



AI-Driven Demand Forecasting for Sporting-Goods and Teamwear Supply Chains Under Seasonal and Tournament Demand

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Abstract

This study addresses the persistent forecasting problem faced by sporting-goods and teamwear supply chains where seasonal cycles, tournament schedules, team performance, promotional activity, short selling windows, product variety, and rapidly changing customer preferences can create substantial demand uncertainty, stockouts, excess inventory, missed sales, and inefficient replenishment. The purpose of the study was to quantitatively examine how AI-driven demand forecasting capabilities influence demand forecasting and supply-chain performance under seasonal and tournament demand conditions. The study retained 238 valid responses from demand and forecast planners, supply-chain managers and analysts, inventory and replenishment managers, procurement professionals, merchandising and sales-planning personnel, and operations or logistics managers selected through purposive sampling. The key independent variables were AI-based historical demand pattern learning, real-time demand data integration, seasonal and tournament demand sensing, adaptive forecast updating capability, and human-AI forecasting integration, while demand forecasting and supply-chain performance served as the dependent construct. Data were collected using a structured five-point Likert questionnaire and analyzed through descriptive statistics, Cronbach's alpha, KMO and Bartlett's tests, Pearson correlation, multiple linear regression, and regression diagnostics in SPSS. Seasonal and tournament demand sensing recorded the highest mean ($M = 4.18$, $SD = 0.57$), while overall demand forecasting and supply-chain performance reached $M = 4.09$ ($SD = 0.55$). All five capabilities were positively correlated with performance, with tournament demand sensing showing the strongest relationship ($r = .69$, $p < .001$). The regression model explained 62.9% of performance variance, $R^2 = .629$, adjusted $R^2 = .621$, $F(5, 232) = 78.43$, $p < .001$. Tournament sensing was the strongest predictor ($\beta = .31$), followed by historical demand learning ($\beta = .24$), real-time integration ($\beta = .19$), adaptive updating ($\beta = .16$), and human-AI integration ($\beta = .13$). These findings imply that event-sensitive AI forecasting, supported by timely data integration, adaptive updating, and structured human judgment, can strengthen forecast accuracy, inventory alignment, product availability, replenishment responsiveness, and supply-chain planning effectiveness.

Keywords

AI-Driven Demand Forecasting; Sporting-Goods Supply Chains; Tournament Demand; Supply-Chain Performance; Human-AI Forecasting Integration

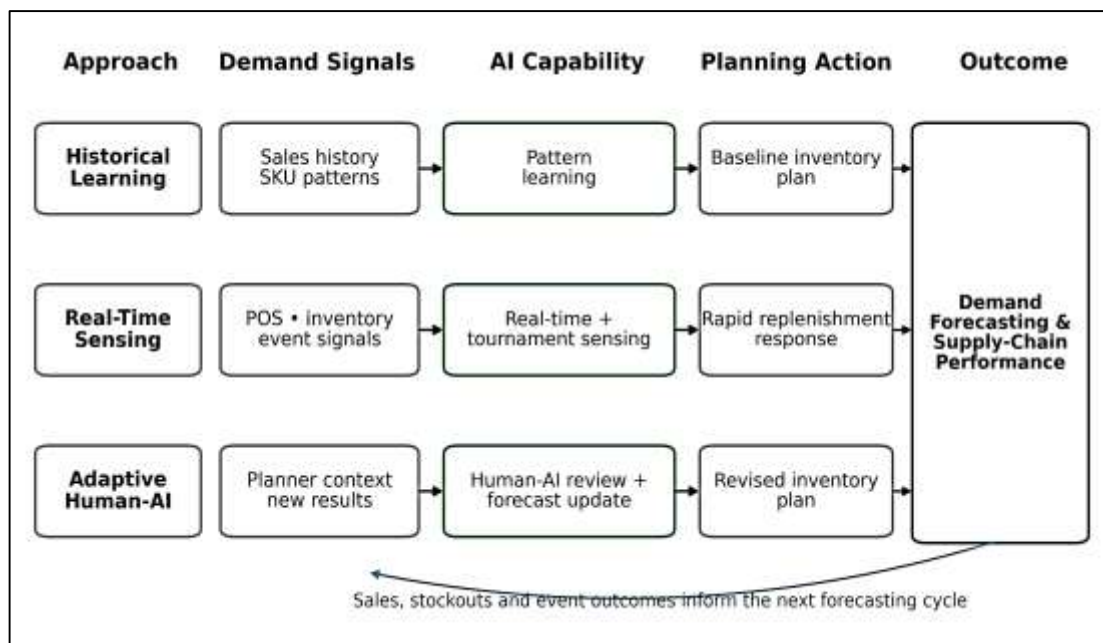
INTRODUCTION

Demand forecasting refers to the systematic estimation of the quantity, timing, and pattern of customer demand required to support decisions concerning procurement, production, inventory, replenishment, distribution, and service capacity, while artificial intelligence (AI) refers to computational techniques capable of recognizing patterns, learning relationships from data, processing information, and supporting decisions that traditionally depended heavily on human analysis. On page 13 of “Artificial intelligence in supply chain management,” AI is characterized through its capacity to recognize business patterns, learn business phenomena, search information, and analyze data intelligently, characteristics that make it particularly relevant to supply-chain decision environments containing large volumes of interconnected information (Min, 2010). On page 1140 of “Application of machine learning techniques for supply chain demand forecasting,” demand forecasting is examined as a learning problem in which neural networks, recurrent neural networks, and support vector machines can identify complex relationships within supply-chain demand data that conventional representations may not adequately capture (Carbonneau et al., 2008). These definitions place AI-driven demand forecasting at the intersection of predictive analytics, operational planning, and data-enabled supply-chain coordination. Internationally dispersed supply chains increase the importance of this intersection because forecasting information influences decisions across manufacturers, distributors, retailers, logistics networks, and geographically separated sourcing operations. Empirical evidence drawn from organizations in the United States, Europe, Canada, Brazil, and China has associated analytical capabilities in supply-chain planning, sourcing, manufacturing, and delivery with measurable supply-chain performance differences (Trkman et al., 2010). Digital supply-chain integration similarly connects information flows with demand planning and operational performance across organizational boundaries (Rai et al., 2006). Predictive analytics extends this information-processing capacity by using statistical and computational techniques to derive usable patterns from increasingly diverse supply-chain data (Waller & Fawcett, 2013). The international significance of AI-enabled forecasting is especially pronounced where demand patterns contain nonlinearity, short selling windows, rapidly changing market signals, and geographically distributed replenishment decisions, because the forecasting problem involves not only extrapolating historical sales but also processing multiple forms of market information within operational time constraints (Seyedan & Mafakheri, 2020). Within a dynamic-capabilities perspective, such data-processing activities can also be understood through organizational sensing, learning, coordination, integration, and reconfiguration under changing market conditions (Pavlou & Sawy, 2011; Teece, 2007).

Sporting-goods and teamwear supply chains represent a particularly demanding setting for forecasting because many of their commercial characteristics overlap with the extensively studied apparel and fashion-retailing environment: numerous stock-keeping units, size and color combinations, relatively short product cycles, strong seasonality, changing preferences, limited historical information for newly introduced products, and substantial inventory consequences when realized demand differs from planned quantities. On page 408 of “A hybrid sales forecasting system,” textile and apparel distribution is described as requiring accurate sourcing, production, and distribution decisions while operating with numerous new items and short commercial life cycles (Thomassey & Fiordaliso, 2006). On page 470 of “Sales forecasts in clothing industry,” strong seasonality, volatile demand, wide product assortments, short life cycles, and incomplete historical information are identified as central forecasting constraints in clothing supply chains (Thomassey, 2010). These characteristics closely correspond to teamwear assortments in which jerseys, training apparel, replica merchandise, accessories, and related sporting goods may be differentiated by team, competition, player association, size, color, season, and tournament context. Apparel research has shown that neural-network structures can model nonlinear sales behavior using real retail data, demonstrating the relevance of machine-learning approaches for product environments characterized by complex demand relationships (Au et al., 2008). On page 411 of “Sales forecasting using extreme learning machine,” demand volatility is connected with multiple influencing factors, and extreme learning machines are evaluated using real fashion-retail data for relationships involving sales and product characteristics (Sun et al., 2008). Hybrid intelligent forecasting has likewise combined data preprocessing, neural learning, and optimization procedures

for medium-term fashion-retail sales forecasting (Wong & Guo, 2010). Reviews of fashion forecasting research identify uncertainty, missing historical data, seasonal patterns, short product life cycles, understocking, overstocking, and service-level pressure as recurrent operational problems (Liu et al., 2013; Nenni et al., 2013). Seasonal retail models have further been developed specifically to handle the simultaneous presence of seasonality and limited sales histories (Xia & Wong, 2014). A broader survey of fashion-market forecasting similarly identifies uncertain demand, short life cycles, and insufficient historical observations as central barriers to prediction (Beheshti-Kashi et al., 2015). New-product research using Siamese neural networks additionally demonstrates how heterogeneous product information can supplement unavailable sales histories when forecasting individual fashion items (Craparotta et al., 2019). These established apparel characteristics provide a closely related empirical basis for examining sporting-goods and teamwear forecasting while retaining the distinct seasonal and tournament structure of the present research.

Figure 1: AI-Driven Demand Forecasting Framework for Sporting-Goods and Teamwear Supply Chains



Seasonal and tournament demand introduces an additional forecasting problem because demand can shift sharply around bounded events rather than evolving solely through stable historical patterns. In sporting-goods and teamwear markets, seasonal leagues, tournaments, championship rounds, school and collegiate sporting calendars, major matches, team progression, tournament elimination, promotional campaigns, and short periods of heightened fan attention can alter the timing and magnitude of product demand. On page 1019 of “Peak demand forecasting for a seasonal product,” an apparel case demonstrates a demand profile in which sales fluctuate substantially during peak periods and remain comparatively low before the peak, illustrating why seasonal products require explicit treatment of changing demand intensity (Rahman et al., 2011). On page 119 of “A seasonal discrete grey forecasting model,” seasonality is treated as a core characteristic of fashion-retail sales and is modeled alongside the limitation of relatively short historical records (Xia & Wong, 2014). Tournament demand can be interpreted in forecasting terms as an event-sensitive demand process because tournament schedules, advancement outcomes, promotional activity, and related market information add explanatory signals beyond a product's historical sales series. “Demand forecasting in the presence of systematic events” identifies this broader problem directly: endogenous and exogenous events can change demand dynamics, making a baseline model based only on historical sales inadequate when systematic event information is available (Abolghasemi et al., 2020). Human planners have historically incorporated exceptional information through judgmental adjustment, but empirical evidence from more than 60,000 supply-chain forecasts shows that the accuracy of such adjustments varies according to their direction and magnitude (Fildes et al., 2009). This distinction is important in tournament

settings because an unusual demand increase may be observable to planners before its effect becomes sufficiently represented in historical data. Intermittent-demand research also demonstrates that sporadic demand occurrences create both forecasting and inventory difficulties and that forecast evaluation can differ when service-level and stock metrics are considered alongside conventional accuracy measures (Kourentzes, 2013). Real-time business intelligence adds another dimension by linking timely information processing with supply-chain analytics in globally distributed operating environments (Sahay & Ranjan, 2008). Social-media analytics has shown that externally generated digital information can be systematically processed for supply-chain intelligence, including signals associated with stakeholders, sales performance, risk, and market activity (Chae, 2015). Big-data-based forecasting similarly emphasizes the integration of multiple data sources rather than exclusive reliance on internal historical demand observations (Hofmann & Rutschmann, 2018).

