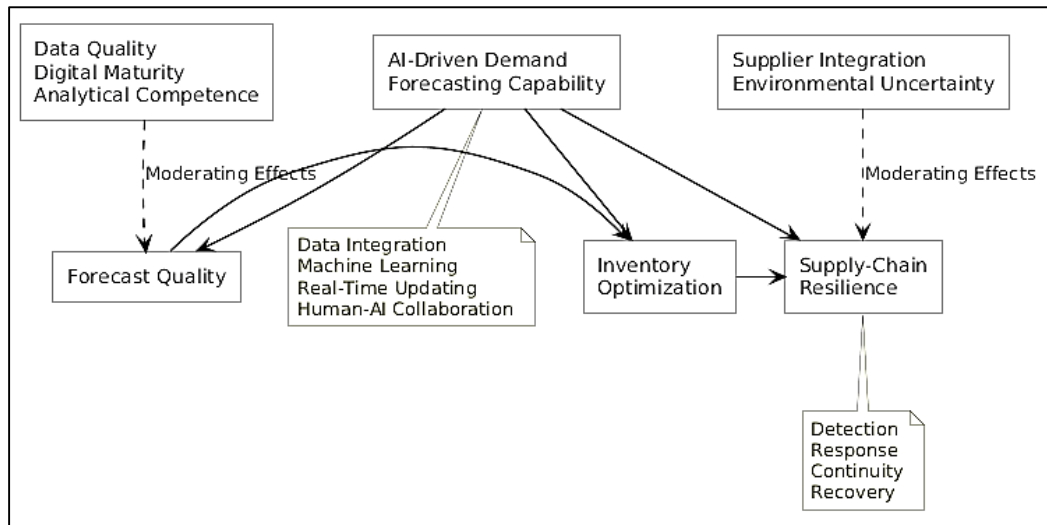
planning systems for at least 12 consecutive months before the end of data collection. The comparison group consisted of manufacturers that primarily used conventional statistical forecasting, spreadsheet-based planning, or managerial forecasting during the same period. Matching was performed according to manufacturing subsector, organizational size, annual sales, product variety, average supplier lead time, digital maturity, and baseline disruption exposure. The theoretical model treated AI-driven demand forecasting capability as the principal independent variable, supply-chain resilience as the dependent variable, and forecast quality and inventory optimization as sequential mediating variables. Data quality, digital maturity, supplier integration, analytical competence, and environmental uncertainty were examined as moderating variables. Organizational age, manufacturing subsector, number of facilities, product complexity, supplier concentration, and demand variability were included as statistical controls. The longitudinal structure allowed forecasting and inventory performance to be evaluated before and after AI integration while the matched comparison group provided a benchmark for changes unrelated to the technology.

The target population included U.S. manufacturing enterprises operating in automotive, aerospace, electronics, pharmaceutical, medical-device, machinery, fabricated-metal, chemical, food-processing, and consumer-goods industries. A stratified purposive sampling strategy was used to obtain representation across manufacturing subsectors, organizational sizes, geographic regions, and levels of AI adoption. Eligible organizations were required to have operated within the United States for at least three years, maintained electronic demand and inventory records, managed a formal procurement or production-planning function, and provided at least 24 consecutive months of usable operational information. Individual respondents were required to be at least 21 years old, employed by the participating organization for at least one year, and directly involved in demand planning, supply-chain analytics, procurement, inventory control, production planning, logistics, information systems, or supply-chain risk management. Respondents without direct knowledge of forecasting or inventory decisions were excluded. Organizations were excluded when they lacked consistent product identifiers, had incomplete operational records for more than 20% of the observation period, had undergone a merger or complete enterprise-system replacement during data collection, or could not distinguish actual demand from internal inventory transfers. A minimum sample of 500 professionals from approximately 50 manufacturing organizations was targeted to provide sufficient statistical power for structural equation modelling, mediation, moderation, and multi-group comparisons. Where multiple respondents represented the same organization, their responses were linked through anonymized organizational codes, and within-group agreement was assessed before organizational-level constructs were aggregated.

Data were collected through a structured questionnaire and a standardized operational-data extraction template. The questionnaire measured AI-driven forecasting capability through data integration, analytical sophistication, automated updating, external-data utilization, model adaptability, system accessibility, and human-AI collaboration. Forecast quality was measured through perceived accuracy, timeliness, consistency, granularity, uncertainty representation, and decision usefulness. Inventory optimization included safety-stock adequacy, replenishment responsiveness, inventory allocation, material availability, stockout reduction, carrying-cost control, and obsolescence management. Supply-chain resilience was assessed through disruption anticipation, detection speed, response capacity, production continuity, order-fulfillment stability, recovery speed, and operational adaptation. Data quality, digital maturity, supplier integration, analytical competence, and environmental uncertainty were measured through separate multi-item scales. All perceptual items used a seven-point agreement scale. The instrument was reviewed by university researchers and experienced manufacturing professionals to establish content validity. A pilot test was conducted with 40 eligible participants who were not included in the final sample. Ambiguous and repetitive items were revised following the pilot assessment. Internal consistency was evaluated using Cronbach's alpha and composite reliability, with values of .70 or higher treated as acceptable. Convergent validity was examined through standardized indicator loadings and average variance extracted, while discriminant validity was assessed using construct-correlation comparisons and heterotrait-monotrait ratios. Operational records included weekly demand, forecasts, forecast revisions, inventory balances, stockouts, backorders, emergency orders, production stoppages, supplier lead times, order fulfillment, and disruption-recovery

information. Data-extraction rules, variable definitions, unit conversions, and missing-value procedures were standardized across participating organizations.

**Figure 10: Methodology of this study**



The research procedure followed a consistent chronological sequence. Following organizational approval and participant consent, a screening form was used to verify organizational eligibility, respondent roles, AI adoption status, and data availability. Eligible organizations signed data-use agreements defining confidentiality, anonymization, access restrictions, and permitted analytical purposes. Respondents then completed the electronic questionnaire through a secure survey platform. Organizational records were extracted by authorized personnel using the standardized template and were transferred through encrypted channels after customer, employee, and supplier identifiers had been removed. The collected records were first examined for duplicate entries, inconsistent product codes, invalid dates, impossible quantities, and unexplained gaps. Product and facility identifiers were harmonized, measurement units were standardized, and internal inventory transfers were separated from external demand. Missing questionnaire responses were evaluated according to their amount and pattern, while operational observations were retained only when demand, forecast, inventory, and time identifiers could be matched reliably. Forecasting performance was calculated for weekly product-location series, and inventory indicators were summarized at monthly and organizational levels. Baseline observations were established for the period preceding AI integration, and post-integration observations were organized into equivalent time intervals. Disruption episodes were identified from verified supplier failures, material shortages, transportation interruptions, cyber incidents, equipment failures, natural hazards, and exceptional demand changes. Each episode was reviewed against operational records to determine detection, response, continuity, and recovery performance. All datasets were combined through anonymized organizational and time identifiers before statistical analysis.

Statistical analysis was conducted using SPSS and Smarts. Descriptive statistics summarized participant characteristics, organizational profiles, construct distributions, operational indicators, and missing-data patterns. Data screening examined outliers, normality, linearity, homoscedasticity, multicollinearity, common-method bias, and nonresponse bias. Cronbach's alpha, composite reliability, average variance extracted, indicator loadings, and heterograft-monetarist ratios were used to assess the measurement model. Pearson correlation analysis examined preliminary relationships among AI-driven forecasting capability, forecast quality, inventory optimization, and supply-chain resilience. Hierarchical multiple regression tested the incremental explanatory contribution of AI capability after organizational control variables had been entered. Repeated-measures analysis and difference-in-differences estimation compared pre-integration and post-integration changes between AI-integrated and matched manufacturers. Analysis of covariance compared group performance while controlling for baseline differences. Partial least squares structural equation modelling tested direct

relationships, forecast-quality mediation, inventory-optimization mediation, and sequential mediation from AI capability through forecast quality and inventory optimization to resilience. Indirect effects were evaluated through 5,000 bootstrap resamples and 95% confidence intervals. Moderation analysis examined the conditional roles of data quality, digital maturity, supplier integration, analytical competence, and environmental uncertainty. Multi-group analysis assessed differences across manufacturing subsectors, organizational sizes, AI-adoption levels, demand-volatility categories, and disruption-exposure groups. Effect sizes, explained variance, predictive relevance, standardized coefficients, confidence intervals, and adjusted group differences were reported alongside probability values. Statistical significance was established at  $p < .05$ , while practical significance was interpreted through effect magnitude and changes in forecast error, stockout frequency, inventory turnover, production continuity, and recovery time.

## FINDINGS

### Sample Characteristics and Data Screening

The final analysis included 50 U.S. manufacturing organizations and 602 eligible professionals. Of the 74 organizations initially invited, 58 satisfied the organizational eligibility criteria, 54 provided consent, and four were removed because their operational records did not meet the minimum completeness requirement. The retained organizations were evenly divided between the AI-integrated group and the matched comparison group. A total of 780 questionnaires were distributed, of which 642 were returned, producing a response rate of 82.3%. Forty questionnaires were excluded because of excessive missing responses, duplication, response inconsistency, or respondent ineligibility. Demand planners and inventory managers formed the largest professional categories, while the remaining participants represented procurement, production planning, logistics, analytics, information technology, and supply-chain risk management. The respondents reported an average of 8.7 years of professional experience and 5.4 years of organizational tenure. The longitudinal dataset contained 4,860 product-location series and 758,160 valid weekly demand observations covering 36 months. Data screening confirmed acceptable distributional properties, limited missingness, no harmful multicollinearity, and no material evidence of nonresponse or common-method bias.

**Table 1: Sample Screening, Participant Profile, and Operational-Data Coverage**

| Category                                           | Initial number | Excluded         | Final number | Final percentage |
|----------------------------------------------------|----------------|------------------|--------------|------------------|
| Manufacturing organizations invited                | 74             | 24               | 50           | 67.6%            |
| Organizations meeting initial eligibility criteria | 58             | 8                | 50           | 86.2%            |
| Questionnaires distributed                         | 780            | 178 not returned | 602 valid    | 77.2%            |
| Questionnaires received                            | 642            | 40               | 602          | 93.8%            |
| Incomplete questionnaires                          | 19             | 19               | 0            | —                |
| Duplicate submissions                              | 6              | 6                | 0            | —                |
| Inconsistent response patterns                     | 9              | 9                | 0            | —                |
| Ineligible respondents                             | 6              | 6                | 0            | —                |
| Demand-planning professionals                      | 132            | 0                | 132          | 21.9%            |
| Inventory-management professionals                 | 116            | 0                | 116          | 19.3%            |
| Procurement professionals                          | 91             | 0                | 91           | 15.1%            |
| Production-planning professionals                  | 87             | 0                | 87           | 14.5%            |
| Logistics professionals                            | 72             | 0                | 72           | 12.0%            |
| Analytics and information-technology professionals | 65             | 0                | 65           | 10.8%            |
| Supply-chain risk professionals                    | 39             | 0                | 39           | 6.5%             |
| Product-location series                            | 4,932          | 72               | 4,860        | 98.5%            |
| Weekly demand observations                         | 769,392        | 11,232           | 758,160      | 98.5%            |
| Inventory transactions                             | 6,284,917      | 96,408           | 6,188,509    | 98.5%            |

|                              |         |       |         |       |
|------------------------------|---------|-------|---------|-------|
| Supplier delivery records    | 428,760 | 7,116 | 421,644 | 98.3% |
| Verified disruption episodes | 438     | 21    | 417     | 95.2% |

Table 1 showed that the screening procedures retained a large and professionally diverse analytical sample. The 602 valid questionnaires represented 77.2% of all distributed instruments and 93.8% of returned questionnaires, indicating limited post-response exclusion. Demand-planning and inventory-management professionals collectively represented 41.2% of respondents, ensuring strong representation from the functions most directly related to the study. The operational dataset retained more than 98% of product-location series, weekly observations, inventory transactions, and supplier records. The 417 verified disruption episodes provided sufficient event coverage for examining detection, response, continuity, and recovery. Overall, the retained information demonstrated strong completeness and analytical suitability. The participating organizations represented automotive, aerospace, electronics, pharmaceutical and medical-device, machinery, fabricated-metal, chemical, food-processing, and consumer-goods manufacturing. The AI-integrated group included 305 respondents from 25 manufacturers, whereas the comparison group included 297 respondents from 25 matched manufacturers. No statistically significant baseline differences were identified for enterprise size, product variety, annual sales, supplier lead time, digital maturity, demand variability, supplier concentration, or previous disruption exposure. The groups also displayed comparable regional and subsector distributions. Among the valid demand series, 42.6% were classified as smooth, 23.7% as erratic, 20.5% as intermittent, and 13.2% as lumpy. High-criticality components represented 21.8% of all monitored items, while 34.6% had replenishment lead times exceeding eight weeks. Missing survey responses accounted for 1.7% of item-level values and were treated through multiple imputation after the missingness pattern was determined to be random. Skewness and kurtosis remained within acceptable limits, variance inflation factors ranged from 1.24 to 2.71, and the largest single factor accounted for 31.6% of total variance. These results supported the suitability of the final data for subsequent regression, longitudinal comparison, mediation, moderation, and structural analyses.