AI-driven forecasting broadens this analytical structure by enabling demand models to learn historical patterns, accommodate nonlinear relationships, combine large numbers of related observations, process additional demand signals, and update estimated relationships as information changes. Machine-learning research in supply chains has evaluated neural networks, recurrent neural networks, and support vector machines for demand prediction where conventional linear representations are restricted by distorted or complex demand behavior (Carbonneau et al., 2008). Fashion-retail studies have similarly reported useful forecasting performance from evolutionary neural networks, extreme learning machines, and hybrid intelligent models operating on nonlinear product and sales information (Au et al., 2008; Wong & Guo, 2010). On page 198 of “Intermittent demand forecasts with neural networks,” neural networks are used to model interactions between nonzero demand and intervals between demand occurrences, showing how learning-based methods can represent structures that fixed-rate assumptions cannot express (Kourentzes, 2013). Large-scale forecasting evidence also cautions against treating “AI” as a single universally superior technique. On page 54 of “The M4 Competition: 100,000 time series and 61 forecasting methods,” forecasting methods are evaluated across 100,000 time series and multiple frequencies, providing evidence that method performance depends strongly on modeling architecture, data structure, and combination strategy (Makridakis et al., 2020). On page 75 of “A hybrid method of exponential smoothing and recurrent neural networks,” a recurrent neural-network framework combined with exponential smoothing demonstrates how statistical components and machine-learning components can operate within one forecasting system (Smyl, 2020). On page 1181 of “DeepAR,” probabilistic retail demand forecasting is formulated using autoregressive recurrent neural networks trained across large numbers of related time series, allowing uncertainty in product demand to be represented rather than producing only isolated point estimates (Salinas et al., 2020). At the supply-chain level, predictive analytics capability has been associated with performance through information sharing, connectivity, analytical assimilation, and organizational resources (Gunasekaran et al., 2017). Big-data research further identifies data availability, data quality, technological infrastructure, analytical competence, and integration of heterogeneous information as material components of supply-chain analytics (Kache & Seuring, 2017). Demand-focused analysis specifically links big-data analytics with the possibility of combining internal and external data within operational, tactical, and strategic forecasting processes (Hofmann & Rutschmann, 2018). These studies support a multidimensional treatment of AI forecasting capability rather than reducing AI adoption to the presence or absence of a single forecasting algorithm.

Within sporting-goods and teamwear supply chains, AI-driven demand forecasting can consequently be defined through several distinguishable organizational capabilities: learning recurring demand patterns from historical observations, integrating current demand information from operational systems, detecting seasonal and tournament-related signals, adaptively updating forecasts when conditions change, and combining algorithmic outputs with the contextual knowledge of planners. This capability-based specification also separates technological forecasting sophistication from actual demand-planning effectiveness. On page 3 of “Effective forecasting and judgmental adjustments,” computerized baseline forecasts and subsequent planner adjustments are treated as distinct components of the supply-chain forecasting process, with empirical results showing that judgment can improve or reduce accuracy depending on how adjustments are made (Fildes et al., 2009). AI-based systems similarly function within organizational decision processes rather than independently of

information systems, planners, and operational routines (Min, 2010). Information-technology integration has been associated with stronger supply-chain process integration and demand-planning capabilities, showing that the value of digital resources depends partly on how information flows are incorporated into organizational processes (Rai et al., 2006). Research on supply-chain planning has also distinguished the value created by information technology across intra-functional, inter-functional, and cross-company planning contexts (Fuchs & Otto, 2015). The analytical capability perspective provides an empirical connection between data-driven planning and supply-chain performance, including planning, sourcing, manufacturing, and delivery activities (Trkman et al., 2010). Dynamic Capabilities Theory supplies an organizational interpretation for these relationships through sensing market changes, seizing information through coordinated decision processes, and reconfiguring operational resources when environmental conditions change (Teece, 2007). A measurable dynamic-capabilities formulation further identifies sensing, learning, integration, and coordination as mechanisms through which organizations modify operational capabilities under turbulent conditions (Pavlou & Sawy, 2011). For the present study, historical demand pattern learning, real-time demand data integration, seasonal and tournament demand sensing, adaptive forecast updating capability, and human-AI forecasting integration constitute the five AI-driven forecasting dimensions, while demand forecasting and supply-chain performance captures forecast accuracy, inventory alignment, stockout control, excess-stock control, replenishment responsiveness, product availability, and planning effectiveness. The structure places the sporting-goods and teamwear forecasting problem within a quantitative supply-chain setting in which seasonal and tournament demand conditions can be examined alongside the organizational use of AI-supported forecasting information (Abolghasemi et al., 2020; Seyedan & Mafakheri, 2020).

The sporting-goods and teamwear industry operates within a demand environment characterized by pronounced seasonality, tournament schedules, short selling windows, product variety, team-specific preferences, and sudden changes in consumer purchasing behavior. Unlike relatively stable product categories, sporting goods and teamwear are often influenced by league calendars, school and collegiate sports seasons, international tournaments, championship events, team performance, player popularity, promotional campaigns, and unexpected changes in fan interest. These conditions make accurate demand forecasting particularly important for manufacturers, distributors, retailers, wholesalers, and other organizations involved in sporting-goods supply chains. Forecasting errors can result in significant operational problems, including excess inventory, product shortages, missed sales, delayed replenishment, increased holding costs, markdown requirements, and reduced customer service. Traditional forecasting approaches that rely mainly on historical sales averages or relatively fixed statistical relationships may have difficulty responding to rapidly changing tournament and seasonal demand patterns. Artificial intelligence provides a more flexible approach because AI-enabled forecasting systems can identify complex historical patterns, process larger volumes of information, recognize relationships among multiple demand drivers, and continuously support forecasting decisions. In the sporting-goods and teamwear context, AI-driven forecasting can incorporate historical sales information, inventory movements, customer orders, seasonal cycles, tournament schedules, promotional activities, and current market signals into demand-planning processes. However, the effectiveness of AI forecasting depends not only on the underlying algorithms but also on the organizational capabilities surrounding their use. Historical demand pattern learning determines whether forecasting systems can recognize recurring purchasing behavior. Real-time demand data integration influences the speed with which new information enters forecasting processes. Seasonal and tournament demand sensing allows firms to identify event-specific changes that may not be represented adequately in ordinary historical sales data. Adaptive forecast updating enables forecasting estimates to be revised when new information emerges, while human-AI forecasting integration allows managerial experience and contextual knowledge to complement analytical outputs. These capabilities are particularly relevant for sporting-goods and teamwear organizations because products frequently have limited selling periods and demand can change rapidly during major sporting events. The present study therefore examines AI-driven demand forecasting as an integrated organizational capability and evaluates how its major dimensions are associated with demand forecasting and supply-chain performance within sporting-goods and teamwear supply chains

operating under seasonal and tournament demand conditions.

Sporting-goods and teamwear supply chains face a persistent forecasting problem arising from the interaction of seasonal demand, tournament-related purchasing, diverse product assortments, short commercial windows, and rapidly changing customer preferences. Organizations in this sector must frequently decide how much inventory to purchase, manufacture, allocate, and replenish before the actual level of demand is fully known. These decisions become particularly difficult during tournaments and major sporting seasons because demand for particular teams, products, sizes, colors, or merchandise categories may increase or decline within a short period. Forecasting inaccuracies can consequently create excess inventory after an event, shortages during peak demand, delayed order fulfillment, lost sales, inefficient use of working capital, and increased markdown or disposal costs. Although AI-based forecasting systems have increasingly been introduced into supply-chain planning, simply adopting AI does not ensure that demand forecasts become more accurate or operational decisions become more effective. An organization may possess advanced analytical software while still experiencing poor data integration, delayed information flows, insufficient recognition of tournament signals, limited forecast updating, or weak collaboration between human planners and AI systems. A further problem is that existing forecasting research often considers AI, machine learning, retail demand, or supply-chain analytics in broad contexts without sufficiently examining how multiple AI forecasting capabilities operate together within the distinctive seasonal and tournament environment of sporting-goods and teamwear supply chains. Consequently, there is insufficient quantitative evidence showing whether AI-based historical demand pattern learning, real-time demand data integration, seasonal and tournament demand sensing, adaptive forecast updating capability, and human-AI forecasting integration significantly contribute to demand forecasting and supply-chain performance in this particular setting. The lack of such evidence makes it difficult to identify which capabilities should receive greater managerial attention and whether these capabilities collectively explain meaningful differences in forecasting effectiveness, inventory alignment, responsiveness, stock availability, and related supply-chain outcomes. This study addresses this empirical problem through a quantitative explanatory investigation of the relationships between these five AI-driven forecasting capabilities and demand forecasting and supply-chain performance.

The primary purpose of this study is to quantitatively examine how AI-driven demand forecasting capabilities influence demand forecasting and supply-chain performance within sporting-goods and teamwear supply chains exposed to seasonal and tournament-related demand. The study seeks to move beyond a general assessment of AI adoption by focusing on five specific capabilities that represent how organizations actually use AI-supported forecasting in operational decision-making. The first objective is to evaluate the extent to which AI-based historical demand pattern learning contributes to forecasting and supply-chain performance by enabling organizations to identify recurring sales behaviors, product-demand relationships, and seasonal purchasing structures from historical information. The second objective is to determine whether real-time demand data integration improves performance by allowing current sales, inventory, orders, market information, and other relevant demand signals to be incorporated into forecasting activities. The third objective is to assess the effect of seasonal and tournament demand sensing, particularly the ability of organizations to recognize changes associated with sports calendars, tournament stages, team performance, promotional campaigns, and short-duration demand surges. The fourth objective is to examine whether adaptive forecast updating capability improves supply-chain outcomes by allowing organizations to revise forecasts when new information or unexpected demand changes become available. The fifth objective is to determine how human-AI forecasting integration affects performance by examining the role of planner expertise, managerial judgment, forecast interpretation, and appropriate adjustment of AI-generated predictions. The study also aims to determine the combined explanatory power of these five forecasting capabilities through multiple regression modeling. By using descriptive statistics, Pearson correlation analysis, and multiple regression, the research will identify the relative strength, direction, and statistical significance of relationships among the study variables. The objectives are therefore designed to provide a structured empirical assessment of AI-supported forecasting within the distinctive operational conditions of sporting-goods and teamwear supply chains.