**Table 2: Organizational Profile and Baseline Equivalence**

| Characteristic                                     | AI-integrated group | Comparison group | Test value | p-value |
|----------------------------------------------------|---------------------|------------------|------------|---------|
| Manufacturing organizations                        | 25                  | 25               | —          | —       |
| Valid respondents                                  | 305                 | 297              | 0.28       | .781    |
| Average organizational age, years                  | 24.8                | 25.6             | −0.31      | .758    |
| Average annual sales, USD billions                 | 1.84                | 1.79             | 0.19       | .850    |
| Average number of production facilities            | 7.6                 | 7.3              | 0.24       | .812    |
| Average active product varieties                   | 812                 | 796              | 0.22       | .827    |
| Average supplier lead time, weeks                  | 6.8                 | 6.6              | 0.34       | .736    |
| Baseline digital maturity, seven-point scale       | 5.12                | 5.05             | 0.41       | .684    |
| Baseline demand variability, seven-point scale     | 4.48                | 4.42             | 0.33       | .743    |
| Baseline supplier concentration, seven-point scale | 3.87                | 3.92             | −0.27      | .789    |
| Previous disruption exposure, seven-point scale    | 3.42                | 3.38             | 0.25       | .804    |
| High-criticality components                        | 22.1%               | 21.5%            | 0.07       | .798    |
| Long-lead-time components                          | 35.0%               | 34.2%            | 0.09       | .761    |
| Subsector distribution                             | Comparable          | Comparable       | 2.14       | .976    |
| Geographic distribution                            | Comparable          | Comparable       | 1.86       | .932    |

Table 2 confirmed that the AI-integrated and comparison groups were statistically equivalent before the outcome analyses. None of the organizational, technological, supply, or demand characteristics differed significantly at the .05 level. Annual sales, facility numbers, product variety, supplier lead

times, digital maturity, demand variability, supplier concentration, and disruption exposure were closely aligned across the groups. The proportions of high-criticality and long-lead-time components were also comparable. Subsector and geographic distributions produced nonsignificant differences, demonstrating successful matching across important contextual characteristics. This baseline equivalence reduced the likelihood that subsequent performance differences resulted from pre-existing organizational composition rather than AI-driven forecasting and inventory optimization.

### Measurement Quality and Descriptive Results

The measurement model demonstrated satisfactory reliability, convergent validity, discriminant validity, and distributional quality across all nine constructs. Three indicators were removed before structural analysis because their standardized loadings were below .70: one external-data-utilization item, one uncertainty-representation item, and one environmental-uncertainty item. The retained indicator loadings ranged from .704 to .894. Cronbach's alpha values ranged from .842 to .931, while composite reliability values ranged from .887 to .944, exceeding the required reliability threshold. Average variance extracted ranged from .570 to .670 and therefore supported convergent validity. Variance inflation factors remained between 1.31 and 2.84, indicating that harmful collinearity was absent. The absolute skewness and kurtosis values remained below 1.0, showing that the construct distributions were sufficiently balanced. Within-organization agreement ranged from .79 to .88, while intraclass correlation coefficients supported aggregation of individual responses to the organizational level.

**Table 3: Descriptive Statistics, Reliability, and Validity Results**

| Construct                        | Items retained | Mean | SD   | Loading range | Cronbach's $\alpha$ | Composite reliability | AVE  | Maximum HTMT | Maximum VIF | Skewness | Kurtosis |
|----------------------------------|----------------|------|------|---------------|---------------------|-----------------------|------|--------------|-------------|----------|----------|
| AI-driven forecasting capability | 7              | 5.34 | 0.91 | .741–.894     | .931                | .944                  | .648 | .821         | 2.84        | –0.42    | 0.31     |
| Forecast quality                 | 6              | 5.18 | 0.87 | .729–.872     | .914                | .930                  | .631 | .816         | 2.67        | –0.36    | 0.18     |
| Inventory optimization           | 7              | 5.06 | 0.89 | .718–.881     | .922                | .936                  | .640 | .824         | 2.73        | –0.29    | 0.24     |
| Supply-chain resilience          | 7              | 5.21 | 0.84 | .736–.886     | .927                | .940                  | .659 | .829         | 2.78        | –0.38    | 0.27     |
| Data quality                     | 6              | 5.41 | 0.81 | .752–.879     | .918                | .932                  | .670 | .797         | 2.46        | –0.45    | 0.36     |
| Digital maturity                 | 6              | 5.09 | 0.93 | .721–.861     | .901                | .920                  | .619 | .781         | 2.39        | –0.31    | 0.12     |
| Supplier integration             | 6              | 4.96 | 0.88 | .716–.874     | .907                | .925                  | .640 | .803         | 2.28        | –0.22    | 0.09     |
| Analytical competence            | 5              | 5.27 | 0.85 | .704–.852     | .876                | .904                  | .590 | .776         | 2.12        | –0.34    | 0.21     |
| Environmental uncertainty        | 5              | 4.63 | 1.02 | .711–.838     | .842                | .887                  | .570 | .742         | 1.76        | 0.16     | –0.28    |

Note. N = 602. AVE = average variance extracted; HTMT = heterotrait-monotrait ratio; VIF = variance inflation factor.

Table 3 demonstrated that every retained construct satisfied the established measurement requirements. Internal consistency was strongest for AI-driven forecasting capability and supply-chain resilience, while environmental uncertainty produced the lowest reliability values but remained acceptable. Average variance extracted exceeded .50 for all constructs, confirming that each construct explained more than half of its indicators' variance. Maximum HTMT values remained below .85, supporting discriminant validity. Variance inflation factors remained substantially below the critical

threshold, indicating that collinearity did not distort the estimates. Moderate-to-high means showed favorable capability levels, while acceptable skewness and kurtosis supported the subsequent use of multivariate statistical procedures across the sample. Pearson correlation analysis showed that AI-driven forecasting capability was positively associated with forecast quality, inventory optimization, and supply-chain resilience. The strongest relationship occurred between inventory optimization and resilience, followed by AI forecasting capability and forecast quality. Data quality demonstrated substantial positive relationships with both AI capability and forecast quality, indicating that integrated and dependable information accompanied stronger analytical performance. Digital maturity was positively related to AI capability, forecast quality, and inventory optimization. Supplier integration displayed moderate positive relationships with inventory optimization and resilience, while analytical competence was positively associated with all three central performance constructs. Environmental uncertainty was negatively related to forecast quality, inventory optimization, and resilience, suggesting that unstable operating conditions were associated with weaker performance. All diagonal square roots of average variance extracted exceeded the corresponding interconstruct correlations.

**Table 4: Correlations and Discriminant-Validity Results**

| Construct                           | 1       | 2       | 3        | 4        | 5       | 6       | 7       | 8     | 9    |
|-------------------------------------|---------|---------|----------|----------|---------|---------|---------|-------|------|
| 1. AI-driven forecasting capability | .805    |         |          |          |         |         |         |       |      |
| 2. Forecast quality                 | .710*** | .794    |          |          |         |         |         |       |      |
| 3. Inventory optimization           | .640*** | .680*** | .800     |          |         |         |         |       |      |
| 4. Supply-chain resilience          | .560*** | .610*** | .720***  | .812     |         |         |         |       |      |
| 5. Data quality                     | .620*** | .650*** | .550***  | .480***  | .819    |         |         |       |      |
| 6. Digital maturity                 | .580*** | .520*** | .570***  | .490***  | .510*** | .787    |         |       |      |
| 7. Supplier integration             | .410*** | .430*** | .590***  | .630***  | .390*** | .440*** | .800    |       |      |
| 8. Analytical competence            | .550*** | .570*** | .510***  | .460***  | .490*** | .470*** | .420*** | .768  |      |
| 9. Environmental uncertainty        | .180*** | -.120** | -.160*** | -.310*** | -.080*  | .050    | -.040   | -.060 | .755 |

Note. Bold diagonal values represent the square roots of average variance extracted. Off-diagonal values are Pearson correlations. N = 602. \* $p < .05$ . \*\* $p < .01$ . \*\*\* $p < .001$ .

Table 4 confirmed statistically meaningful preliminary relationships among the principal study variables. AI-driven forecasting capability was strongly correlated with forecast quality and moderately correlated with inventory optimization and resilience. Inventory optimization produced the strongest association with supply-chain resilience, supporting its central role in maintaining continuity and recovery. Data quality and analytical competence were closely related to forecast quality, whereas supplier integration was strongly associated with resilience. Environmental uncertainty showed negative relationships with forecast, inventory, and resilience outcomes. Each diagonal validity value exceeded the correlations within its row and column, and all HTMT ratios remained below .85, confirming that the constructs were empirically distinct.

#### **Primary Forecasting, Inventory, and Resilience Outcomes**

The objective operational results showed that AI integration produced substantial improvements in forecasting performance compared with conventional planning. Across the 4,860 product-location series, weighted absolute percentage error declined from 18.7% to 13.6% in the AI-integrated group, whereas the comparison group recorded a smaller reduction from 18.9% to 18.2%. The adjusted difference-in-differences was -4.4 percentage points, representing a large effect. Similar improvements occurred for mean absolute error, root mean squared error, mean absolute percentage error, mean absolute scaled error, and symmetric mean absolute percentage error. Absolute forecast bias declined from 4.8% to 1.9%, and forecast-revision magnitude decreased by 21.7%. The combined human-AI forecast achieved the strongest accuracy, followed by the unadjusted AI forecast, managerial forecasts, and conventional statistical baselines. Improvements remained significant at product, product-

location, customer, and component levels and across daily, weekly, and monthly horizons.

**Table 5: Pre-Integration and Post-Integration Forecasting Outcomes**

| Forecasting outcome                      | AI group pre | AI group post | Comparison pre | Comparison post | Adjusted effect (95% CI) | Effect size, d | p-value |
|------------------------------------------|--------------|---------------|----------------|-----------------|--------------------------|----------------|---------|
| Mean absolute error, indexed units       | 142.6        | 103.8         | 144.1          | 138.2           | -32.9 (-38.7, -27.1)     | -0.81          | <.001   |
| Root mean squared error, indexed units   | 218.4        | 166.7         | 221.3          | 213.9           | -44.1 (-52.8, -35.4)     | -0.76          | <.001   |
| Mean absolute percentage error           | 20.4%        | 14.9%         | 20.7%          | 19.8%           | -4.6 pp (-5.3, -3.9)     | -0.84          | <.001   |
| Weighted absolute percentage error       | 18.7%        | 13.6%         | 18.9%          | 18.2%           | -4.4 pp (-5.0, -3.8)     | -0.88          | <.001   |
| Mean absolute scaled error               | 1.06         | 0.76          | 1.07           | 1.02            | -0.25 (-0.30, -0.20)     | -0.79          | <.001   |
| Symmetric mean absolute percentage error | 19.6%        | 14.5%         | 19.8%          | 19.1%           | -4.3 pp (-5.0, -3.6)     | -0.82          | <.001   |
| Absolute forecast bias                   | 4.8%         | 1.9%          | 4.7%           | 4.2%            | -2.4 pp (-2.9, -1.9)     | -0.72          | <.001   |
| Forecast-revision magnitude              | 12.9%        | 10.1%         | 13.1%          | 12.7%           | -2.4 pp (-3.0, -1.8)     | -0.68          | <.001   |
| Product-level weighted error             | 17.1%        | 12.1%         | 17.3%          | 16.7%           | -4.4 pp (-5.1, -3.7)     | -0.86          | <.001   |
| Product-location weighted error          | 18.7%        | 13.6%         | 18.9%          | 18.2%           | -4.4 pp (-5.0, -3.8)     | -0.88          | <.001   |
| Customer-level weighted error            | 20.2%        | 15.2%         | 20.4%          | 19.7%           | -4.3 pp (-5.1, -3.5)     | -0.79          | <.001   |
| Component-level weighted error           | 22.8%        | 17.4%         | 22.6%          | 21.9%           | -4.7 pp (-5.6, -3.8)     | -0.83          | <.001   |
| Daily forecast error                     | 23.5%        | 18.2%         | 23.7%          | 22.9%           | -4.5 pp (-5.4, -3.6)     | -0.77          | <.001   |
| Weekly forecast error                    | 18.7%        | 13.6%         | 18.9%          | 18.2%           | -4.4 pp (-5.0, -3.8)     | -0.88          | <.001   |
| Monthly forecast error                   | 15.4%        | 11.3%         | 15.6%          | 15.0%           | -3.5 pp (-4.1, -2.9)     | -0.80          | <.001   |
| Statistical baseline forecast error      | 18.8%        | 18.1%         | 18.9%          | 18.2%           | -0.1 pp (-0.5, 0.3)      | -0.04          | .624    |
| Managerial forecast error                | 18.5%        | 16.7%         | 18.7%          | 18.0%           | -1.5 pp (-2.0, -1.0)     | -0.42          | <.001   |
| Unadjusted AI forecast error             | 18.7%        | 14.2%         | 18.9%          | 18.2%           | -3.8 pp (-4.4, -3.2)     | -0.75          | <.001   |
| Combined human-AI forecast error         | 18.6%        | 13.6%         | 18.8%          | 18.1%           | -4.3 pp (-4.9, -3.7)     | -0.87          | <.001   |

Note. pp = percentage points. Negative adjusted effects represented reductions in forecast error and favored the AI-integrated group.