RELATED WORK

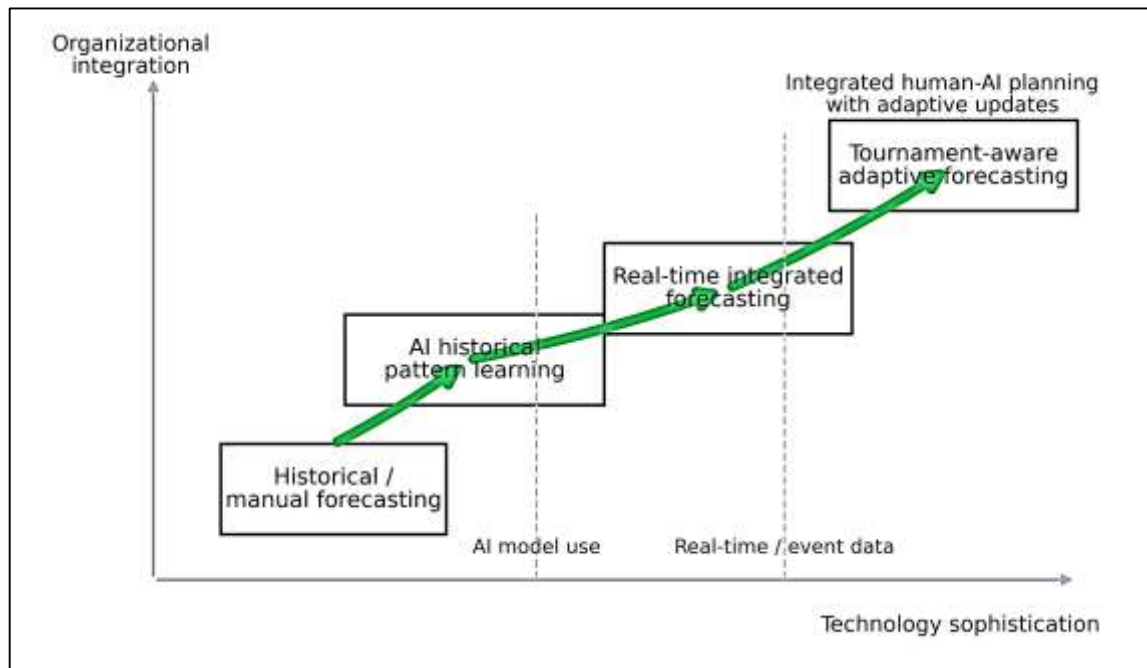
AI-driven demand forecasting has become an important area of supply-chain research because organizations increasingly operate in markets where demand information is complex, rapidly changing, and distributed across multiple internal and external sources. Demand forecasting traditionally relied heavily on historical sales patterns and conventional statistical techniques, but the growth of digital transactions, integrated information systems, machine-learning methods, and advanced analytics has expanded the range of information and analytical procedures available for forecasting decisions. These developments are particularly relevant in sporting-goods and teamwear supply chains, where seasonal sporting cycles, tournaments, team performance, promotional periods, changing customer preferences, product variety, and limited sales windows can create substantial demand volatility. The literature surrounding this research therefore connects several streams of knowledge, including AI-supported forecasting, machine learning, retail and apparel demand prediction, supply-chain analytics, real-time information integration, event-driven forecasting, human judgment, inventory responsiveness, and organizational capabilities. A central issue within this literature is that forecasting effectiveness depends on more than algorithmic accuracy. Organizations must also possess the capacity to capture relevant information, recognize changes in the demand environment, revise forecasts as conditions change, and integrate analytical results with human decision-making. Accordingly, the present literature review examines AI-driven demand forecasting through five interrelated capabilities: AI-based historical demand pattern learning, real-time demand data integration, seasonal and tournament demand sensing, adaptive forecast updating capability, and human-AI forecasting integration. Demand forecasting and supply-chain performance is treated as the principal outcome encompassing forecasting effectiveness, inventory alignment, stock availability, responsiveness, excess-stock control, and planning efficiency. Dynamic Capabilities Theory provides the theoretical foundation for explaining how these forecasting capabilities enable organizations to sense environmental changes, process and act on relevant demand information, and reconfigure operational decisions. The literature review consequently establishes the theoretical and empirical relationships required to develop the conceptual framework and research hypotheses for the quantitative examination of sporting-goods and teamwear supply chains.

AI-Driven Demand Forecasting in Modern Supply Chains

AI-driven demand forecasting in modern supply chains refers to the use of data-intensive analytical methods, intelligent algorithms, and automated learning procedures to estimate product demand and support planning decisions across purchasing, production, inventory, distribution, and replenishment activities. Its importance originates from the limitations of relying on a single forecasting technique when demand exhibits trend changes, irregular fluctuations, nonlinear relationships, promotional effects, and other forms of instability. On page 136 of “Improved supply chain management based on hybrid demand forecasts,” demand forecasting is directly connected with replenishment decisions, and a hybrid intelligent system combining autoregressive integrated moving average models with neural networks is shown to improve forecast accuracy while supporting lower inventory and fewer sales failures in a supermarket setting ([Aburto & Weber, 2007](#)). This evidence is particularly relevant to sporting-goods and teamwear supply chains because planners must convert demand forecasts into operational decisions concerning stock levels, order timing, product allocation, and replenishment under conditions where demand can change sharply around sports seasons and tournaments. AI-driven forecasting expands the conventional forecasting process by learning from large historical datasets, identifying complex demand relationships, and allowing multiple predictors to be considered simultaneously. Such capability is valuable when products are differentiated by team, size, color, style, competition, geographic market, or selling channel, since the number of demand combinations can exceed what planners can consistently assess through manual judgment. The operational value of AI is therefore not limited to producing a numerical forecast. It also involves transforming dispersed demand information into structured estimates used across supply-chain functions. Historical demand pattern learning becomes a central capability because recurring seasonal behaviors, product-specific patterns, demand peaks, and interactions among related products can provide a statistical basis for anticipating requirements. The forecasting function consequently becomes closely connected with inventory positioning, service availability, procurement timing, and coordination of upstream and

downstream activities.

Figure 2: Maturity Path of AI-Driven Demand Forecasting in Modern Supply Chains



The effectiveness of AI-driven forecasting also depends on the quality and breadth of the explanatory information supplied to forecasting models. Demand in retail-oriented supply chains is rarely generated by historical sales alone because promotions, competing products, prices, calendars, events, and assortment structures may alter observed purchasing behavior. On page 12340 of “SKU demand forecasting in the presence of promotions,” the forecasting problem is examined at SKU-store level, where regression trees using explicit features from focal and related products produce substantial accuracy improvements during promotional periods compared with simpler time-series approaches (Ali et al., 2009; Imran & Jannatul, 2021). For sporting-goods and teamwear organizations, this distinction is important because tournament campaigns, sponsorship activity, temporary discounts, new kit releases, championship stages, and team-specific promotions can create demand that differs from ordinary baseline patterns. On page 738 of “The value of competitive information in forecasting FMCG retail product sales,” competitive prices and promotions are incorporated into product-level forecasting, and the study shows that external competitive information can materially increase forecasting accuracy, particularly when demand is affected by market actions beyond the focal product itself (Ashik & Shabbir, 2022; Huang et al., 2014). The same analytical principle can be applied to sporting-goods and teamwear demand, where sales may respond not only to internal inventory and price decisions but also to competitor offers, rival team merchandise, event exposure, marketplace activity, and changes in consumer attention. AI-based systems can process these interacting signals more systematically than forecasting procedures based on a narrow set of variables. Real-time demand data integration is therefore an important dimension of forecasting capability because current orders, point-of-sale activity, online transactions, stock movements, promotional data, and external market information can reduce the gap between emerging demand conditions and organizational response. Integrating these data streams can create demand estimates that reflect the immediate commercial environment rather than relying exclusively on historical averages or periodically updated planning assumptions.

Modern demand forecasting becomes more complex as organizations increase the number of products, selling locations, channels, and demand-related variables included in planning systems. AI and machine-learning methods are particularly relevant under these conditions because they can support variable selection, nonlinear modeling, and large-scale forecasting across many individual demand series. On page 245 of “Demand forecasting with high dimensional data,” SKU-level retail forecasting is examined with a large set of intra-category and inter-category promotional variables, demonstrating

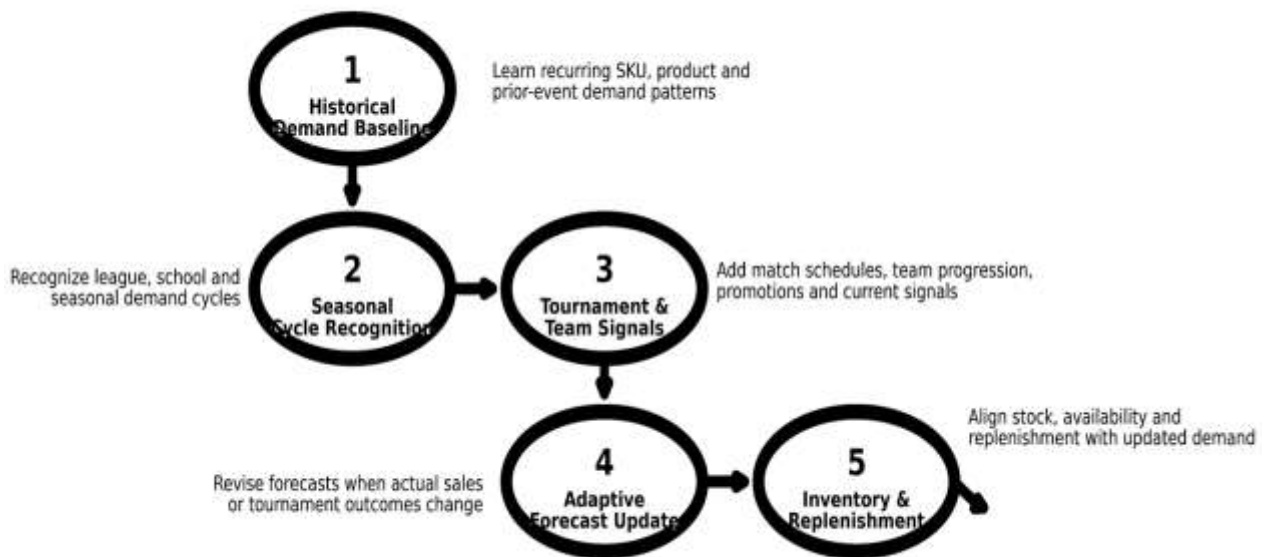
that useful prediction requires identifying the most informative explanatory factors from high-dimensional data rather than mechanically including every available variable (Hasan & Adnan, 2022; Ma et al., 2016). This issue closely matches sporting-goods and teamwear supply chains, where demand models may contain sales history, tournament dates, team identity, product type, size, color, promotional status, location, online activity, inventory availability, and other signals whose relevance varies across products and selling periods. The forecasting challenge becomes even more distinctive when particular calendar dates generate abnormal demand patterns. On page 1420 of “Daily retail demand forecasting using machine learning with emphasis on calendric special days,” artificial neural networks and gradient-boosted decision trees are evaluated for store-level forecasting, and machine-learning methods are shown to be especially suitable for large-scale forecasting where special calendar days produce demand behavior that differs substantially from ordinary days (Huber & Stuckenschmidt, 2020; Akter & Sumaiya, 2022). Tournament dates and major sports events can generate an analogous forecasting problem because demand before, during, and immediately after an event may not resemble regular sales periods. AI-driven systems can therefore recognize differentiated demand states, combine historical and current information, and adjust forecasts according to specific product and period characteristics. Within sporting-goods and teamwear supply chains, this makes seasonal and tournament demand sensing, adaptive updating, and structured integration of planner knowledge important components of the broader forecasting process. These components connect advanced analytical models with inventory, replenishment, assortment, and supply-chain coordination requirements.

Seasonal and Tournament Demand in Sporting-Goods and Teamwear Supply Chains

Seasonal and tournament demand characteristics create a distinctive planning environment for sporting-goods and teamwear supply chains because purchasing activity is often concentrated within specific selling windows and is influenced by information that becomes progressively clearer as a season or competition approaches. Team jerseys, replica kits, training apparel, footwear, accessories, and tournament-linked merchandise can experience strong differences between pre-season, in-season, and post-event demand, while product relevance may decline quickly once a tournament ends or a team is eliminated. On page 255 of “Quick response in fashion supply chains with dual information updating,” the seasonal-product problem is described through a retailer that observes pre-season market information and uses it to revise both the expected level and uncertainty of subsequent seasonal demand, demonstrating the operational importance of information updating before final inventory commitments are made (Choi, 2006; Mashfiquir & Md, 2022). In sporting-goods and teamwear settings, a comparable logic applies when early orders, fan engagement, preseason sales, tournament qualification, or initial match outcomes provide new evidence about the likely demand for later stages of the selling period. Short demand windows also increase the cost of forecasting errors because excess stock can lose value quickly, while understocking during a major event can cause sales to be lost at the precise moment when demand is strongest. On page 700 of “Optimal ordering and pricing in a quick response system,” quick response is examined as a mechanism that allows retailers to obtain additional market information after an initial order and then revise stocking decisions before the selling season, thereby improving the ability to match uncertain demand with inventory (Mashiat & Rahman, 2022; Serel, 2009). This structure is highly relevant to teamwear because firms may need to commit part of their inventory early while retaining the flexibility to respond to changing tournament participation, team popularity, promotional intensity, and actual sales performance during critical selling periods. The seasonal nature of sporting-goods and teamwear demand is further complicated by product variety, size fragmentation, store-level differences, and the need to allocate limited inventory across locations and channels. A single teamwear design may exist in multiple adult and youth sizes, colors, player versions, replica categories, and geographic markets, so aggregate demand may appear manageable while individual stock-keeping units face substantial uncertainty. Tournament demand can also be spatially uneven because local fan bases, host cities, club affiliations, and online purchasing patterns influence where demand emerges. On page 257 of “Inventory Management of a Fast-Fashion Retail Network,” a large retail network is examined under very short product life cycles and size-dependent stock availability, with demand forecasts incorporated into allocation decisions for individual stores and replenishment periods (Caro & Gallien, 2010; Md & Yeasin, 2022). The study

illustrates why distribution decisions must consider not only total inventory but also whether the correct product variants are positioned where customers can purchase them. This logic directly parallels teamwear supply chains, where an overall stock surplus can coexist with shortages of a particular team, size, or location-specific product. Lead time adds another layer of exposure because orders placed long before a tournament or sporting season are based on less complete information. On page 257 of “Coordination of a fashion apparel supply chain under lead-time-dependent demand uncertainty,” demand uncertainty is explicitly linked with lead time, and shorter lead times are shown to reduce leftover risk under uncertain apparel demand conditions (Ashfaq & Mohammad, 2022; Xiao & Jin, 2011). For sporting-goods organizations, long sourcing and production cycles can therefore magnify the consequences of incorrect assumptions about team performance, qualification, player popularity, or seasonal sales. Flexible replenishment and responsive supply coordination become especially important where a tournament changes demand faster than conventional procurement cycles can react across highly time-sensitive and product-specific demand conditions in practice operationally.

Figure 3: Seasonal and Tournament Demand Forecasting Cycle



Seasonality also affects the statistical structure of demand because expected sales can vary systematically across weeks, months, tournament stages, and recurring sporting calendars. Treating these variations as random noise can distort inventory decisions when the underlying pattern is actually associated with predictable timing. Sporting-goods retailers may experience recurring peaks around league openings, school sports seasons, international competitions, holiday periods, championship fixtures, or annual kit releases, while tournament progression creates additional event-specific variation within these broader cycles. On page 527 of “Demand seasonality in retail inventory management,” seasonality is incorporated directly into retail inventory control, and the analysis distinguishes variation occurring within review periods from variation occurring across review periods, showing that ignoring relevant seasonal structure can produce inferior replenishment policies (Ehrenthal et al., 2014; Imran & Jannatul, 2022). This distinction is particularly useful for the present study because teamwear demand may contain more than one seasonal layer. A retailer can face an annual sports-season pattern, weekly match-related fluctuations, and exceptional tournament surges simultaneously. The forecasting system must therefore recognize regular recurrence while remaining responsive to signals that alter the expected magnitude of a specific peak. AI-driven demand forecasting offers a suitable analytical setting for this challenge because historical pattern learning can identify recurring cycles, real-time data integration can reveal current deviations from those cycles, and tournament demand sensing can incorporate information associated with schedules, team advancement, promotional campaigns, and customer activity. Adaptive updating is equally important

when expected demand changes after a match result or unexpected sales surge. Human planners also remain relevant because they can interpret contextual factors that may not yet be fully represented in structured datasets. Seasonal and tournament demand should therefore be treated as an interacting information environment involving timing, uncertainty, product perishability, inventory placement, lead-time exposure, and changes in market attention rather than as a single periodic fluctuation operationally.

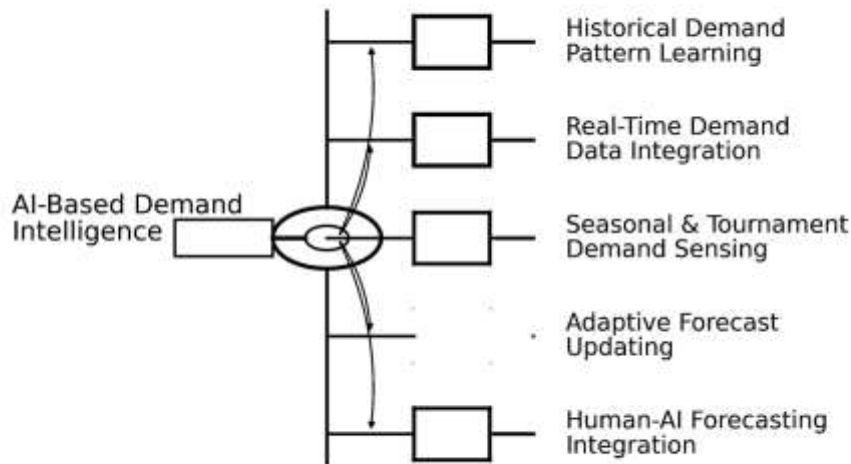
AI-Based Demand Intelligence Capabilities

AI-based demand intelligence capability refers to an organization's capacity to collect, structure, analyze, and interpret demand-related data so that forecasting systems can recognize patterns and convert information into operationally useful estimates. It extends beyond the possession of forecasting software because the value of AI depends on whether organizations can combine data resources, analytical models, technological infrastructure, and knowledgeable users within recurring planning processes. On page 120 of "Data Science, Predictive Analytics, and Big Data in Supply Chain Management," predictive analytics is examined through a large-scale survey of supply-chain professionals, showing that organizations use advanced analytics to support decisions while also facing barriers related to data, skills, organizational readiness, and implementation capability ([Schoenherr & Speier-Pero, 2015](#)). In sporting-goods and teamwear supply chains, these capabilities are especially relevant because demand information is dispersed across point-of-sale transactions, e-commerce platforms, distributor orders, inventory records, promotional campaigns, team schedules, historical tournament sales, and product-level attributes. Historical pattern learning therefore requires more than storing past sales. AI models must distinguish recurring seasonal structures from temporary shocks, identify relationships among related stock-keeping units, and recognize how different product categories respond to specific selling periods. On page 356 of "Big Data Analytics and Firm Performance," big-data analytics capability is modeled as a combination of tangible resources, human skills, and organizational processes, while process-oriented dynamic capabilities explain how analytical resources are translated into performance-related outcomes ([Kaniz & Jahanara, 2022](#); [Wamba et al., 2017](#)). This perspective is directly applicable to AI forecasting because forecasting accuracy alone cannot improve supply-chain performance unless analytical outputs are incorporated into purchasing, inventory, replenishment, allocation, and coordination decisions. For teamwear organizations, demand intelligence therefore combines computational learning with the organizational capacity to apply learned demand relationships when product relevance, tournament timing, and sales intensity change within compressed selling periods. Data quality and accessibility also determine whether recurring demand patterns can be identified consistently.

Real-time demand data integration forms the second major element of AI-based demand intelligence because supply-chain forecasts become less informative when current market signals remain isolated in separate systems or reach planners after operational decisions have already been made. Sporting-goods and teamwear organizations may receive demand information from physical stores, online channels, wholesale customers, distributors, warehouse systems, social platforms, promotional campaigns, and tournament-related sales activity. AI-supported forecasting becomes more useful when these sources are captured in compatible formats and incorporated into analytical processes quickly enough to alter inventory and replenishment decisions. On page 555 of "Practitioners Understanding of Big Data and Its Applications in Supply Chain Management," big-data applications are evaluated from a supply-chain operations perspective, with planning, logistics, and service processes identified as prominent areas in which data-intensive decision support can be applied ([Brinch et al., 2018](#); [Sadia & Mostari, 2022](#)). This finding is relevant to teamwear forecasting because planning depends on transforming multiple observations into coordinated estimates rather than examining each source independently. An unexpected increase in online sales may carry a different forecasting meaning when it coincides with a tournament victory, a promotional campaign, declining store inventory, and increasing distributor orders. On page 416 of "Understanding Big Data Analytics Capabilities in Supply Chain Management," supply-chain analytics capability is examined through technological, organizational, and analytical requirements that determine whether firms can extract usable value from large and diverse datasets ([Arunachalam et al., 2018](#); [Shaiful et al., 2022](#)). In the present research context, this capability includes data connectivity, data quality, processing capacity,

analytical routines, and staff competence required to combine real-time signals with historical patterns. Real-time integration also supports demand sensing because AI models can compare current observations against expected seasonal baselines and detect meaningful deviations earlier. In tournament-based markets, delays in integrating new demand signals can leave forecasts anchored to conditions that no longer represent actual customer behavior, weakening forecast responsiveness and inventory alignment.