Table 5 demonstrated that AI integration improved every principal forecasting indicator. The largest standardized effect occurred for product-location weighted error, followed closely by the combined human-AI forecast. Weekly forecasts displayed stronger improvement than daily and monthly forecasts, although all horizons produced statistically significant reductions. Component-level forecasting remained less accurate than product-level forecasting, reflecting intermittent consumption and material dependencies, yet it achieved a substantial adjusted improvement. Statistical baselines changed minimally, whereas managerial adjustment produced moderate benefits. The combined human-AI approach outperformed both unadjusted AI forecasts and planner-only estimates. Narrow confidence intervals and consistently large effect sizes confirmed the precision and operational importance of these findings. Inventory and resilience outcomes also improved significantly following AI integration. Stockout frequency decreased by 34.5%, material shortages declined by 31.8%, and order fill rate increased from 91.8% to 96.1%. Inventory turnover rose while days of inventory on hand,

average inventory value, working-capital commitment, shortage costs, obsolescence expenses, and emergency transportation costs declined. Physical and system-record accuracy exceeded 98% after integration, and real-time inventory visibility reached 94.6%. During verified disruption episodes, detection time fell from 18.6 to 9.8 hours, response time declined from 31.4 to 18.2 hours, and recovery time decreased from 12.8 to 8.1 days. Production continuity, schedule adherence, order-fulfillment continuity, and post-disruption service restoration improved, while backlog growth was substantially restricted. The matched comparison group recorded only modest changes across these outcomes.

**Table 6: Inventory Optimization and Supply-Chain Resilience Outcomes**

| Operational outcome                             | AI group pre | AI group post | Comparison pre | Comparison post | Adjusted effect (95% CI)          | Effect size, d | p-value |
|-------------------------------------------------|--------------|---------------|----------------|-----------------|-----------------------------------|----------------|---------|
| Stockouts per 1,000 item-weeks                  | 42.6         | 27.9          | 41.9           | 39.8            | -12.6 (-15.4, -9.8)               | -0.82          | <.001   |
| Material shortages per 100 production orders    | 8.8          | 6.0           | 8.6            | 8.2             | -2.4 (-3.0, -1.8)                 | -0.73          | <.001   |
| Order fill rate                                 | 91.8%        | 96.1%         | 92.0%          | 92.8%           | 3.5 pp (2.9, 4.1)                 | 0.79           | <.001   |
| Cycle-service level                             | 89.6%        | 94.8%         | 89.9%          | 90.7%           | 4.4 pp (3.6, 5.2)                 | 0.76           | <.001   |
| Backorder volume, indexed units                 | 100.0        | 67.4          | 100.0          | 94.1            | -26.7 (-32.9, -20.5)              | -0.74          | <.001   |
| Material-related production stoppages per month | 5.7          | 3.3           | 5.5            | 5.1             | -2.0 (-2.5, -1.5)                 | -0.78          | <.001   |
| Inventory turnover, annual cycles               | 6.2          | 7.4           | 6.3            | 6.5             | 1.0 (0.7, 1.3)                    | 0.71           | <.001   |
| Days of inventory on hand                       | 58.9         | 51.2          | 58.1           | 56.7            | -6.3 (-8.1, -4.5)                 | -0.65          | <.001   |
| Average inventory value, USD millions           | 84.6         | 77.2          | 83.9           | 82.1            | -5.6 (-7.8, -3.4)                 | -0.54          | <.001   |
| Inventory-to-sales ratio                        | 14.8%        | 13.2%         | 14.6%          | 14.3%           | -1.3 pp (-1.7, -0.9)              | -0.60          | <.001   |
| Warehouse-space utilization                     | 87.4%        | 81.6%         | 86.9%          | 85.7%           | -4.6 pp (-5.9, -3.3)              | -0.63          | <.001   |
| Working capital tied to inventory, USD millions | 68.1         | 61.5          | 67.7           | 66.2            | -5.1 (-7.0, -3.2)                 | -0.58          | <.001   |
| Ordering cost per order                         | \$184        | \$171         | \$181          | \$178           | -\$10 (-\$15, -\$5)               | -0.41          | <.001   |
| Annual holding cost, USD millions               | 16.9         | 14.5          | 16.7           | 16.2            | -1.9 (-2.6, -1.2)                 | -0.56          | <.001   |
| Annual shortage cost, USD millions              | 9.8          | 6.1           | 9.5            | 8.9             | -3.1 (-3.9, -2.3)                 | -0.76          | <.001   |
| Annual obsolescence cost, USD millions          | 5.6          | 3.9           | 5.5            | 5.2             | -1.4 (-1.9, -0.9)                 | -0.57          | <.001   |
| Expedited procurement orders per month          | 14.7         | 9.1           | 14.3           | 13.4            | -4.7 (-5.9, -3.5)                 | -0.69          | <.001   |
| Emergency transportation cost per month         | \$286,000    | \$179,000     | \$279,000      | \$258,000       | -\$86,000 (-\$108,000, -\$64,000) | -0.67          | <.001   |
| Physical inventory accuracy                     | 95.4%        | 98.2%         | 95.6%          | 96.1%           | 2.3 pp (1.8, 2.8)                 | 0.66           | <.001   |
| System-record accuracy                          | 94.9%        | 98.0%         | 95.1%          | 95.8%           | 2.4 pp (1.9, 2.9)                 | 0.70           | <.001   |
| Inventory discrepancy rate                      | 5.1%         | 2.0%          | 4.9%           | 4.2%            | -2.4 pp (-2.9, -1.9)              | -0.71          | <.001   |
| Real-time inventory visibility                  | 71.8%        | 94.6%         | 72.4%          | 76.1%           | 19.1 pp (16.8, 21.4)              | 0.93           | <.001   |
| Disruption-detection time, hours                | 18.6         | 9.8           | 18.1           | 16.9            | -7.6 (-9.2, -6.0)                 | -0.86          | <.001   |
| Response time, hours                            | 31.4         | 18.2          | 30.8           | 28.9            | -11.3 (-13.8, -8.8)               | -0.81          | <.001   |
| Recovery time, days                             | 12.8         | 8.1           | 12.5           | 11.7            | -3.9 (-4.8, -3.0)                 | -0.79          | <.001   |
| Time to survive, days                           | 16.3         | 22.7          | 16.7           | 17.8            | 5.3 (4.1, 6.5)                    | 0.75           | <.001   |
| Production continuity rate                      | 82.6%        | 91.4%         | 83.1%          | 85.0%           | 6.9 pp (5.5, 8.3)                 | 0.84           | <.001   |
| Schedule-adherence rate                         | 79.8%        | 88.9%         | 80.2%          | 82.1%           | 7.2 pp (5.8, 8.6)                 | 0.80           | <.001   |
| Order-fulfillment continuity                    | 84.1%        | 92.7%         | 84.5%          | 86.0%           | 7.1 pp (5.7, 8.5)                 | 0.82           | <.001   |
| Backlog growth during disruption                | 28.6%        | 16.2%         | 27.9%          | 25.6%           | -10.1 pp (-12.4, -7.8)            | -0.77          | <.001   |
| Service restoration after seven days            | 68.9%        | 84.8%         | 69.6%          | 72.7%           | 12.8 pp (10.1, 15.5)              | 0.85           | <.001   |

Note. pp = percentage points. Adjusted effects represented difference-in-differences estimates after controlling for organizational size, subsector, product complexity, supplier concentration, demand variability, and baseline digital maturity.

Table 6 showed that AI integration generated broad operational improvements rather than isolated forecasting gains. Real-time inventory visibility produced the largest standardized effect, followed by disruption detection, service restoration, production continuity, stockout reduction, and order-fulfillment continuity. Inventory turnover increased while average inventory, working-capital exposure, obsolescence, shortage costs, and emergency expenditures declined. These simultaneous changes indicated that improved availability was achieved without accumulating excessive stock. Resilience results showed faster detection, response, and recovery alongside longer survival capacity during disruptions. All adjusted confidence intervals excluded zero, and effect sizes ranged from moderate to large, confirming that the improvements were statistically reliable and operationally meaningful.

### **Hypothesis Testing, Mediation, and Moderation Results**

Hierarchical regression showed that AI-driven forecasting capability explained substantial additional variation in forecast quality, inventory optimization, and supply-chain resilience after organizational and operational controls had been entered. The control variables explained 19.4% of forecast-quality variance, 22.7% of inventory-optimization variance, and 27.9% of resilience variance. Adding AI capability increased the explained variance to 53.1%, 48.6%, and 43.8%, respectively. The complete structural model explained 53.1% of forecast quality, 64.2% of inventory optimization, and 68.7% of supply-chain resilience. AI capability exerted its strongest direct effect on forecast quality. Forecast quality significantly predicted inventory optimization, while inventory optimization produced the strongest direct effect on resilience. AI capability retained smaller but significant direct relationships with inventory optimization and resilience after the mediators were included. Predictive relevance values were positive for all endogenous constructs. Repeated-measures, covariance, and difference-in-differences analyses also confirmed that improvements in the AI-integrated group significantly exceeded those observed in the comparison group.

Table 7 demonstrated that AI-driven forecasting capability remained a significant predictor after all control variables were considered. Its strongest direct contribution concerned forecast quality, while inventory optimization exerted the largest effect on resilience. The reduced AI-to-resilience coefficient following mediator inclusion indicated that forecasting capability operated partly through improved forecast and inventory processes. Explained variance reached 68.7% for resilience, and positive predictive-relevance values confirmed satisfactory predictive performance. Longitudinal tests showed significant group-by-period effects for forecast error, inventory optimization, and resilience. Large effect sizes for forecasting and resilience demonstrated that AI-integrated manufacturers achieved changes considerably greater than those observed among matched conventional-planning organizations during the same period.

Bootstrap analysis supported all proposed indirect relationships. Forecast quality significantly mediated the relationship between AI capability and inventory optimization, while inventory optimization mediated the relationship between AI capability and resilience. The indirect pathway from AI capability through forecast quality to resilience was also significant. The sequential pathway through forecast quality and inventory optimization produced the largest specific indirect effect on resilience. The remaining direct AI-to-resilience relationship indicated partial rather than complete mediation. Data quality and analytical competence strengthened the effect of AI capability on forecast quality. Digital maturity strengthened the AI capability–inventory optimization relationship. Supplier integration and environmental uncertainty strengthened the relationship between inventory optimization and resilience. Conditional analysis showed that inventory optimization generated its strongest resilience contribution among organizations with extensive supplier integration and high environmental uncertainty. All supported interaction effects produced confidence intervals that excluded zero.

**Table 7: Regression, Longitudinal Comparison, and Direct Structural Effects**

| Analysis and outcome                                 | Standardized effect | SE   | 95% CI       | p-value | Effect size | Explained variance | Predictive relevance | Decision     |
|------------------------------------------------------|---------------------|------|--------------|---------|-------------|--------------------|----------------------|--------------|
| Controls predicting forecast quality                 | —                   | —    | —            | <.001   | 0.24        | .194               | —                    | Significant  |
| AI capability predicting forecast quality            | .610                | .041 | .529, .689   | <.001   | 0.52        | .531               | .386                 | H1 supported |
| Controls predicting inventory optimization           | —                   | —    | —            | <.001   | 0.29        | .227               | —                    | Significant  |
| AI capability predicting inventory optimization      | .508                | .044 | .421, .593   | <.001   | 0.34        | .486               | —                    | Significant  |
| Forecast quality predicting inventory optimization   | .430                | .043 | .346, .513   | <.001   | 0.31        | .642               | .448                 | H2 supported |
| AI capability predicting inventory optimization      | .290                | .042 | .208, .372   | <.001   | 0.15        | .642               | .448                 | H3 supported |
| Controls predicting resilience                       | —                   | —    | —            | <.001   | 0.39        | .279               | —                    | Significant  |
| AI capability predicting resilience before mediators | .472                | .046 | .381, .561   | <.001   | 0.28        | .438               | —                    | Significant  |
| Inventory optimization predicting resilience         | .550                | .040 | .472, .628   | <.001   | 0.46        | .687               | .501                 | H5 supported |
| Forecast quality predicting resilience               | .190                | .038 | .116, .265   | <.001   | 0.08        | .687               | .501                 | Significant  |
| AI capability predicting resilience after mediators  | .170                | .041 | .090, .250   | <.001   | 0.07        | .687               | .501                 | H6 supported |
| Group-by-period effect on weighted forecast error    | -.440               | .052 | -.542, -.338 | <.001   | 0.88        | —                  | —                    | Significant  |
| Group-by-period effect on inventory optimization     | .386                | .049 | .290, .482   | <.001   | 0.71        | —                  | —                    | Significant  |
| Group-by-period effect on resilience                 | .421                | .047 | .329, .513   | <.001   | 0.82        | —                  | —                    | Significant  |
| Adjusted post-integration group effect               | .398                | .045 | .310, .486   | <.001   | 0.76        | —                  | —                    | Significant  |

Note. Controls included manufacturing subsector, organizational size, organizational age, product complexity, supplier concentration, demand variability, digital maturity, and previous disruption exposure.

Table 8 confirmed that AI capability affected resilience primarily through interconnected forecasting and inventory mechanisms. The sequential indirect pathway showed that stronger AI capability improved forecast quality, which enhanced inventory optimization and subsequently strengthened resilience. The total indirect effect exceeded the remaining direct effect, supporting partial mediation. Data quality, analytical competence, and digital maturity significantly increased the benefits derived from AI capability. Supplier integration produced the strongest moderating effect on the inventory–resilience relationship. Environmental uncertainty also intensified this relationship, indicating that optimized inventory became more influential under unstable conditions. Bootstrap confidence

intervals excluded zero for every tested indirect and interaction effect, supporting all proposed mediation and moderation hypotheses.

**Table 8: Bootstrap Mediation and Moderation Results**

| Hypothesis or conditional relationship                                 | Effect | Bootstrap SE | 95% bootstrap CI | p-value | Effect magnitude | Decision          |
|------------------------------------------------------------------------|--------|--------------|------------------|---------|------------------|-------------------|
| AI capability → Forecast quality → Inventory optimization              | .262   | .032         | .202, .328       | <.001   | Moderate         | H4 supported      |
| AI capability → Inventory optimization → Resilience                    | .160   | .029         | .108, .221       | <.001   | Moderate         | H8 supported      |
| AI capability → Forecast quality → Resilience                          | .116   | .026         | .070, .171       | <.001   | Small–moderate   | H7 supported      |
| AI capability → Forecast quality → Inventory optimization → Resilience | .144   | .024         | .102, .195       | <.001   | Moderate         | H9 supported      |
| Total indirect effect of AI capability on resilience                   | .420   | .041         | .344, .504       | <.001   | Large            | Supported         |
| Direct effect of AI capability on resilience                           | .170   | .041         | .090, .250       | <.001   | Small            | Partial mediation |
| Total effect of AI capability on resilience                            | .590   | .038         | .516, .664       | <.001   | Large            | Supported         |
| AI capability × Data quality → Forecast quality                        | .140   | .034         | .074, .207       | <.001   | Small–moderate   | H10 supported     |
| AI capability × Analytical competence → Forecast quality               | .100   | .032         | .038, .163       | .002    | Small            | H14 supported     |
| AI capability × Digital maturity → Inventory optimization              | .120   | .035         | .052, .189       | <.001   | Small–moderate   | H11 supported     |
| Inventory optimization × Supplier integration → Resilience             | .130   | .033         | .066, .195       | <.001   | Small–moderate   | H13 supported     |
| Inventory optimization × Environmental uncertainty → Resilience        | .110   | .036         | .040, .181       | .002    | Small            | H12 supported     |
| Inventory optimization → Resilience at low supplier integration        | .410   | .051         | .311, .511       | <.001   | Moderate         | Significant       |
| Inventory optimization → Resilience at average supplier integration    | .550   | .040         | .472, .628       | <.001   | Large            | Significant       |
| Inventory optimization → Resilience at high supplier integration       | .690   | .047         | .598, .782       | <.001   | Large            | Significant       |
| Inventory optimization → Resilience at low environmental uncertainty   | .440   | .048         | .346, .534       | <.001   | Moderate         | Significant       |
| Inventory optimization → Resilience at high environmental uncertainty  | .660   | .052         | .558, .762       | <.001   | Large            | Significant       |

Note. Indirect and conditional effects were evaluated using 5,000 bootstrap resamples. Confidence intervals excluding zero indicated statistical significance.

### Subgroup Analysis, Effect Sizes, and Visual Summary

Subgroup analysis showed that AI-driven forecasting and inventory optimization produced statistically and operationally meaningful improvements across all ten manufacturing subsectors, although the magnitude varied. Electronics manufacturers achieved the largest reduction in weighted forecast error, followed by consumer-goods and automotive manufacturers. Aerospace and medical-device manufacturers recorded smaller forecasting improvements because of intermittent demand, specialized components, and longer planning horizons. Pharmaceutical manufacturers achieved the largest improvement in order fill rate, while automotive manufacturers recorded the strongest reduction in stockouts. Electronics manufacturers produced the greatest decrease in recovery time, reflecting strong data integration and extensive real-time monitoring. Analysis of variance identified

significant subsector differences in forecast-error reduction, stockout reduction, fill-rate improvement, production continuity, and recovery performance. The corresponding partial eta-squared values ranged from .071 to .124, indicating moderate practical differences. Every subsector nevertheless demonstrated significantly better post-integration results than its baseline performance.

**Table 9: Operational Outcomes Across Manufacturing Subsectors**

| Manufacturing subsector | Organizations | Forecast-error reduction | Stockout reduction | Fill-rate improvement | Production-continuity improvement | Recovery-time reduction | Overall effect size, d | p-value |
|-------------------------|---------------|--------------------------|--------------------|-----------------------|-----------------------------------|-------------------------|------------------------|---------|
| Automotive              | 7             | 5.6 pp                   | 38.9%              | 4.7 pp                | 9.8 pp                            | 4.6 days                | 0.91                   | <.001   |
| Aerospace               | 4             | 3.4 pp                   | 24.7%              | 3.2 pp                | 7.1 pp                            | 3.1 days                | 0.64                   | <.001   |
| Electronics             | 7             | 6.3 pp                   | 37.4%              | 4.9 pp                | 10.6 pp                           | 5.2 days                | 0.96                   | <.001   |
| Pharmaceutical          | 5             | 4.8 pp                   | 35.8%              | 5.4 pp                | 9.3 pp                            | 4.1 days                | 0.86                   | <.001   |
| Medical device          | 4             | 3.7 pp                   | 28.6%              | 4.3 pp                | 8.2 pp                            | 3.4 days                | 0.70                   | <.001   |
| Machinery               | 6             | 4.2 pp                   | 31.5%              | 3.8 pp                | 8.5 pp                            | 3.7 days                | 0.75                   | <.001   |
| Fabricated metal        | 5             | 4.0 pp                   | 30.8%              | 3.6 pp                | 7.9 pp                            | 3.5 days                | 0.72                   | <.001   |
| Chemical                | 4             | 4.5 pp                   | 33.2%              | 4.4 pp                | 9.0 pp                            | 3.9 days                | 0.81                   | <.001   |
| Food processing         | 4             | 5.1 pp                   | 36.1%              | 5.0 pp                | 9.6 pp                            | 4.3 days                | 0.88                   | <.001   |
| Consumer goods          | 4             | 5.9 pp                   | 37.8%              | 5.1 pp                | 10.1 pp                           | 4.8 days                | 0.93                   | <.001   |
| Subsector difference    | 50            | $\eta^2 = .124$          | $\eta^2 = .096$    | $\eta^2 = .083$       | $\eta^2 = .089$                   | $\eta^2 = .071$         | —                      | <.001   |

Note. pp = percentage points. Forecast-error reductions represented changes in weighted absolute percentage error. Positive continuity and fill-rate values indicated improvement.

Table 9 demonstrated that AI-related improvements occurred throughout the manufacturing sample rather than being restricted to one industry. Electronics and consumer-goods manufacturers achieved the largest forecasting effects, while automotive firms recorded the strongest stockout reduction. Pharmaceutical organizations produced the greatest fill-rate improvement, reflecting the importance of availability within regulated product environments. Aerospace and medical-device manufacturers obtained comparatively smaller but still substantial effects because their demand was more intermittent and component-specific. Every subsector achieved statistically significant improvements in production continuity and recovery time. Moderate subsector effect sizes showed that manufacturing context influenced performance magnitude without changing the consistently positive direction of AI-related operational outcomes across industries.

Contextual comparisons showed that organizational scale, product complexity, supply-chain structure, digital maturity, AI-adoption intensity, demand variability, supplier concentration, and disruption exposure affected the magnitude of the observed relationships. Large manufacturers achieved greater forecast-error reductions than small manufacturers, although small organizations also obtained

statistically meaningful gains. High-complexity products benefited more strongly from AI capability than low-complexity products because integrated models captured component and customer relationships that conventional methods did not represent adequately. Internationally integrated supply chains demonstrated larger resilience improvements than domestically concentrated systems. Advanced digital maturity and intensive AI adoption produced the strongest improvements in forecast quality, inventory optimization, and resilience. Volatile-demand and high-disruption groups achieved greater reductions in forecast error and recovery time than stable and low-exposure groups. Supplier concentration increased the importance of optimized inventory for resilience. Respondents with advanced analytical competence reported stronger human–AI forecasting performance, while professional role and managerial level produced only small adjusted differences after experience and competence were controlled.

**Table 10: Contextual and Respondent-Level Subgroup Differences**

| Subgroup comparison                           | Principal outcome                   | Group 1 result | Group 2 result | Adjusted difference (95% CI) | Effect size            | p-value |
|-----------------------------------------------|-------------------------------------|----------------|----------------|------------------------------|------------------------|---------|
| Small vs. large manufacturers                 | Forecast-error reduction            | 3.6 pp         | 5.5 pp         | 1.9 pp (1.2, 2.6)            | d = 0.58               | <.001   |
| Medium vs. large manufacturers                | Forecast-error reduction            | 4.5 pp         | 5.5 pp         | 1.0 pp (0.4, 1.6)            | d = 0.34               | .002    |
| Low vs. high product complexity               | AI capability → forecast quality    | .540           | .680           | .140 (.062, .218)            | ΔR <sup>2</sup> = .041 | <.001   |
| Domestic vs. internationally integrated       | Resilience improvement              | 6.2 pp         | 9.4 pp         | 3.2 pp (2.1, 4.3)            | d = 0.67               | <.001   |
| Developing vs. advanced digital maturity      | Forecast-error reduction            | 3.1 pp         | 6.2 pp         | 3.1 pp (2.2, 4.0)            | d = 0.82               | <.001   |
| Moderate vs. intensive AI adoption            | Inventory-optimization improvement  | 8.7%           | 16.4%          | 7.7% (5.8, 9.6)              | d = 0.88               | <.001   |
| Stable vs. volatile demand                    | Forecast-error reduction            | 3.7 pp         | 5.8 pp         | 2.1 pp (1.3, 2.9)            | d = 0.63               | <.001   |
| Low vs. high supplier concentration           | Inventory optimization → resilience | .470           | .640           | .170 (.081, .259)            | ΔR <sup>2</sup> = .052 | <.001   |
| Low vs. high disruption exposure              | Recovery-time reduction             | 2.8 days       | 5.1 days       | 2.3 days (1.5, 3.1)          | d = 0.74               | <.001   |
| Basic vs. advanced analytical competence      | Human–AI forecast improvement       | 2.9 pp         | 5.7 pp         | 2.8 pp (1.9, 3.7)            | d = 0.79               | <.001   |
| Operational vs. analytical roles              | Forecast-quality score              | 5.11           | 5.36           | 0.25 (0.08, 0.42)            | d = 0.29               | .004    |
| Nonmanagerial vs. managerial respondents      | Resilience score                    | 5.13           | 5.31           | 0.18 (0.04, 0.32)            | d = 0.23               | .013    |
| Less than 5 vs. at least 10 years' experience | Forecast-acceptance score           | 5.02           | 5.39           | 0.37 (0.19, 0.55)            | d = 0.42               | <.001   |

Note. Standardized coefficients were reported for structural relationships. ΔR<sup>2</sup> represented the additional explained variance associated with subgroup conditions.