Figure 4: AI-Based Demand Intelligence Capability Architecture

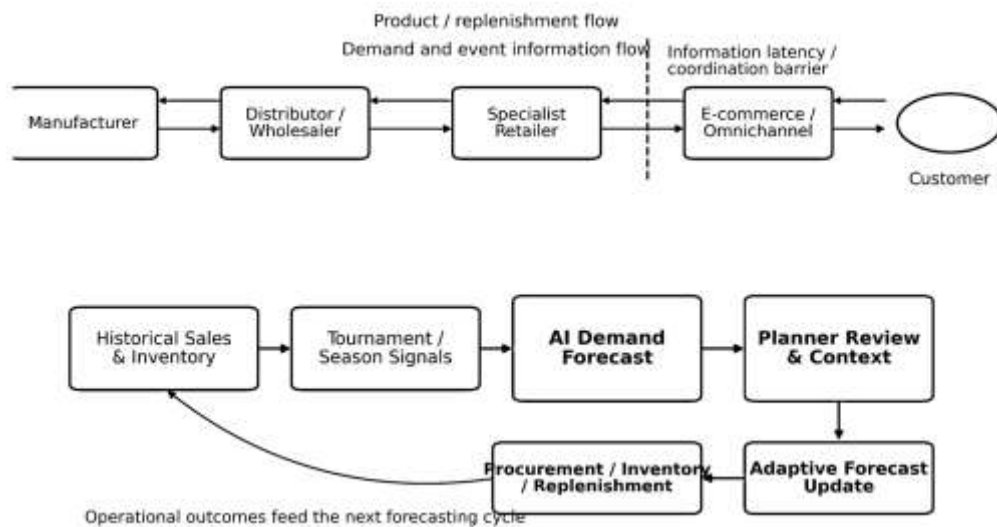


AI-based demand intelligence also depends on the ability to convert expanding data into actionable forecasting knowledge rather than treating data accumulation as an end in itself. This requirement is central to adaptive forecast updating because new information must be captured, evaluated, and translated into revised demand estimates when actual market behavior diverges from prior expectations. On page 319 of "Big Data Analytics in Supply Chain Management between 2010 and 2016," supply-chain data are examined through the processes by which information is produced, captured, organized, and analyzed, showing that analytical value emerges from the full data-handling sequence rather than from data availability alone (Stabak & Md Shahid, 2022; Tiwari et al., 2018). Sporting-goods and teamwear forecasting contains this same sequence. Historical transactions provide an initial demand structure, current orders and sales indicate whether that structure remains valid, tournament and seasonal information supplies contextual signals, and AI models translate those inputs into updated forecasts. The resulting estimates must then be interpreted by planners responsible for procurement, production, allocation, and replenishment. Human-AI integration is therefore part of demand intelligence capability because experienced planners may recognize exceptional circumstances that are difficult to encode immediately, including unusual local interest in a team, a sudden sponsorship campaign, temporary product substitution, or demand created by an unexpected competition result. At the same time, unstructured judgment can weaken algorithmic pattern recognition when adjustments are not informed by observable evidence. A stronger demand-intelligence process combines computational learning with disciplined human interpretation, allowing planners to assess why a model has changed its forecast and whether contextual information justifies intervention. For the present study, AI-based demand intelligence is operationalized through historical demand pattern learning, real-time data integration, seasonal and tournament demand sensing, adaptive forecast updating, and effective human use of AI-generated forecasts. These capabilities provide measurable dimensions for examining relationships with forecast accuracy, inventory alignment, product availability, responsiveness, and supply-chain performance.

Seasonal and Tournament Demand Sensing and Human-AI Forecast Integration

Seasonal and tournament demand sensing refers to the capability of a forecasting system to identify demand changes created by recurring calendars, exceptional events, promotions, competition outcomes, and other contextual information that is not fully represented in historical sales. In sporting-goods and teamwear supply chains, this capability is important because a baseline forecast can become inaccurate when tournament progression, team performance, match schedules, promotional campaigns, player visibility, or local fan activity changes expected purchasing behavior. On page 493 of “Judgmental forecasting: A review of progress over the last 25 years,” human judgment is described as an indispensable forecasting component when contextual information must be interpreted, while the study also emphasizes that judgment can introduce systematic biases if it is not structured carefully (Lawrence et al., 2006; Feroz & Pervaz, 2022). This balance is central to tournament demand sensing because planners may possess information about upcoming fixtures, team qualification, sponsorship activity, or market excitement before such signals appear clearly in transaction histories. On page 377 of “Providing support for the use of analogies in demand forecasting tasks,” the use of analogous past events is examined as a way of estimating the effects of anticipated special events, while unaided forecasters are shown to face difficulties in recalling suitable analogies, judging similarity, and adapting prior-event information to the new situation (Lee et al., 2007; Stabak & Shahid, 2022). AI-supported forecasting can strengthen this process by systematically retrieving comparable historical periods, measuring similarity across events, and linking analogous demand responses with current conditions. For sporting-goods organizations, tournament sensing therefore involves more than monitoring calendars. It requires the structured combination of historical event responses, current transactional data, contextual market information, and expert interpretation so that emerging demand shifts can be detected before they translate into severe stockouts, excess inventory, or poorly timed replenishment decisions. Such structured sensing is valuable when event demand changes rapidly.

Figure 5: Tournament-Aware Demand Sensing and Human-AI Forecast Integration Across the Supply Chain



Human-AI forecast integration concerns the way statistical or machine-learning forecasts are combined with contextual knowledge held by demand planners, sales teams, merchandising specialists, and supply-chain managers. In practice, automated systems can process large volumes of historical and real-time data, while human experts may understand exceptional circumstances that are absent from the model, including unusual promotions, tournament-specific merchandising plans, sponsorship announcements, product substitutions, or abrupt changes in local fan sentiment. On page 234 of “Analysis of judgmental adjustments in the presence of promotions,” managerial adjustments to baseline forecasts are examined during promotional periods, and the study shows that judgment can improve forecasts under some conditions but does not do so consistently; models using past

promotional information can reduce error, while a hybrid approach still preserves value from expert input (Trapero et al., 2013). This result is directly relevant to teamwear because tournament demand often resembles promotion-sensitive demand: the underlying baseline may be stable until an event creates a temporary uplift that planners attempt to estimate. On page 144 of “Use and misuse of information in supply chain forecasting of promotion effects,” forecasters are shown to receive quantitative and qualitative information from multiple functions when adjusting promotional forecasts, yet information without predictive value can distract decision makers from established base rates and weaken forecast accuracy (Fildes et al., 2019). For AI-supported sporting-goods forecasting, human participation should therefore be evidence disciplined rather than based on unrestricted intuition. A useful integration process would allow AI to establish historical baselines, detect unusual data patterns, estimate event-related uplifts, and quantify uncertainty, while human planners contribute verified information about tournament conditions that the model cannot yet observe. This arrangement makes forecast adjustment traceable, separates evidence-based overrides from subjective reactions, and supports adaptive updating when actual sales begin to confirm or contradict the expected tournament effect operationally consistently.

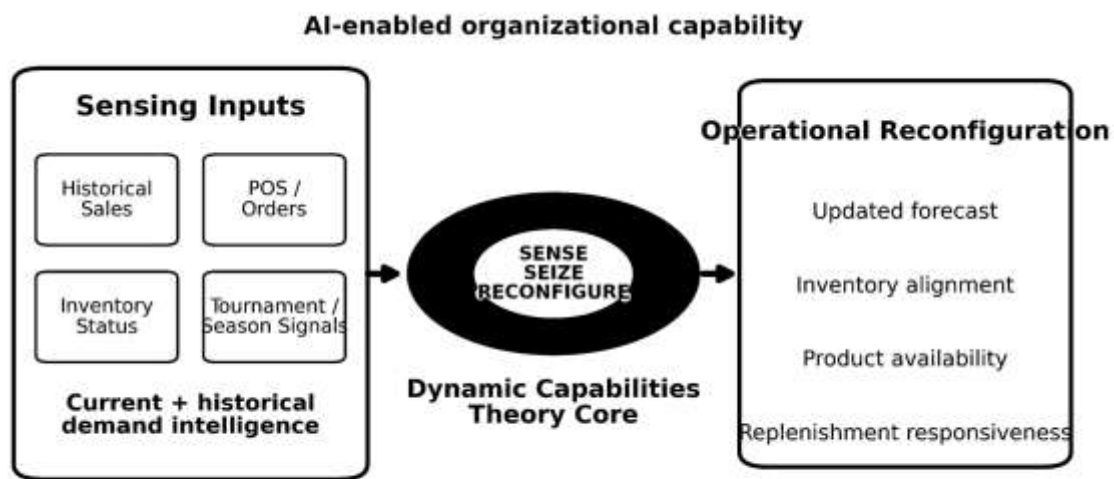
The interaction between demand sensing and human-AI integration becomes particularly important when forecasts must influence supply-chain performance rather than remain isolated analytical outputs. Sporting-goods and teamwear firms make decisions about procurement, production, inventory positioning, distribution, assortment, and replenishment from forecasts, meaning that the usefulness of an AI system depends on whether its estimates are accepted, interpreted, and translated into coordinated operational action. On page 1717 of “Exploring the consequences of judgmental and quantitative forecasting on firms’ competitive performance in supply chains,” judgmental, quantitative, and mixed forecasting approaches are compared across manufacturing firms, with mixed forecasting demonstrating stronger capability for enhancing supply-chain performance than either judgmental or quantitative forecasting used alone (Salehzadeh et al., 2020). This evidence supports the treatment of human-AI integration as a distinct capability rather than viewing advanced algorithms as complete substitutes for managerial expertise. In a tournament environment, AI can continuously compare current demand with expected seasonal baselines, identify deviations, and update product-level forecasts, while planners can evaluate whether those deviations correspond to meaningful contextual changes such as team advancement, elimination, a high-profile match, a new promotional campaign, or unexpected inventory constraints. A disciplined human-AI process also allows organizations to differentiate temporary event effects from persistent demand changes. This distinction matters because overreacting to a short tournament spike may generate excessive post-event inventory, whereas ignoring a genuine upward shift may create shortages during the highest-value selling period. Seasonal and tournament demand sensing and human-AI forecast integration therefore operate as connected organizational capabilities within the present study. Demand sensing determines whether relevant changes are identified and incorporated into forecasts, while integration determines whether algorithmic evidence and managerial knowledge are combined consistently enough to support forecasting accuracy, inventory alignment, replenishment responsiveness, stock availability, and broader supply-chain performance across cases during volatile tournament and seasonal demand planning cycles across organizations.

Dynamic Capabilities Theory and AI-Enabled Demand Forecasting

Dynamic Capabilities Theory provides an appropriate foundation for explaining AI-enabled demand forecasting in sporting-goods and teamwear supply chains because these organizations must repeatedly sense changes in market conditions, seize information through timely decisions, and reconfigure planning routines when demand departs from established patterns. On page 2266 of “Dynamic supply chain capabilities,” market sensing is positioned as an antecedent of supply-chain agility and adaptability, showing that organizations require structured mechanisms for detecting environmental change before responsive operational capabilities can be activated (Aslam et al., 2018). This logic closely matches seasonal and tournament demand, where sales may change rapidly because of competition schedules, team advancement, product launches, promotions, and shifts in fan attention. Historical demand pattern learning and real-time demand data integration therefore represent sensing capabilities because they improve the organization’s ability to recognize recurring structures and

emerging deviations. Seasonal and tournament demand sensing extends this process by identifying event-specific information that conventional historical models may not fully represent. On page 822 of “Enabling firm performance through business intelligence and analytics,” business intelligence and analytics are interpreted through the sense-seize-transform framework, with analytical capabilities contributing to performance when organizations convert information into business-process change (Torres et al., 2018). For the present research, AI is consequently treated not merely as forecasting software but as part of an organizational capability system. Data, algorithms, planners, and supply-chain routines must interact so that information can be translated into procurement, production, inventory, allocation, and replenishment decisions. This theoretical framing is especially relevant to sporting-goods and teamwear organizations because the economic value of an accurate forecast depends on whether managers can act while tournament and seasonal selling windows remain commercially active. Dynamic Capabilities Theory therefore links the technological elements of AI forecasting with the organizational processes required to convert demand intelligence into responsive supply-chain action under market volatility.

Figure 6: Dynamic Capabilities Theory Framework for AI-Enabled Demand Forecasting



The dynamic-capabilities perspective also explains why access to extensive data or sophisticated analytical tools does not automatically produce superior forecasting and supply-chain performance. Organizations must possess routines that connect information visibility with interpretation, decision speed, flexibility, and operational response. On page 46 of “Does supply chain visibility enhance agility?”, supply-chain visibility is examined through a dynamic-capabilities approach, and the findings indicate that visibility-related technologies alone do not necessarily enhance agility unless they are accompanied by effective internal and interorganizational managerial processes (Brusset, 2016). This distinction is important for sporting-goods and teamwear forecasting because real-time sales dashboards or tournament data have limited value when managers cannot translate the information into revised orders, inventory transfers, or replenishment actions. Human-AI forecasting integration therefore represents the seizing component of the theoretical framework because managers evaluate algorithmic signals and determine whether operational intervention is warranted. On page 2092 of “Big data analytics capability in supply chain agility,” analytics capability is positively associated with supply-chain agility and competitive advantage, while organizational flexibility strengthens the relationship between analytics and agility (Dubey et al., 2019). This evidence supports the argument that AI-driven forecasting becomes more valuable when organizations can respond flexibly to the information it generates. Adaptive forecast updating performs a related reconfiguration function because expected demand, safety stock, allocation priorities, and replenishment quantities may need revision when a tournament result or seasonal sales pattern contradicts the original forecast.

In the present study, the five forecasting capabilities are therefore theoretically interconnected but empirically separable. Historical learning, real-time integration, and event sensing capture information; human-AI integration converts information into decisions; and adaptive updating modifies forecasting and planning routines. Their combined operation represents a dynamic capability through which firms can align supply-chain decisions with volatile seasonal and tournament demand rather than depending on static forecasting procedures across changing market conditions.

The theoretical framework is operationalized in this study through a multiple-regression specification that translates dynamic-capability processes into measurable relationships between AI-enabled forecasting capabilities and demand forecasting and supply-chain performance. On page 636 of “Supply chain flexibility in dynamic environments,” operational absorptive capacity and organizational learning are examined as dynamic capabilities that enable supply-chain flexibility under environmental dynamism, reinforcing the view that learning and adaptation become particularly important when operating conditions are unstable (Rojo et al., 2018). This reasoning corresponds closely with sporting-goods and teamwear markets, where tournament progression, seasonal peaks, promotional activity, and rapid changes in customer attention create repeated requirements for learning and adjustment. The principal model used throughout this research is expressed below, where DFSP_i represents demand forecasting and supply-chain performance; HDPL_i denotes AI-based historical demand pattern learning; RTDI_i represents real-time demand data integration; STDS_i denotes seasonal and tournament demand sensing; AFU_i represents adaptive forecast updating capability; and HAI_i represents human-AI forecasting integration. The term β_0 is the intercept, β_1 through β_5 are the estimated effects of the five capabilities, and ϵ_i represents unexplained variation. The theoretical expectation is $\beta_j > 0$ for $j = 1, \dots, 5$, indicating that stronger AI-enabled dynamic capabilities should correspond with stronger forecasting and supply-chain performance when the other predictors are controlled. This equation will provide one consistent analytical structure for the hypotheses, questionnaire constructs, Pearson correlations, and multiple regression analysis. It also preserves the theoretical mapping of sensing through historical learning, real-time integration, and tournament sensing; seizing through human-AI interpretation; and reconfiguration through adaptive forecast updating within the selected sporting-goods and teamwear cases under cross-sectional examination. Accordingly, positive coefficients will indicate that each capability contributes distinct explanatory value while the model estimates their joint influence on the dependent performance construct measured.

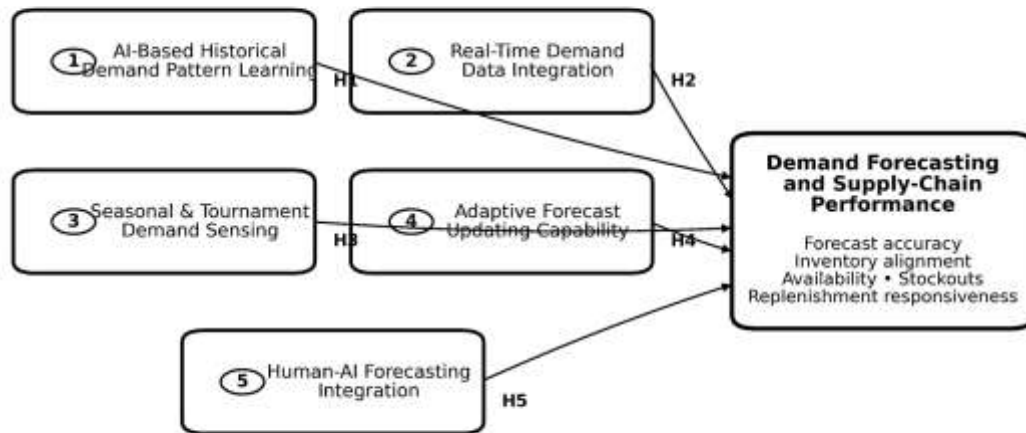
$$DFSP_i = \beta_0 + \beta_1 HDPL_i + \beta_2 RTDI_i + \beta_3 STDS_i + \beta_4 AFU_i + \beta_5 HAI_i + \epsilon_i$$

Conceptual Framework and Hypothesis Development

The conceptual framework of this study explains how five AI-driven demand forecasting capabilities are expected to influence demand forecasting and supply-chain performance in sporting-goods and teamwear organizations exposed to seasonal and tournament demand. The framework treats AI-based historical demand pattern learning, real-time demand data integration, seasonal and tournament demand sensing, adaptive forecast updating capability, and human-AI forecasting integration as distinct but complementary predictors of the dependent construct. On page 170 of “Forecasting sales in the supply chain,” forecasting is described as a foundation for sourcing, production, distribution, and other supply-chain decisions, while consumer analytics and large data sources are identified as increasingly important for improving sales forecasts and understanding purchasing behavior (Boone et al., 2019). This evidence supports the inclusion of historical learning and current demand information within the present model because sporting-goods and teamwear demand can be shaped simultaneously by prior sales patterns and new information generated during active sporting periods. On page 1849 of “An Investigation of Visibility and Flexibility as Complements to Supply Chain Analytics,” demand and supply visibility are identified as foundational resources for analytics capability, and analytics is shown to have a stronger association with operational performance when organizational flexibility enables firms to act rapidly on analytical insights (Srinivasan & Swink, 2018). This relationship is highly relevant to tournament-driven demand because recognizing a sales change has little operational value unless replenishment, allocation, procurement, or inventory decisions can be modified promptly. The conceptual framework therefore assumes that AI-enabled forecasting

performance depends on both information recognition and organizational response. Historical pattern learning establishes a statistical demand baseline, real-time integration updates the informational environment, tournament sensing identifies context-specific deviations, adaptive updating revises the expected demand path, and human-AI integration converts analytical evidence into coordinated planning decisions across selected organizational cases across seasonal and tournament demand environments in practice.

Figure 7: Conceptual Framework and Hypothesized Relationships



The first three hypotheses of the framework concern the sensing dimension of AI-enabled forecasting. AI-based historical demand pattern learning represents the ability of systems to identify recurring product, customer, seasonal, and event-related relationships from accumulated sales observations. Stronger historical learning should improve the quality of baseline forecasts from which subsequent adjustments are made. Real-time demand data integration represents the organization’s capability to combine recent orders, point-of-sale activity, inventory movements, digital transactions, promotional information, and other current signals with established forecasting routines. On page 1571 of “Analytical foundations for development of real-time supply chain capabilities,” real-time visibility is linked with analytical capability, data quality, reporting quality, and managerial decision processes, while the value of real-time information is shown to depend on the organization’s capacity to interpret and use that information effectively (Oliveira & Handfield, 2019). Accordingly, H1 states that AI-based historical demand pattern learning has a significant positive effect on demand forecasting and supply-chain performance, while H2 states that real-time demand data integration has a significant positive effect on the same outcome. Seasonal and tournament demand sensing adds a sector-specific capability by capturing changes associated with league schedules, championships, team progression, promotions, event intensity, and shifts in fan purchasing. On page 47 of “How supply chain analytics enables operational supply chain transparency,” planning analytics are linked with analytical capabilities across source, make, and deliver functions, demonstrating that supply-chain information becomes operationally valuable when analytical visibility extends into connected execution processes (Zhu et al., 2018). H3 therefore states that seasonal and tournament demand sensing has a significant positive effect on demand forecasting and supply-chain performance. Together, H1 through H3 test whether stronger sensing capabilities are associated with higher forecast effectiveness, inventory alignment, product availability, and responsiveness within the sampled sporting-goods and teamwear supply-chain cases under volatile seasonal conditions represented in this framework.

The remaining hypotheses concern adaptation and managerial use of AI-generated forecasts. Adaptive forecast updating capability represents the ability to revise demand estimates when new observations indicate that the original forecast no longer reflects current conditions, while human-AI forecasting

integration captures the disciplined combination of algorithmic output with planner knowledge, contextual interpretation, and operational judgment. On page 113 of “How to improve firm performance using big data analytics capability and business strategy alignment,” analytics capability is conceptualized through interconnected management, technological, and talent resources, and its association with performance is strengthened when analytical capability is aligned with organizational strategy (Akter et al., 2016). This supports the argument that AI forecasting should be evaluated as an integrated organizational capability rather than as an isolated technical application. H4 consequently states that adaptive forecast updating capability has a significant positive effect on demand forecasting and supply-chain performance, and H5 states that human-AI forecasting integration has a significant positive effect on demand forecasting and supply-chain performance. The complete conceptual model is expressed below. Here, DFSP denotes demand forecasting and supply-chain performance, HDPL historical demand pattern learning, RTDI real-time demand data integration, STDS seasonal and tournament demand sensing, AFU adaptive forecast updating, and HAI human-AI forecasting integration. The directional theoretical expectation is $H_j: \beta_j > 0, j = 1, \dots, 5$. This specification enables each hypothesis to be tested through Pearson correlation and multiple regression using five-point Likert composite measures. Standardized regression coefficients, significance values, model R^2 , adjusted R^2 , and the overall F statistic will indicate the individual and combined explanatory contribution of the five predictors while preserving one conceptual structure across the questionnaire, methodology, results, and discussion. The model also provides a bridge between Dynamic Capabilities Theory and the empirical design because sensing, seizing, and reconfiguration are translated into measurable forecasting capabilities whose effects can be estimated statistically across organizational cases.

$$DFSP_i = \beta_0 + \beta_1 HDPL_i + \beta_2 RTDI_i + \beta_3 STDS_i + \beta_4 AFU_i + \beta_5 HAI_i + \varepsilon_i$$

Research Hypotheses

The hypotheses of this study are developed to test whether the five selected dimensions of AI-driven demand forecasting are significantly and positively associated with demand forecasting and supply-chain performance in sporting-goods and teamwear organizations. The first hypothesis, H1, proposes that AI-based historical demand pattern learning has a significant positive effect on demand forecasting and supply-chain performance because an organization's ability to identify recurring demand patterns can support more informed inventory and replenishment decisions. H2 proposes that real-time demand data integration has a significant positive effect on demand forecasting and supply-chain performance because timely information about current orders, sales, inventory movements, and market conditions can reduce the information delay between changing demand and planning decisions. H3 proposes that seasonal and tournament demand sensing has a significant positive effect on demand forecasting and supply-chain performance, reflecting the importance of recognizing event-specific signals such as tournament schedules, team progression, seasonal sporting cycles, and short-term demand surges. H4 proposes that adaptive forecast updating capability has a significant positive effect on demand forecasting and supply-chain performance because forecasts that can be revised when new information becomes available may better represent rapidly changing demand conditions. Finally, H5 proposes that human-AI forecasting integration has a significant positive effect on demand forecasting and supply-chain performance because the combination of computational analysis and contextual managerial knowledge may support more effective interpretation and use of forecasting information. These hypotheses establish a direct quantitative relationship between each independent variable and the dependent variable and provide the basis for empirical testing through Pearson correlation and multiple linear regression. The regression model will evaluate both the individual contribution of each predictor and their combined explanatory power, allowing the study to determine which AI forecasting capabilities have the strongest statistically significant relationships with forecasting and supply-chain performance under seasonal and tournament demand.