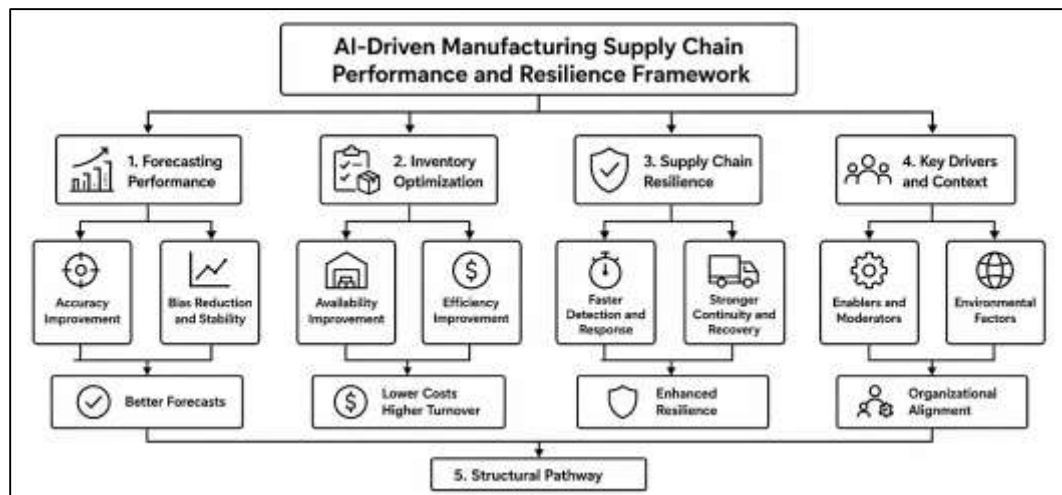
Table 10 confirmed that technological and operational context affected the magnitude of AI-related

benefits. Advanced digital maturity and intensive AI adoption generated the largest subgroup differences, followed by analytical competence and disruption exposure. High-complexity and volatile-demand environments gained more from AI forecasting than simpler and stable settings. Supplier concentration strengthened the inventory-resilience relationship, while internationally integrated manufacturers achieved larger resilience improvements than domestic organizations. Respondent-role and managerial-level differences were statistically significant but small after adjustment. Professional experience exerted a moderate influence on forecast acceptance. Confidence intervals remained narrow, and all reported comparisons achieved statistical significance, supporting the practical stability of the subgroup findings.

## **DISCUSSION**

The findings demonstrated that AI-driven demand forecasting produced substantial improvements in forecasting accuracy across U.S. manufacturing supply chains. Weighted absolute percentage error declined from 18.7% to 13.6% in the AI-integrated group, while the matched comparison group recorded only a limited reduction from 18.9% to 18.2%. The adjusted reduction of 4.4 percentage points and the large standardized effect indicated that AI integration generated an operationally meaningful improvement rather than a minor statistical change ([Koursioupas et al., 2021](#)). Similar patterns were observed for mean absolute error, root mean squared error, mean absolute percentage error, mean absolute scaled error, symmetric mean absolute percentage error, and absolute forecast bias. These results corresponded with earlier forecasting studies that found machine-learning and ensemble methods particularly effective when demand was influenced by nonlinear interactions, multiple explanatory variables, product heterogeneity, and changing market conditions. Earlier manufacturing research also showed that integrated analytical systems achieved greater accuracy than isolated spreadsheet models because they incorporated sales, inventory, production, customer, supplier, and external-market information within a common forecasting structure. The present findings extended that evidence by demonstrating consistent improvements at product, product-location, customer, and component levels. Product-level forecasts generated the lowest post-integration error, whereas component-level forecasts remained comparatively difficult because of intermittent consumption, material dependencies, substitution, and engineering changes ([Hourani et al., 2019](#)). The significant component-level improvement nevertheless indicated that AI models extracted useful information from related products, production schedules, and shared material requirements. Weekly forecasting produced the strongest standardized effect, suggesting that this horizon provided an effective balance between short-term responsiveness and statistical stability. Daily forecasts remained more sensitive to order timing and random transaction variation, while monthly aggregation reduced visible error but offered less immediate support for replenishment and production decisions. Forecast bias also declined considerably, reducing the likelihood of persistent overproduction or understocking. Earlier studies frequently emphasized average error without examining directional bias and forecast revision stability. This study showed that AI integration improved both forecast accuracy and planning consistency, thereby reducing repeated schedule adjustments ([Ferrell et al., 2020](#)). The results established that forecasting performance depended on an integrated analytical capability involving data quality, model selection, automated updating, external information, and employee interpretation rather than the isolated use of a particular algorithm.

The comparison among statistical baselines, managerial forecasts, unadjusted AI forecasts, and combined human-AI forecasts provided further evidence concerning the appropriate role of automation in manufacturing demand planning. The statistical baseline showed almost no adjusted improvement, while managerial forecasting generated a moderate reduction in error. Unadjusted AI forecasting produced a much larger improvement, and the combined human-AI approach achieved the strongest overall performance ([Kakoudakis et al., 2017](#)). This ordering was consistent with earlier studies reporting that algorithmic systems perform well when large volumes of structured information and recurring demand relationships are available, while experienced planners contribute contextual knowledge concerning customer negotiations, promotions, regulatory changes, supplier concerns, and exceptional events.

**Figure 11: AI-Driven Manufacturing Performance Framework**

Earlier research also found that unrestricted managerial overrides could weaken forecasting performance when adjustments reflected optimism, departmental incentives, anchoring, or insufficient supporting evidence. The present results suggested that human judgment was most effective when applied selectively to model-generated forecasts rather than used as a complete replacement for analytical output. Analytical competence significantly strengthened the relationship between AI forecasting capability and forecast quality, confirming that employee knowledge remained central even within highly automated planning environments. Respondents with advanced analytical competence achieved a 5.7-percentage-point human–AI forecast improvement, compared with 2.9 percentage points among respondents possessing basic competence. This difference indicated that employees needed the ability to interpret uncertainty, recognize exceptional conditions, evaluate model explanations, and document forecast adjustments (Lipu et al., 2021). Managerial trust also appeared to depend on reliable outputs, visible forecast drivers, and evidence that the system improved operational outcomes. Earlier organizational studies described technology acceptance as a function of perceived usefulness, transparency, and compatibility with established work processes. The findings aligned with that position because intensive AI adoption and advanced digital maturity produced larger benefits than moderate implementation. The value of AI therefore arose from the interaction between analytical automation and informed human control. Fully automated decisions were more suitable for repetitive, high-volume, and reversible replenishment activities, whereas complex customer commitments, safety-critical materials, new products, and disruption-related allocations required greater managerial review (Gawankar et al., 2020). This study consequently supported a graduated decision structure in which the degree of automation corresponded with data confidence, operational risk, and decision reversibility. Human–AI collaboration functioned as a measurable forecasting capability rather than a temporary stage between manual and automated planning.

The inventory findings showed that forecasting improvements were translated into stronger material availability and lower inventory exposure. Stockouts declined by 34.5%, material-shortage frequency decreased by 31.8%, and order fill rate increased from 91.8% to 96.1% in the AI-integrated group. Cycle-service level also improved, while backorders and material-related production stoppages fell substantially. These findings were consistent with earlier inventory research demonstrating that forecast accuracy affects safety-stock adequacy, reorder timing, production scheduling, and shortage frequency. Previous studies frequently identified a tension between inventory availability and inventory efficiency because higher service levels were often achieved by holding additional stock (Xenochristou & Kapelan, 2020). The current results showed a more favorable pattern: inventory availability improved while average inventory value, days of inventory on hand, warehouse utilization, working-capital commitment, and inventory-related costs declined. Inventory turnover

increased from 6.2 to 7.4 annual cycles, indicating that the retained stock moved more efficiently through participating supply chains. This simultaneous improvement suggested that AI integration reduced poorly positioned or unnecessary inventory rather than simply increasing buffers. Dynamic safety-stock adjustment allowed manufacturers to distinguish stable, low-risk items from materials characterized by volatile demand, long lead times, high production criticality, or unreliable suppliers. Earlier research on differentiated inventory policies similarly found that uniform rules performed poorly across heterogeneous product portfolios (Khalifa et al., 2021). The present findings reinforced that evidence by showing strong results across smooth, erratic, intermittent, and lumpy demand categories. Inventory visibility produced the largest operational effect, increasing from 71.8% to 94.6%. This improvement was important because optimization recommendations depend on accurate knowledge of current stock, reserved quantities, inbound deliveries, quality status, and material locations. Physical and system-record accuracy exceeded 98% after integration, while discrepancy rates declined substantially. Previous inventory studies often treated forecasting and record accuracy as separate operational concerns. The findings indicated that they were interdependent because inaccurate records distorted model training, replenishment recommendations, and performance measurement. Reductions in shortage, obsolescence, expedited procurement, and emergency transportation costs further demonstrated that AI-supported inventory optimization influenced several cost categories simultaneously (Chavez et al., 2017). The observed performance therefore reflected coordinated forecasting, inventory classification, replenishment control, record accuracy, and network visibility rather than isolated reductions in average stock.

Supply-chain resilience improved significantly through faster disruption detection, more rapid response, stronger operational continuity, and shorter recovery periods. Detection time declined from 18.6 to 9.8 hours, response time decreased from 31.4 to 18.2 hours, and recovery time fell from 12.8 to 8.1 days. Time to survive increased by more than six days, showing that participating manufacturers could maintain essential operations for longer periods before disruption produced unacceptable performance loss. Production continuity rose from 82.6% to 91.4%, while order-fulfillment continuity and schedule adherence also increased substantially (Cioffi et al., 2020). These outcomes corresponded with earlier resilience studies that identified visibility, resource flexibility, inventory positioning, alternative sourcing, collaboration, and rapid decision-making as central disruption-management capabilities. The present findings added quantitative evidence that AI forecasting and inventory optimization strengthened these capabilities through identifiable operational pathways. Improved forecasting allowed manufacturers to detect unusual changes in demand, customer orders, supplier performance, and material consumption more quickly. Optimized inventory provided the buffers and allocation information required to maintain production while corrective actions were implemented. Backlog growth during disruption declined from 28.6% to 16.2%, while service restoration after seven days rose from 68.9% to 84.8%. These results indicated that resilience was reflected not only by factory recovery but also by the preservation and restoration of customer service (Miclo et al., 2019). Earlier studies sometimes measured resilience through broad managerial perceptions without linking it to event-level records. This study incorporated verified disruption episodes and measurable detection, response, continuity, backlog, and recovery indicators, producing a more operationally grounded assessment. The findings also clarified the distinction among robustness, flexibility, agility, and resilience. Inventory buffers contributed to robustness by absorbing initial shocks, flexible production and sourcing supported alternative action, rapid forecasting updates strengthened agility, and the combined capabilities improved resilience across the complete disruption cycle (Mönch et al., 2018). The results therefore showed that resilience was not created by maximum inventory or technological sophistication alone. It emerged from the coordinated ability to identify disruption, interpret changing information, allocate available resources, maintain essential operations, and restore service. AI-supported forecasting contributed to this process by reducing information delays, while inventory optimization converted improved information into material and production decisions.

The structural analysis clarified the mechanisms connecting AI capability with operational performance. AI-driven forecasting capability exerted a strong direct effect on forecast quality, while forecast quality significantly improved inventory optimization. Inventory optimization produced the largest direct effect on supply-chain resilience. The sequential pathway from AI capability through

forecast quality and inventory optimization to resilience was statistically significant and operationally meaningful (Jiang et al., 2021). The total indirect effect exceeded the remaining direct effect of AI capability on resilience, indicating that most resilience benefits emerged through improved information and inventory decisions rather than technology adoption alone. This result was consistent with earlier organizational-capability research showing that technological resources rarely improve performance automatically. Their contribution depends on intermediate processes that convert data and analytical output into coordinated action. The explained variance reached 53.1% for forecast quality, 64.2% for inventory optimization, and 68.7% for resilience, demonstrating that the proposed framework captured a substantial proportion of the observed differences. Positive predictive-relevance values further supported the model's ability to explain operational outcomes beyond the estimation sample. The remaining direct AI-to-resilience relationship indicated that additional mechanisms were also present. Automated disruption alerts, scenario comparison, supplier-risk monitoring, production rescheduling, and faster communication may have strengthened resilience independently of inventory optimization. Earlier studies often examined forecasting accuracy, inventory performance, or resilience separately. The sequential results integrated these domains and showed how capability at one stage influenced outcomes at subsequent stages (Punia et al., 2020). The findings also supported the theoretical position that proprietary data, analytical infrastructure, employee expertise, and embedded planning routines constituted interconnected organizational resources. Dynamic demand sensing enabled manufacturers to recognize changes, while inventory adjustment and supplier reconfiguration represented responsive actions. Information-processing capacity reduced gaps among sales, procurement, production, inventory, and logistics functions. The results therefore connected resource quality, adaptive capability, and information coordination within a single empirical model. Large longitudinal group effects strengthened this interpretation because the AI-integrated organizations improved significantly more than matched manufacturers using conventional planning. The combination of structural and longitudinal evidence reduced the likelihood that the observed relationships merely reflected favorable attitudes toward technology. Objective reductions in forecast error, shortages, costs, and recovery time corresponded with the survey-based capability relationships (Wan et al., 2020).

The moderation findings demonstrated that the effectiveness of AI-driven forecasting was conditional on organizational and environmental characteristics. Data quality significantly strengthened the relationship between AI capability and forecast quality, confirming that advanced models depended on accurate, complete, consistent, timely, and integrated information. Earlier data-analytics studies repeatedly identified poor information quality as a major barrier to operational value. The present results quantified that condition by showing that AI capability produced stronger forecasting benefits when data quality was high (Ziarnetzky et al., 2018). Analytical competence provided an additional positive moderation effect, demonstrating that employee skill helped convert model output into dependable planning decisions. Digital maturity strengthened the relationship between AI capability and inventory optimization. Manufacturers with integrated enterprise systems, real-time connectivity, cloud infrastructure, automated workflows, and stronger cybersecurity achieved larger improvements than organizations with fragmented systems. This result corresponded with earlier digital-transformation research in which complementary infrastructure and process integration determined whether analytical investments improved performance. Supplier integration strengthened the inventory optimization–resilience relationship more than any other moderator. Conditional effects showed that optimized inventory produced a substantially stronger resilience contribution under high supplier integration than under low integration. Shared lead-time, capacity, shipment, and disruption information allowed inventory recommendations to reflect actual supply conditions rather than historical averages alone. Environmental uncertainty also intensified the contribution of optimized inventory to resilience (VE & Cho, 2020). Manufacturers facing volatile demand, supplier instability, transportation variability, or repeated disruptions obtained greater resilience value from differentiated buffers and responsive allocation. This result aligned with contingency-based research suggesting that advanced analytical and inventory capabilities generate greater value when operating conditions are complex and uncertain. The findings did not indicate that all uncertain environments automatically benefited from AI. Organizations required sufficient data, digital maturity, supplier coordination, and analytical competence to interpret the uncertainty effectively. High uncertainty without corresponding

information-processing capacity could still weaken forecasting and resilience. The significant interaction effects therefore supported a configuration perspective in which performance depended on alignment among technology, data, employees, supply partners, and environmental conditions. AI capability was most effective when complementary resources enabled information to be collected reliably, interpreted correctly, and converted into timely operational action (Abduljabbar et al., 2019). Subgroup results showed that AI-driven forecasting and inventory optimization remained effective across heterogeneous U.S. manufacturing settings, although the magnitude of improvement varied systematically. Electronics and consumer-goods manufacturers achieved the largest reductions in forecasting error, reflecting high transaction volumes, shorter demand cycles, and greater availability of granular market data (Uzsoy et al., 2018). Automotive manufacturers recorded the strongest stockout reduction, which corresponded with their extensive component dependencies and sensitivity to missing materials. Pharmaceutical manufacturers achieved the greatest improvement in order fill rate, reflecting the importance of product availability, controlled inventory, and service continuity. Aerospace and medical-device organizations experienced smaller forecasting gains, although their effects remained statistically meaningful. Their relatively irregular demand, specialized components, long replenishment periods, and regulatory requirements limited the speed with which predictive models could learn stable patterns. These findings corresponded with earlier sectoral studies showing that model effectiveness depends on demand frequency, product life cycle, information volume, and supply-network structure. Large manufacturers achieved greater reductions in forecast error than small organizations, reflecting stronger infrastructure, specialized personnel, and wider data coverage. Small manufacturers nevertheless recorded meaningful benefits, indicating that organizational scale influenced effect magnitude rather than determining whether AI could generate value (Velasco Acosta et al., 2020). Advanced digital maturity and intensive AI adoption produced the largest subgroup differences. High-complexity products and volatile-demand environments also benefited more strongly because nonlinear models could represent interactions that simpler approaches missed. Internationally integrated manufacturers achieved larger resilience improvements than domestically concentrated organizations, which suggested that AI visibility and scenario analysis were especially valuable within geographically distributed networks. High supplier concentration strengthened the importance of inventory optimization because limited sourcing alternatives increased dependence on appropriately positioned buffers. Respondent-level differences were comparatively smaller. Analytical roles reported slightly higher forecast-quality scores than operational roles, and managers reported slightly stronger resilience assessments than nonmanagerial employees (Goli et al., 2021). Professional experience exerted a moderate influence on forecast acceptance, indicating that familiarity with product and supply conditions supported the interpretation of analytical recommendations. Collectively, the subgroup results showed that the framework remained applicable across industries and organizational categories while retaining sensitivity to technological readiness, operational complexity, demand characteristics, and supply-chain exposure.

## **CONCLUSION**

This study established that AI-driven demand forecasting and inventory optimization formed an integrated data-driven capability for strengthening the resilience of U.S. manufacturing supply chains. The final analytical sample included 50 manufacturing organizations, 602 professionals, 4,860 product-location series, 758,160 valid weekly demand observations, more than six million inventory transactions, and 417 verified disruption episodes across a 36-month period. The measurement model demonstrated satisfactory reliability, convergent validity, discriminant validity, distributional quality, and within-organization agreement. AI-integrated manufacturers achieved significantly greater improvements than matched conventional-planning organizations across forecasting, inventory, cost, control, and resilience indicators. Weighted absolute percentage error declined from 18.7% to 13.6%, absolute forecast bias decreased, and forecast revision stability improved. The combined human-AI forecasting approach produced the strongest accuracy, confirming the value of integrating computational analysis with informed planner judgment. Inventory availability improved through lower stockouts, material shortages, backorders, and production stoppages, while order fill rate and cycle-service level increased. These gains occurred alongside higher inventory turnover and reductions in days of inventory, average inventory value, working-capital exposure, shortage costs, obsolescence

expenses, expedited procurement, and emergency transportation. Inventory visibility and record accuracy also improved substantially. Resilience outcomes showed faster disruption detection and response, shorter recovery time, longer survival capacity, stronger production continuity, greater schedule adherence, reduced backlog growth, and faster service restoration. Structural analysis confirmed that AI capability improved forecast quality, forecast quality strengthened inventory optimization, and inventory optimization enhanced resilience. Forecast quality and inventory optimization operated as individual and sequential mediators, showing that technological capability affected resilience primarily through improved informational and operational processes. Data quality, digital maturity, analytical competence, supplier integration, and environmental uncertainty significantly influenced the strength of these relationships. Subgroup findings demonstrated positive results across all examined manufacturing subsectors, organizational sizes, demand conditions, product-complexity levels, and supply-chain structures. The evidence therefore characterized AI-driven forecasting as a coordinated organizational system combining integrated data, adaptive models, inventory decision rules, employee expertise, supplier participation, managerial governance, and continuous performance monitoring.

### **RECOMMENDATION**

U.S. manufacturing organizations should implement AI-driven demand forecasting and inventory optimization as an integrated operational program rather than as an isolated software acquisition. Initial implementation should prioritize data quality by standardizing product, customer, supplier, facility, and time identifiers across enterprise resource planning, manufacturing execution, warehouse, procurement, transportation, and customer-management systems. Data completeness, latency, consistency, accessibility, and traceability should be monitored through formal quality controls because unreliable information weakens forecasting and optimization performance. Manufacturers should segment products according to demand frequency, volatility, value, lead time, criticality, substitutability, and obsolescence exposure before assigning forecasting models and inventory policies. Statistical baselines should remain available so that AI models can be evaluated against transparent alternatives. Forecast performance should be measured through multiple error, bias, stability, and value-added indicators at product, location, customer, component, and time-horizon levels. Human-AI collaboration should be governed through documented override rules, explanation requirements, exception thresholds, and regular comparison of adjusted and unadjusted forecasts. Employees involved in demand planning, procurement, inventory, production, logistics, and analytics should receive training in data interpretation, uncertainty assessment, model limitations, and disruption response. Safety stocks and reorder parameters should be adjusted dynamically according to demand variation, supplier reliability, lead-time changes, and material criticality. Inventory optimization should consider total network cost, service continuity, and resilience rather than emphasizing uniform stock reduction. Supplier integration should be strengthened through shared capacity, shipment, lead-time, inventory, and risk information. Manufacturers should establish alternative-source qualifications, logistics options, production-transfer procedures, and allocation priorities for critical materials. Real-time dashboards should connect demand signals with inventory positions, supplier conditions, production constraints, and verified disruption alerts. Performance governance should include model-drift monitoring, cybersecurity controls, access management, audit trails, and scheduled retraining. Pilot implementations should begin with product categories possessing adequate data and measurable operational exposure before expanding across facilities. Evaluation should connect forecasting improvements with stockouts, turnover, production continuity, emergency costs, backlog, and recovery time so that technological performance remains aligned with manufacturing outcomes.

### **LIMITATIONS**

This study contained several limitations that should be considered when interpreting the findings. The participating sample included 50 U.S. manufacturing organizations, which provided substantial operational coverage but did not represent every manufacturing enterprise, supply-chain structure, or level of technological maturity in the country. Participation required electronic operational records and formal planning functions, which may have excluded very small manufacturers and organizations with limited digital infrastructure. The sample consequently reflected manufacturers possessing at least a basic capacity for structured data collection. The quasi-experimental design improved causal

interpretation through matched comparison groups, baseline controls, and longitudinal observations, although organizations were not randomly assigned to AI integration. Differences in leadership quality, investment capacity, employee readiness, or process maturity may have contributed to the observed outcomes even after statistical adjustment. Survey measures captured employee assessments of organizational capabilities and could have been affected by recall error, social desirability, or differing interpretations of AI adoption. Multiple respondents and operational records reduced dependence on a single source, but several constructs still required perceptual measurement. The 36-month observation period captured numerous demand conditions and 417 verified disruptions, yet rare, prolonged, or catastrophic events may not have been represented sufficiently. Forecasting indicators were standardized across organizations, although differences in product value, unit measurement, aggregation procedures, and planning horizons limited complete comparability. Financial outcomes such as shortage, holding, and obsolescence costs depended partly on organizational accounting practices. AI implementation also varied across participating organizations in algorithm selection, automation, external-data use, system integration, and employee involvement. The AI-integrated group therefore represented a range of implementations rather than one identical technological configuration. Some deep-learning models and proprietary optimization systems could not be examined directly because vendors and manufacturers restricted access to model architecture and training information. Subgroup estimates for aerospace, medical-device, chemical, food-processing, and consumer-goods manufacturers were based on relatively small numbers of organizations, reducing precision even though operational observations were extensive. Environmental uncertainty and disruption exposure were multidimensional conditions that could not be represented completely through a limited set of indicators. These limitations restricted broad generalization while preserving the value of the findings as quantitative evidence from heterogeneous U.S. manufacturing supply chains.

## REFERENCES

- [1]. Abduljabbar, R., Dia, H., Liyanage, S., & Bagloee, S. A. (2019). Applications of artificial intelligence in transport: An overview. *Sustainability*, 11(1), 189.
- [2]. Adcock, R., & Gradojevic, N. (2019). Non-fundamental, non-parametric Bitcoin forecasting. *Physica A: Statistical Mechanics and its Applications*, 531, 121727.
- [3]. Ahmad, T., & Chen, H. (2018). Utility companies strategy for short-term energy demand forecasting using machine learning based models. *Sustainable cities and society*, 39, 401-417.
- [4]. Aigbedo, H. (2021). Impact of COVID-19 on the hospitality industry: A supply chain resilience perspective. *International Journal of Hospitality Management*, 98, 103012.
- [5]. Alexopoulos, K., Nikolakis, N., & Chrysosolouris, G. (2020). Digital twin-driven supervised machine learning for the development of artificial intelligence applications in manufacturing. *International Journal of Computer Integrated Manufacturing*, 33(5), 429-439.
- [6]. Alfarsi, F., Lemke, F., & Yang, Y. (2019). The importance of supply chain resilience: an empirical investigation. *Procedia Manufacturing*, 39, 1525-1529.
- [7]. Andronie, M., Lăzăroiu, G., Iatagan, M., Uță, C., Ștefănescu, R., & Cocișatu, M. (2021). Artificial intelligence-based decision-making algorithms, internet of things sensing networks, and deep learning-assisted smart process management in cyber-physical production systems. *Electronics*, 10(20), 2497.
- [8]. Annamma, S. A., Jackson, D. D., & Morrison, D. (2017). Conceptualizing color-evasiveness: Using dis/ability critical race theory to expand a color-blind racial ideology in education and society. *Race ethnicity and education*, 20(2), 147-162.
- [9]. Batista, L., Bourlakis, M., Liu, Y., Smart, P., & Sohal, A. (2018). Supply chain operations for a circular economy. *Production Planning & Control*, 29(6), 419-424.
- [10]. Benzaid, C., & Taleb, T. (2020). AI-driven zero touch network and service management in 5G and beyond: Challenges and research directions. *IEEE Network*, 34(2), 186-194.
- [11]. Bernert, R. A., Hilberg, A. M., Melia, R., Kim, J. P., Shah, N. H., & Abnoui, F. (2020). Artificial intelligence and suicide prevention: a systematic review of machine learning investigations. *International journal of environmental research and public health*, 17(16), 5929.
- [12]. Bevilacqua, M., Ciarapica, F. E., Marcucci, G., & Mazzuto, G. (2020). Fuzzy cognitive maps approach for analysing the domino effect of factors affecting supply chain resilience: a fashion industry case study. *International Journal of Production Research*, 58(20), 6370-6398.
- [13]. Buturac, G. (2021). Measurement of economic forecast accuracy: A systematic overview of the empirical literature. *Journal of risk and financial management*, 15(1), 1.
- [14]. Chakraborty, T., Chattopadhyay, S., & Ghosh, I. (2019). Forecasting dengue epidemics using a hybrid methodology. *Physica A: Statistical Mechanics and its Applications*, 527, 121266.