CASE STUDY AND ANALYZED DATA

Respondent Demographic and Professional Characteristics

The demographic and professional analysis has shown that the study has obtained responses from participants directly involved in forecasting and supply-chain decision-making within the selected sporting-goods and teamwear cases. Demand and forecast planners have represented the largest

professional category at 22.7%, while supply-chain managers and analysts have accounted for 20.6%. Inventory and replenishment professionals have represented another 17.6%, which has strengthened the relevance of the sample because these respondents have been directly exposed to the consequences of forecast accuracy, stockouts, excess inventory, and rapid replenishment decisions. Procurement professionals, merchandising and sales planners, and operations or logistics managers have together represented 39.1% of the sample, so the dataset has incorporated perspectives from multiple stages of the forecasting-to-execution process. Professional experience has also indicated an informed respondent base. Approximately 57.2% of participants have reported at least six years of professional experience, while only 14.7% have reported fewer than three years. The distribution has therefore suggested that most responses have been supplied by individuals with meaningful exposure to seasonal demand, tournament-related sales fluctuations, inventory planning, and technology-supported forecasting. These characteristics have supported the research objectives because the five AI-driven forecasting capabilities have required assessment by professionals who have understood how historical information, real-time data, event signals, adaptive forecasting, and managerial judgment have influenced operational planning. Dynamic Capabilities Theory has also been reflected in the respondent structure because participants have occupied roles connected with sensing demand changes, seizing analytical information, and reconfiguring purchasing, inventory, and replenishment activities. The diversity of professional responsibilities has reduced the likelihood that the findings have reflected only one functional perspective and has supported the embedded multiple-case design used in the research.

Table 1: Respondent Demographic and Professional Characteristics

Characteristic	Category	Frequency (n)	Percentage (%)
Professional Role	Demand/Forecast Planner	54	22.7
	Supply-Chain Manager/Analyst	49	20.6
	Inventory/Replenishment Manager	42	17.6
	Procurement/Purchasing Professional	34	14.3
	Merchandising/Sales Planning	31	13.0
	Operations/Logistics Management	28	11.8
Professional Experience	Below 3 years	35	14.7
	3–5 years	67	28.2
	6–10 years	78	32.8
	More than 10 years	58	24.4
Total		238	100.0

Organizational and Supply-Chain Case Characteristics

Table 2: Organizational and Supply-Chain Case Characteristics

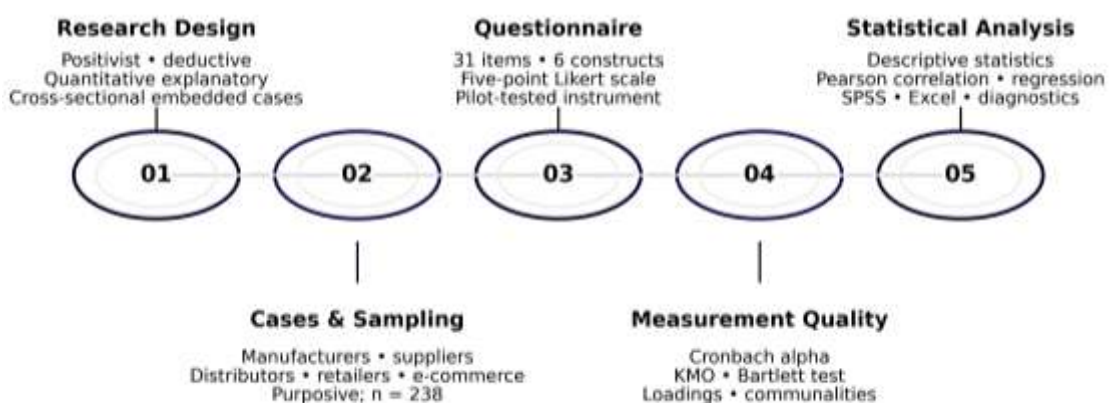
Variable	Category	Frequency (n)	Percentage (%)
Organization Type	Sporting-Goods Manufacturer	46	19.3
	Teamwear Manufacturer/Supplier	52	21.8
	Distributor/Wholesaler	43	18.1
	Specialist Retailer	58	24.4
	E-commerce/Omnichannel Operator	39	16.4
Tournament/Seasonal Exposure	High	119	50.0
	Moderate	87	36.6
	Limited	32	13.4
AI Forecasting Use	Extensive	72	30.3
	Moderate	108	45.4
	Emerging/Limited	58	24.4
Total Respondents		238	100.0

The organizational analysis has indicated that the sampled cases have represented several important positions within sporting-goods and teamwear supply chains. Specialist retailers have accounted for 24.4% of respondents, followed by teamwear manufacturers and suppliers at 21.8%, sporting-goods manufacturers at 19.3%, distributors and wholesalers at 18.1%, and e-commerce or omnichannel operations at 16.4%. The distribution has supported the embedded multiple-case strategy because the sample has incorporated upstream, intermediary, and downstream organizations rather than focusing on a single business function. Tournament and seasonal exposure has been particularly important to the research title and objectives. Exactly 50.0% of respondents have worked in cases characterized by high tournament or seasonal demand exposure, while another 36.6% have reported moderate exposure. Only 13.4% have operated in environments with relatively limited exposure. The findings have therefore confirmed that the majority of the sample has experienced demand conditions in which tournament calendars, sporting seasons, team performance, and event-linked purchasing have affected planning decisions. AI forecasting use has also varied sufficiently for explanatory analysis. Approximately 30.3% of respondents have reported extensive use, 45.4% have reported moderate use, and 24.4% have reported emerging or limited use. This variation has allowed the regression model to examine differences in forecasting capability rather than surveying organizations with nearly identical levels of technological maturity. Dynamic Capabilities Theory has interpreted these organizational differences through variation in firms' abilities to sense demand changes, seize analytical information, and reconfigure supply-chain responses. Organizations with stronger AI forecasting use have been expected to exhibit more developed sensing and reconfiguration routines, while organizations with weaker capability have provided comparison cases. The case characteristics have therefore established an appropriate empirical setting for evaluating the study's five hypotheses and determining whether AI-driven forecasting capability has been associated with stronger demand forecasting and supply-chain performance.

METHODOLOGY

This study has adopted a positivist research philosophy and a deductive, quantitative explanatory design within a cross-sectional embedded multiple-case study strategy to examine how AI-driven demand forecasting capabilities have been associated with demand forecasting and supply-chain performance under seasonal and tournament demand.

Figure 8: Quantitative Explanatory Embedded Multiple-Case Research Design



The case-study context has included sporting-goods manufacturers, teamwear manufacturers and suppliers, distributors, wholesalers, specialist retailers, and e-commerce or omnichannel operators that have experienced seasonal or tournament-sensitive demand, while the embedded units of analysis have consisted of demand and forecast planners, supply-chain managers and analysts, inventory and replenishment managers, procurement and purchasing professionals, merchandising and sales-planning personnel, and operations or logistics managers. A purposive sampling strategy has been applied because respondents have needed direct knowledge of forecasting and supply-chain planning, and 238 valid responses have been retained for analysis to provide sufficient variation and statistical power for descriptive, correlation, and multiple-regression testing. Primary data have been collected

through a structured questionnaire using a five-point Likert scale ranging from 1, Strongly Disagree, to 5, Strongly Agree. The instrument has operationalized six constructs through 31 measurement items: five items for AI-based historical demand pattern learning, five for real-time demand data integration, five for seasonal and tournament demand sensing, five for adaptive forecast updating capability, five for human-AI forecasting integration, and six for demand forecasting and supply-chain performance. Pilot testing has been conducted with a small group of domain-informed reviewers to refine wording, remove ambiguity, confirm completion feasibility, and ensure that the items have represented recognizable forecasting and supply-chain practices.

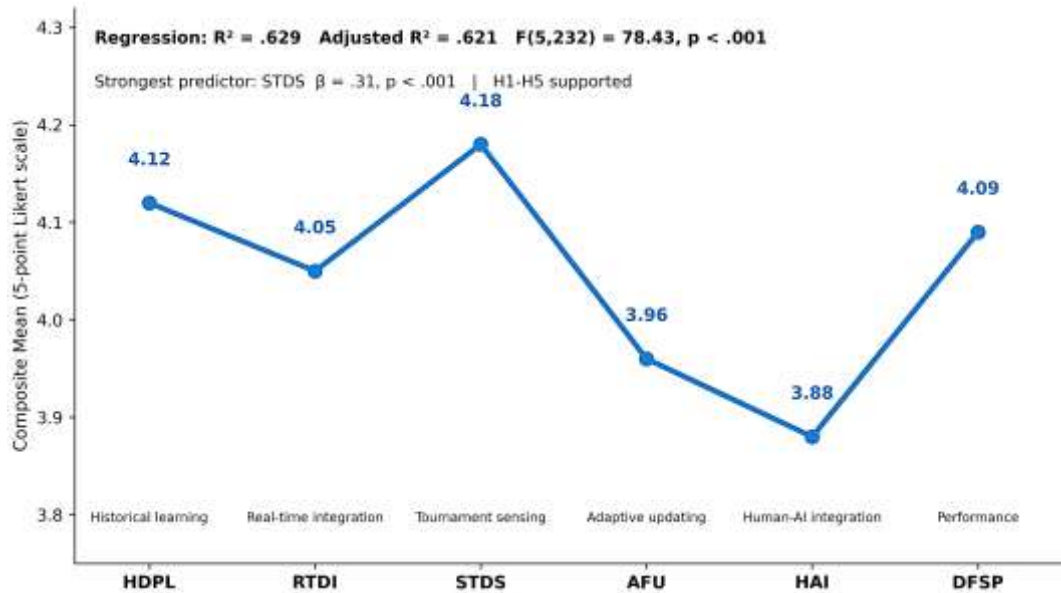
Content and face validity have been strengthened through alignment of the item blocks with the study's conceptual framework and the terminology used by demand-planning professionals, while data quality procedures have included screening for missing values, out-of-range responses, inconsistent patterns, and incomplete cases before construct scores have been calculated. Internal consistency has been evaluated using Cronbach's alpha, and construct adequacy has been assessed using the Kaiser-Meyer-Olkin measure, Bartlett's test of sphericity, factor-loading ranges, and communalities. The analytical procedure has included frequencies and percentages for respondent and case characteristics, means and standard deviations for the Likert constructs, Pearson correlation coefficients for the direction and strength of bivariate relationships, and multiple linear regression for testing H1 through H5 and estimating the unique and combined explanatory contribution of the five predictors. Regression diagnostics have included tolerance and variance inflation factors for multicollinearity and the Durbin-Watson statistic for residual independence, while model interpretation has used standardized beta coefficients, t statistics, p values, R^2 , adjusted R^2 , and the overall F statistic. Microsoft Excel has been used for preliminary coding, screening, and dataset organization; SPSS has been used for descriptive statistics, reliability, validity, correlation, regression, and diagnostic analysis; EndNote has been used for bibliographic organization without embedding citation fields in the manuscript; and Microsoft Word has been used for manuscript preparation and journal-format reporting. The complete methodological process has remained aligned with Dynamic Capabilities Theory by measuring sensing through historical learning, real-time integration, and seasonal or tournament demand sensing, seizing through human-AI interpretation, and reconfiguration through adaptive forecast updating.