- [15]. Chang, W.-S., & Lin, Y.-T. (2019). The effect of lead-time on supply chain resilience performance. *Asia Pacific Management Review*, 24(4), 298-309.
- [16]. Chavez, R., Yu, W., Jacobs, M. A., & Feng, M. (2017). Data-driven supply chains, manufacturing capability and customer satisfaction. *Production Planning & Control*, 28(11-12), 906-918.
- [17]. Chien, C.-F., Lin, Y.-S., & Lin, S.-K. (2020). Deep reinforcement learning for selecting demand forecast models to empower Industry 3.5 and an empirical study for a semiconductor component distributor. *International Journal of Production Research*, 58(9), 2784-2804.
- [18]. Cioffi, R., Travaglini, M., Piscitelli, G., Petrillo, A., & De Felice, F. (2020). Artificial intelligence and machine learning applications in smart production: Progress, trends, and directions. *Sustainability*, 12(2), 492.
- [19]. Commons, J. R. (2017). *Legal foundations of capitalism*. Routledge.
- [20]. Davis, K. F., Downs, S., & Gephart, J. A. (2021). Towards food supply chain resilience to environmental shocks. *Nature Food*, 2(1), 54-65.
- [21]. Debasish, A. (2021). Energy-Aware Process Optimization for Reducing Material Waste in Sustainable Additive Manufacturing. *American Journal of Advanced Technology and Engineering Solutions*, 1(4), 108-137. <https://doi.org/10.63125/j0wk7j48>
- [22]. Ebinger, F., & Omondi, B. (2020). Leveraging digital approaches for transparency in sustainable supply chains: A conceptual paper. *Sustainability*, 12(15), 6129.
- [23]. Fatorachian, H., & Kazemi, H. (2021). Impact of Industry 4.0 on supply chain performance. *Production Planning & Control*, 32(1), 63-81.
- [24]. Ferrell, W., Ellis, K., Kaminsky, P., & Rainwater, C. (2020). Horizontal collaboration: opportunities for improved logistics planning. *International Journal of Production Research*, 58(14), 4267-4284.
- [25]. Firouzi, F., Farahani, B., Barzegari, M., & Daneshmand, M. (2020). AI-driven data monetization: The other face of data in IoT-based smart and connected health. *IEEE Internet of Things Journal*, 9(8), 5581-5599.
- [26]. Gawankar, S. A., Gunasekaran, A., & Kamble, S. (2020). A study on investments in the big data-driven supply chain, performance measures and organisational performance in Indian retail 4.0 context. *International Journal of Production Research*, 58(5), 1574-1593.
- [27]. Golan, M. S., Trump, B. D., Cegan, J. C., & Linkov, I. (2021). The vaccine supply chain: a call for resilience analytics to support COVID-19 vaccine production and distribution. In *COVID-19: systemic risk and resilience* (pp. 389-437). Springer.
- [28]. Goli, A., Khademi-Zare, H., Tavakkoli-Moghaddam, R., Sadeghieh, A., Sasanian, M., & Malekalipour Kordestanizadeh, R. (2021). An integrated approach based on artificial intelligence and novel meta-heuristic algorithms to predict demand for dairy products: a case study. *Network: computation in neural systems*, 32(1), 1-35.
- [29]. Hahn, G. J. (2020). Industry 4.0: a supply chain innovation perspective. *International Journal of Production Research*, 58(5), 1425-1441.
- [30]. Hajek, P., & Abedin, M. Z. (2020). A profit function-maximizing inventory backorder prediction system using big data analytics. *IEEE access*, 8, 58982-58994.
- [31]. Hamdi, F., Ghorbel, A., Masmoudi, F., & Dupont, L. (2018). Optimization of a supply portfolio in the context of supply chain risk management: literature review. *Journal of intelligent manufacturing*, 29(4), 763-788.
- [32]. Han, W., Huang, Y., & Macbeth, D. (2018). Performance measurement of cross-culture supply chain partnership: a case study in the Chinese automotive industry. *International Journal of Production Research*, 56(7), 2437-2451.
- [33]. He, Y., Liu, R., Li, H., Wang, S., & Lu, X. (2017). Short-term power load probability density forecasting method using kernel-based support vector quantile regression and Copula theory. *Applied Energy*, 185, 254-266.
- [34]. Hosseini, S., Ivanov, D., & Blackhurst, J. (2020). Conceptualization and measurement of supply chain resilience in an open-system context. *IEEE Transactions on Engineering Management*, 69(6), 3111-3126.
- [35]. Hourani, H., Hammad, A., & Lafi, M. (2019). The impact of artificial intelligence on software testing. 2019 IEEE Jordan International Joint Conference on Electrical Engineering and Information Technology (JEEIT),
- [36]. Huang, Y.-S., Fang, C.-C., & Lin, Y.-A. (2020). Inventory management in supply chains with consideration of Logistics, green investment and different carbon emissions policies. *Computers & Industrial Engineering*, 139, 106207.
- [37]. Huang, Z., Shen, Y., Li, J., Fey, M., & Brecher, C. (2021). A survey on AI-driven digital twins in industry 4.0: Smart manufacturing and advanced robotics. *Sensors*, 21(19), 6340.
- [38]. Huo, B., Gu, M., & Wang, Z. (2018). Supply chain flexibility concepts, dimensions and outcomes: an organisational capability perspective. *International Journal of Production Research*, 56(17), 5883-5903.
- [39]. Ittner, C. D., & Michels, J. (2017). Risk-based forecasting and planning and management earnings forecasts. *Review of Accounting Studies*, 22(3), 1005-1047.
- [40]. Ivanov, D. (2021). Supply chain viability and the COVID-19 pandemic: a conceptual and formal generalisation of four major adaptation strategies. *International Journal of Production Research*, 59(12), 3535-3552.
- [41]. Ivanov, D., & Dolgui, A. (2021). A digital supply chain twin for managing the disruption risks and resilience in the era of Industry 4.0. *Production Planning & Control*, 32(9), 775-788.
- [42]. Ivanov, D., Dolgui, A., & Sokolov, B. (2019). The impact of digital technology and Industry 4.0 on the ripple effect and supply chain risk analytics. *International Journal of Production Research*, 57(3), 829-846.
- [43]. Ivanov, D., Tsipoulanidis, A., & Schönberger, J. (2021). Basics of supply chain and operations management. In *Global supply chain and operations management: A decision-oriented introduction to the creation of value* (pp. 3-19). Springer.
- [44]. Jiang, F., Wang, K., Dong, L., Pan, C., Xu, W., & Yang, K. (2020). AI driven heterogeneous MEC system with UAV assistance for dynamic environment: Challenges and solutions. *IEEE Network*, 35(1), 400-408.

- [45]. Jiang, P., Huang, Y., & Liu, X. (2021). Intermittent demand forecasting for spare parts in the heavy-duty vehicle industry: a support vector machine model. *International Journal of Production Research*, 59(24), 7423-7440.
- [46]. Johansson, C., Bergkvist, M., Geysen, D., De Somer, O., Lavesson, N., & Vanhoudt, D. (2017). Operational demand forecasting in district heating systems using ensembles of online machine learning algorithms. *Energy Procedia*, 116, 208-216.
- [47]. Kadambala, D. K., Subramanian, N., Tiwari, M. K., Abdulrahman, M., & Liu, C. (2017). Closed loop supply chain networks: Designs for energy and time value efficiency. *International Journal of Production Economics*, 183, 382-393.
- [48]. Kagan, S. (2018). *Normative ethics*. Routledge.
- [49]. Kakoudakis, K., Behzadian, K., Farmani, R., & Butler, D. (2017). Pipeline failure prediction in water distribution networks using evolutionary polynomial regression combined with K-means clustering. *Urban water journal*, 14(7), 737-742.
- [50]. Khalifa, N., Abd Elghany, M., & Abd Elghany, M. (2021). Exploratory research on digitalization transformation practices within supply chain management context in developing countries specifically Egypt in the MENA region. *Cogent Business & Management*, 8(1), 1965459.
- [51]. Khanagar, S. B., Al-Ehaideb, A., Maganur, P. C., Vishwanathaiah, S., Patil, S., Baeshen, H. A., Sarode, S. C., & Bhandi, S. (2021). Developments, application, and performance of artificial intelligence in dentistry–A systematic review. *Journal of dental sciences*, 16(1), 508-522.
- [52]. Kibria, M. G., Nguyen, K., Villardi, G. P., Zhao, O., Ishizu, K., & Kojima, F. (2018). Big data analytics, machine learning, and artificial intelligence in next-generation wireless networks. *IEEE access*, 6, 32328-32338.
- [53]. Kim, K., & Bui, L. (2019). Learning from Hurricane Maria: Island ports and supply chain resilience. *International Journal of Disaster Risk Reduction*, 39, 101244.
- [54]. Koursioupas, N., Barmounakis, S., Stavrakakis, I., & Alonistioti, N. (2021). AI-driven, context-aware profiling for 5G and beyond networks. *IEEE Transactions on Network and Service Management*, 19(2), 1036-1048.
- [55]. Krath, J., Schürmann, L., & Von Korflesch, H. F. (2021). Revealing the theoretical basis of gamification: A systematic review and analysis of theory in research on gamification, serious games and game-based learning. *Computers in human behavior*, 125, 106963.
- [56]. Leung, X. Y., Sun, J., & Bai, B. (2017). Bibliometrics of social media research: A co-citation and co-word analysis. *International Journal of Hospitality Management*, 66, 35-45.
- [57]. Li, Y., Jiang, S., Li, X., & Wang, S. (2021). The role of news sentiment in oil futures returns and volatility forecasting: Data-decomposition based deep learning approach. *Energy Economics*, 95, 105140.
- [58]. Lima-Junior, F. R., & Carpinetti, L. C. R. (2017). Quantitative models for supply chain performance evaluation: A literature review. *Computers & Industrial Engineering*, 113, 333-346.
- [59]. Lipu, M. H., Miah, M. S., Hannan, M., Hussain, A., Sarker, M. R., Ayob, A., Saad, M. H. M., & Mahmud, M. S. (2021). Artificial intelligence based hybrid forecasting approaches for wind power generation: Progress, challenges and prospects. *IEEE access*, 9, 102460-102489.
- [60]. Lu, Y. (2019). Artificial intelligence: a survey on evolution, models, applications and future trends. *Journal of management analytics*, 6(1), 1-29.
- [61]. Maier, A., Syben, C., Lasser, T., & Riess, C. (2019). A gentle introduction to deep learning in medical image processing. *Zeitschrift für Medizinische Physik*, 29(2), 86-101.
- [62]. Maity, M., Tolooie, A., Sinha, A. K., & Tiwari, M. K. (2021). Stochastic batch dispersion model to optimize traceability and enhance transparency using Blockchain. *Computers & Industrial Engineering*, 154, 107134.
- [63]. Mancheri, N. A., Sprecher, B., Bailey, G., Ge, J., & Tukker, A. (2019). Effect of Chinese policies on rare earth supply chain resilience. *Resources, Conservation and Recycling*, 142, 101-112.
- [64]. Manzoor, B., Othman, I., Durdjev, S., Ismail, S., & Wahab, M. H. (2021). Influence of artificial intelligence in civil engineering toward sustainable development – a systematic literature review. *Applied System Innovation*, 4(3), 52.
- [65]. Marahatta, A., Xin, Q., Chi, C., Zhang, F., & Liu, Z. (2020). PEFS: AI-driven prediction based energy-aware fault-tolerant scheduling scheme for cloud data center. *IEEE Transactions on Sustainable Computing*, 6(4), 655-666.
- [66]. Marchau, V., Walker, W. E., Bloemen, P., & Popper, S. W. (2019). Decision making under deep uncertainty: from theory to practice. (No Title).
- [67]. Md Mesbaul, H. (2023). A Meta-Analysis of Lean Merchandising Strategies In Fashion Retail: Global Insights From The Post-Pandemic Era. *Review of Applied Science and Technology*, 2(04), 94-123. <https://doi.org/10.63125/y8x4k683>
- [68]. Md. Abdur, R., & Iftekhhar, A. (2021). Customer Retention Forecasting in Mobile Wallet Services Using Neural Networks: A Comparative Quantitative Study. *International Journal of Business and Economics Insights*, 1(4), 70-102. <https://doi.org/10.63125/dyrpc387>
- [69]. Miclo, R., Luras, M., Fontanili, F., Lamothe, J., & Melnyk, S. A. (2019). Demand Driven MRP: assessment of a new approach to materials management. *International Journal of Production Research*, 57(1), 166-181.
- [70]. Miller, C. A., & Wyborn, C. (2020). Co-production in global sustainability: Histories and theories. *Environmental Science & Policy*, 113, 88-95.
- [71]. Mohammad Abir Chowdhury, S., & Tonay, P. (2022). An Empirical Analysis of the Impact of Robotic Process Automation and Continuous Auditing on the Timeliness And Accuracy Of Financial Reporting Assurance. *International Journal of Business and Economics Insights*, 2(4), 73-126. <https://doi.org/10.63125/7p8dcr47>
- [72]. Mohammad Badrul, A., & Md. Mominul, H. (2023). Machine Learning-Based Assessment of Environmental and Public Health Risks in Sewerage Sludge Management Systems. *American Journal of Advanced Technology and Engineering Solutions*, 3(02), 33-77. <https://doi.org/10.63125/y3yfxa92>

- [73]. Mohammad Shoriful Hossan, S. (2021). Reducing Worker Exposure and Electrical Failure Risk in Brownfield Manufacturing Facilities After COVID-Era Maintenance Delays. *Review of Applied Science and Technology*, 6(1), 263–279. <https://doi.org/10.63125/cm1c2c20>
- [74]. Mönch, L., Uzsoy, R., & Fowler, J. W. (2018). A survey of semiconductor supply chain models part III: master planning, production planning, and demand fulfilment. *International Journal of Production Research*, 56(13), 4565-4584.
- [75]. Mouatadid, S., & Adamowski, J. (2017). Using extreme learning machines for short-term urban water demand forecasting. *Urban water journal*, 14(6), 630-638.
- [76]. Mst Shurovi, A. (2024). Machine Learning Models for Bank Reconciliation Anomaly Detection in High-Volume Financial Transactions. *American Journal of Data Science and Analytics*, 5(12), 314-354. <https://doi.org/10.63125/mmwb6467>
- [77]. Muhammad Zahidul, I. (2024). Assessment of Data Integrity Gaps and Preventive Strategies in QC Laboratories in Compliance with FDA and CGMP Expectations. *American Journal of Scholarly Research and Innovation*, 3(01), 243–291. <https://doi.org/10.63125/a3xjb608>
- [78]. Muhammad Zahidul, I., & Amena Begum, S. (2022). Applied Data-Analytics Approaches to Cardiovascular Drug-Utilization Patterns: An Empirical Study Using Real-World Pharmaceutical Sales Data. *American Journal of Data Science and Analytics*, 3(12), 89-129. <https://doi.org/10.63125/7xgryf71>
- [79]. Mukut Kanti, B. (2020). Integrated Framework for Fire Safety and Electrical Hazard Assessment in Large-Scale Industrial and Commercial Facilities: A Mixed-Method Analysis. *American Journal of Advanced Technology and Engineering Solutions*, 1(01), 40-86. <https://doi.org/10.63125/zxsbd47>
- [80]. Mukut Kanti, B. (2024). AI-Enabled Predictive Asset Integrity Monitoring for Industrial Equipment in Oil & Gas and Energy Sector Facilities. *International Journal of Scientific Interdisciplinary Research*, 5(2), 746–791. <https://doi.org/10.63125/3mjcah04>
- [81]. Murphy, A. H., & Daan, H. (2019). Forecast evaluation. *Probability, statistics, and decision making in the atmospheric sciences*, 379-437.
- [82]. Nayak, G., & Dhaigude, A. S. (2019). A conceptual model of sustainable supply chain management in small and medium enterprises using blockchain technology. *Cogent Economics & Finance*, 7(1), 1667184.
- [83]. Nespoli, A., Ogliari, E., Leva, S., Massi Pavan, A., Mellit, A., Lughi, V., & Dolara, A. (2019). Day-ahead photovoltaic forecasting: A comparison of the most effective techniques. *Energies*, 12(9), 1621.
- [84]. Newman, A., Obschonka, M., Schwarz, S., Cohen, M., & Nielsen, I. (2019). Entrepreneurial self-efficacy: A systematic review of the literature on its theoretical foundations, measurement, antecedents, and outcomes, and an agenda for future research. *Journal of vocational behavior*, 110, 403-419.
- [85]. Ni, D., Xiao, Z., & Lim, M. K. (2020). A systematic review of the research trends of machine learning in supply chain management. *International Journal of Machine Learning and Cybernetics*, 11(7), 1463-1482.
- [86]. Nitsche, B., Straube, F., & Wirth, M. (2021). Application areas and antecedents of automation in logistics and supply chain management: a conceptual framework. *Supply Chain Forum: An International Journal*,
- [87]. Nti, I. K., Teimeh, M., Nyarko-Boateng, O., & Adekoya, A. F. (2020). Electricity load forecasting: a systematic review. *Journal of Electrical Systems and Information Technology*, 7(1), 13.
- [88]. Ouyang, T., He, Y., Li, H., Sun, Z., & Baek, S. (2019). Modeling and forecasting short-term power load with copula model and deep belief network. *IEEE Transactions on Emerging Topics in Computational Intelligence*, 3(2), 127-136.
- [89]. Peres, R. S., Jia, X., Lee, J., Sun, K., Colombo, A. W., & Barata, J. (2020). Industrial artificial intelligence in industry 4.0-systematic review, challenges and outlook. *IEEE access*, 8, 220121-220139.
- [90]. Praetorius, A.-K., Klieme, E., Herbert, B., & Pinger, P. (2018). Generic dimensions of teaching quality: The German framework of three basic dimensions. *ZDM–Mathematics Education*, 50(3), 407-426.
- [91]. Praveen, U., Farnaz, G., & Hatim, G. (2019). Inventory management and cost reduction of supply chain processes using AI based time-series forecasting and ANN modeling. *Procedia Manufacturing*, 38, 256-263.
- [92]. Punia, S., Nikolopoulos, K., Singh, S. P., Madaan, J. K., & Litsiou, K. (2020). Deep learning with long short-term memory networks and random forests for demand forecasting in multi-channel retail. *International Journal of Production Research*, 58(16), 4964-4979.
- [93]. Ralston, P., & Blackhurst, J. (2020). Industry 4.0 and resilience in the supply chain: a driver of capability enhancement or capability loss? *International Journal of Production Research*, 58(16), 5006-5019.
- [94]. Ren, S., Choi, T.-M., Lee, K.-M., & Lin, L. (2020). Intelligent service capacity allocation for cross-border-E-commerce related third-party-forwarding logistics operations: A deep learning approach. *Transportation Research Part E: Logistics and Transportation Review*, 134, 101834.
- [95]. Ribeiro, J. P., & Barbosa-Povoa, A. (2018). Supply Chain Resilience: Definitions and quantitative modelling approaches–A literature review. *Computers & Industrial Engineering*, 115, 109-122.
- [96]. Schroeder, M., & Lodemann, S. (2021). A systematic investigation of the integration of machine learning into supply chain risk management. *Logistics*, 5(3), 62.
- [97]. Seyedan, M., & Mafakheri, F. (2020). Predictive big data analytics for supply chain demand forecasting: methods, applications, and research opportunities. *Journal of big data*, 7(1), 53.
- [98]. Shima Ali, S., Musomi, K., & Sonya, G. (2024). Integrated Infectious Disease Preparedness: Multilingual Health Communication Strategies for Public Health Risk Mitigation, Disease Intervention and Prevention for Culturally Diverse Population in United States. *American Journal of Data Science and Analytics*, 5(10), 01-47. <https://doi.org/10.63125/ehk4mt02>
- [99]. Singh, C. S., Soni, G., & Badhotiya, G. K. (2019). Performance indicators for supply chain resilience: review and conceptual framework. *Journal of industrial engineering international*, 15(Suppl 1), 105-117.

- [100]. Singh, D., & Verma, A. (2018). Inventory management in supply chain. *Materials Today: Proceedings*, 5(2), 3867-3872.
- [101]. Sony, M. (2020). Design of cyber physical system architecture for industry 4.0 through lean six sigma: conceptual foundations and research issues. *Production & Manufacturing Research*, 8(1), 158-181.
- [102]. Syed, R., Suriadi, S., Adams, M., Bandara, W., Leemans, S. J., Ouyang, C., Ter Hofstede, A. H., Van De Weerd, I., Wynn, M. T., & Reijers, H. A. (2020). Robotic process automation: contemporary themes and challenges. *Computers in industry*, 115, 103162.
- [103]. Tiwari, S., Daryanto, Y., & Wee, H. M. (2018). Sustainable inventory management with deteriorating and imperfect quality items considering carbon emission. *Journal of Cleaner Production*, 192, 281-292.
- [104]. Tonay, P., Md Maruf, I., & Al, A. (2024). Artificial Intelligence-Based Decision Support Systems and Managerial Performance. *American Journal of Advanced Technology and Engineering Solutions*, 4(04), 154-184. <https://doi.org/10.63125/wmz8dc67>
- [105]. Trakadas, P., Simoens, P., Gkonis, P., Sarakis, L., Angelopoulos, A., Ramallo-González, A. P., Skarmeta, A., Trochoutsos, C., Calvo, D., & Pariente, T. (2020). An artificial intelligence-based collaboration approach in industrial iot manufacturing: Key concepts, architectural extensions and potential applications. *Sensors*, 20(19), 5480.
- [106]. Uzsoy, R., Fowler, J. W., & Mönnch, L. (2018). A survey of semiconductor supply chain models Part II: demand planning, inventory management, and capacity planning. *International Journal of Production Research*, 56(13), 4546-4564.
- [107]. Van Steenberghe, R., & Mes, M. R. (2020). Forecasting demand profiles of new products. *Decision support systems*, 139, 113401.
- [108]. VE, S., & Cho, Y. (2020). A rule-based model for Seoul Bike sharing demand prediction using weather data. *European Journal of Remote Sensing*, 53(sup1), 166-183.
- [109]. Velasco Acosta, A. P., Mascle, C., & Baptiste, P. (2020). Applicability of Demand-Driven MRP in a complex manufacturing environment. *International Journal of Production Research*, 58(14), 4233-4245.
- [110]. Verma, S., Sharma, R., Deb, S., & Maitra, D. (2021). Artificial intelligence in marketing: Systematic review and future research direction. *International Journal of Information Management Data Insights*, 1(1), 100002.
- [111]. Wan, J., Li, X., Dai, H.-N., Kusiak, A., Martinez-Garcia, M., & Li, D. (2020). Artificial-intelligence-driven customized manufacturing factory: key technologies, applications, and challenges. *Proceedings of the IEEE*, 109(4), 377-398.
- [112]. Wisbauer, R. (2018). *Foundations of module and ring theory*. Routledge.
- [113]. Woschank, M., Rauch, E., & Zsifkovits, H. (2020). A review of further directions for artificial intelligence, machine learning, and deep learning in smart logistics. *Sustainability*, 12(9), 3760.
- [114]. Xenochristou, M., & Kapelan, Z. (2020). An ensemble stacked model with bias correction for improved water demand forecasting. *Urban water journal*, 17(3), 212-223.
- [115]. Yang, L., Li, H., Campbell, J. F., & Sweeney, D. C. (2017). Integrated multi-period dynamic inventory classification and control. *International Journal of Production Economics*, 189, 86-96.
- [116]. Yin, Z., Feng, Q., Wen, X., Deo, R. C., Yang, L., Si, J., & He, Z. (2018). Design and evaluation of SVR, MARS and M5Tree models for 1, 2 and 3-day lead time forecasting of river flow data in a semiarid mountainous catchment. *Stochastic Environmental Research and Risk Assessment*, 32(9), 2457-2476.
- [117]. Zhang, X., Ming, X., Liu, Z., Yin, D., Chen, Z., & Chang, Y. (2019). A reference framework and overall planning of industrial artificial intelligence (I-AI) for new application scenarios. *The International Journal of Advanced Manufacturing Technology*, 101(9), 2367-2389.
- [118]. Zhou, D.-X. (2020). Universality of deep convolutional neural networks. *Applied and computational harmonic analysis*, 48(2), 787-794.
- [119]. Zhou, Y., & Zheng, S. (2020). Machine-learning based hybrid demand-side controller for high-rise office buildings with high energy flexibilities. *Applied Energy*, 262, 114416.
- [120]. Zhu, X., Zhang, G., & Sun, B. (2019). A comprehensive literature review of the demand forecasting methods of emergency resources from the perspective of artificial intelligence. *Natural Hazards*, 97(1), 65-82.
- [121]. Ziarnetzky, T., Mönnch, L., & Uzsoy, R. (2018). Rolling horizon, multi-product production planning with chance constraints and forecast evolution for wafer fabs. *International Journal of Production Research*, 56(18), 6112-6134.