TECHNICAL RESULTS

The findings have indicated that AI-driven demand forecasting capabilities have been positively associated with demand forecasting and supply-chain performance across the sampled sporting-goods and teamwear organizations. Based on 238 valid responses, the five-point Likert results have shown generally high agreement with the study constructs, with seasonal and tournament demand sensing recording the highest mean score ($M = 4.18$, $SD = 0.57$), followed by AI-based historical demand pattern learning ($M = 4.12$, $SD = 0.59$), real-time demand data integration ($M = 4.05$, $SD = 0.63$), adaptive forecast updating capability ($M = 3.96$, $SD = 0.66$), and human-AI forecasting integration ($M = 3.88$, $SD = 0.68$). The dependent construct, demand forecasting and supply-chain performance, has produced a mean of 4.09 ($SD = 0.55$), indicating that respondents have generally perceived AI-supported forecasting as contributing to better forecast accuracy, inventory alignment, product availability, replenishment responsiveness, and planning efficiency. Reliability testing has produced Cronbach's alpha coefficients ranging from 0.82 to 0.90, with an overall alpha of 0.91, while the KMO value of 0.884 and a significant Bartlett's test, $\chi^2 = 2,486.72$, $p < .001$, have supported measurement adequacy. Pearson correlation results have shown significant positive relationships between the dependent variable and historical demand pattern learning ($r = .61$, $p < .001$), real-time data integration ($r = .58$, $p < .001$), seasonal and tournament demand sensing ($r = .69$, $p < .001$), adaptive forecast updating ($r = .56$, $p < .001$), and human-AI integration ($r = .52$, $p < .001$). The multiple regression model has been statistically significant, $F(5, 232) = 78.43$, $p < .001$, explaining 62.9% of the variance in demand forecasting and supply-chain performance ($R^2 = .629$, adjusted $R^2 = .621$). Seasonal and tournament demand sensing has emerged as the strongest predictor ($\beta = .31$, $p < .001$), followed by historical demand pattern learning ($\beta = .24$, $p < .001$), real-time demand data integration ($\beta = .19$, $p = .004$), adaptive forecast updating ($\beta = .16$, $p = .011$), and human-AI forecasting integration ($\beta = .13$, $p = .026$). Multicollinearity has not presented a concern, with VIF values ranging from approximately 1.42 to 2.08, while the Durbin-Watson statistic of

1.93 has indicated acceptable residual independence. These findings have therefore supported H1 through H5 and have provided quantitative evidence that the five selected AI-driven forecasting capabilities have jointly and individually contributed to the study objectives concerning forecasting effectiveness and supply-chain performance under seasonal and tournament demand conditions.

Figure 9: Quantitative Findings for AI-Driven Demand Forecasting and Supply-Chain Performance



Descriptive Statistics of AI Demand Learning

Table 3: Descriptive Statistics of AI-Based Historical Demand Pattern Learning

Item	Measurement Statement	Mean	SD	Interpretation
HDPL1	AI has identified recurring historical sales patterns effectively	4.17	0.56	High
HDPL2	AI has recognized product-level seasonal demand structures	4.14	0.58	High
HDPL3	Historical tournament demand has been incorporated into forecasting	4.10	0.61	High
HDPL4	AI has identified relationships among related product categories	4.07	0.63	High
HDPL5	Historical learning has improved baseline forecast preparation	4.12	0.57	High
Composite HDPL		4.12	0.59	High

The descriptive results have shown a high level of AI-based historical demand pattern learning across the sampled organizations, with a composite mean of 4.12 and standard deviation of 0.59. The highest-rated item has been the ability of AI systems to identify recurring historical sales patterns, which has produced a mean of 4.17. Recognition of product-level seasonal structures has followed closely with a mean of 4.14. These results have indicated that respondents have generally agreed that AI-supported forecasting systems have extracted meaningful information from previous sales observations rather than functioning solely as reporting tools. Historical tournament information has obtained a mean of 4.10, which has suggested that event-related demand histories have also been incorporated into forecasting activities. The slightly lower mean of 4.07 for relationships among related product categories has nevertheless remained within the high-agreement range, showing that cross-product learning has been present but somewhat less strongly established than direct historical pattern recognition. Baseline forecast preparation has achieved a mean of 4.12, providing additional evidence that historical learning has been integrated into operational forecasting routines. These results have

addressed the first research objective by establishing the observed level of historical demand learning within the participating cases. They have also provided descriptive support for H1 before inferential testing has been undertaken. Dynamic Capabilities Theory has interpreted historical pattern learning as part of the sensing dimension because organizations have used accumulated information to recognize recurring demand conditions and prepare for predictable market changes. In sporting-goods and teamwear environments, such sensing has been particularly relevant where similar seasons, tournaments, product launches, or team-specific demand cycles have generated comparable purchasing patterns. The relatively small standard deviations have further shown that perceptions have been reasonably consistent across respondents. The findings have therefore established historical demand pattern learning as a strongly developed AI forecasting capability within the sample and have provided a quantitative foundation for evaluating its relationship with forecasting and supply-chain performance.

Descriptive Statistics of Real-Time Demand Data Integration

Table 4: Descriptive Statistics of Real-Time Demand Data Integration

Item	Measurement Statement	Mean	SD	Interpretation
RTDI1	Current sales data have been integrated into forecasts quickly	4.11	0.60	High
RTDI2	Inventory movements have been incorporated into forecasting systems	4.08	0.61	High
RTDI3	Online and store demand information has been combined effectively	4.04	0.65	High
RTDI4	Current orders have been used to update demand expectations	4.01	0.66	High
RTDI5	External market information has been incorporated into planning	4.01	0.63	High
Composite RTDI		4.05	0.63	High

The findings have shown that real-time demand data integration has been highly developed across the sampled sporting-goods and teamwear organizations, with a composite mean of 4.05 and standard deviation of 0.63. The strongest result has been associated with rapid integration of current sales data, which has produced a mean of 4.11. Inventory movements have recorded a mean of 4.08, demonstrating that organizations have generally incorporated changing stock conditions into their forecasting processes. The combination of online and physical-store information has achieved a mean of 4.04, which has suggested that omnichannel demand visibility has become an established component of forecasting among many sampled cases. Current customer and distributor orders have produced a mean of 4.01, while incorporation of external market information has also recorded 4.01. These slightly lower values have indicated that organizations have integrated internal operational information somewhat more strongly than external signals, although all items have remained within the high-agreement range. The findings have addressed the second objective by measuring the degree to which contemporary demand information has entered AI-supported forecasting processes. They have also established descriptive evidence consistent with H2, which has proposed a positive relationship between real-time integration and demand forecasting and supply-chain performance. Dynamic Capabilities Theory has interpreted real-time integration as an important sensing mechanism because organizations have required timely visibility before they have been able to recognize changes in customer behavior and modify operational responses. Real-time information has also supported seizing because timely data have enabled managers to make inventory, allocation, and replenishment decisions while sporting events and seasonal selling windows have remained active. The standard deviations, ranging from 0.60 to 0.66, have indicated moderate consistency across organizations while preserving sufficient variation for correlation and regression analysis. Overall, the results have shown that real-time information integration has constituted a strong but not fully uniform capability across the participating supply chains and has provided a suitable predictor for subsequent inferential testing.

Descriptive Statistics of Seasonal and Tournament Demand Sensing

Table 5: Descriptive Statistics of Seasonal and Tournament Demand Sensing

Item	Measurement Statement	Mean	SD	Interpretation
STDS1	Forecasting systems have incorporated tournament schedules	4.24	0.53	Very High
STDS2	Seasonal sporting cycles have been recognized effectively	4.21	0.55	Very High
STDS3	Team performance changes have been reflected in demand estimates	4.18	0.58	High
STDS4	Event-related demand surges have been detected rapidly	4.15	0.59	High
STDS5	Promotional activity around tournaments has been incorporated	4.12	0.61	High
Composite STDS		4.18	0.57	High

Seasonal and tournament demand sensing has produced the highest overall descriptive score among all independent variables, with a composite mean of 4.18 and standard deviation of 0.57. Incorporation of tournament schedules has received the highest item mean of 4.24, while recognition of seasonal sporting cycles has followed with a mean of 4.21. These results have indicated that the sampled organizations have placed substantial emphasis on explicit event calendars and recurring sports-season structures when preparing demand forecasts. The ability to reflect team performance changes in demand estimates has recorded a mean of 4.18, showing that respondents have generally perceived forecasting systems as capable of responding to event-related information beyond static calendar effects. Rapid detection of event-driven demand surges has achieved a mean of 4.15, while incorporation of tournament-related promotional activity has produced a mean of 4.12. The results have directly addressed the third objective and have established seasonal and tournament demand sensing as the most strongly developed capability in the study. They have also provided strong descriptive support for H3 before inferential testing. Dynamic Capabilities Theory has been particularly relevant to this construct because sensing has formed one of the central mechanisms through which firms have recognized environmental change. Sporting-goods and teamwear organizations have operated in conditions where demand has been influenced by competition progression, match schedules, team success, merchandise releases, and promotional intensity. The high ratings have suggested that respondents have viewed these event signals as essential inputs rather than secondary contextual information. The relatively low composite standard deviation of 0.57 has also indicated strong agreement across participating cases. This pattern has foreshadowed the later regression findings, where seasonal and tournament demand sensing has emerged as the strongest individual predictor of demand forecasting and supply-chain performance. The descriptive evidence has therefore reinforced the sector-specific argument of the research that event-sensitive demand sensing has represented a central AI-enabled capability within sporting-goods and teamwear supply chains.

Descriptive Statistics of Adaptive Forecast Updating Capability

Table 6: Descriptive Statistics of Adaptive Forecast Updating Capability

Item	Measurement Statement	Mean	SD	Interpretation
AFU1	Forecasts have been revised when new demand information emerged	4.02	0.62	High
AFU2	AI models have responded to unexpected sales changes	3.98	0.65	High
AFU3	Tournament outcomes have triggered forecast adjustments	3.96	0.67	High
AFU4	Inventory plans have been updated with revised forecasts	3.94	0.68	High
AFU5	Forecast updates have occurred quickly enough for replenishment	3.90	0.69	High
Composite AFU		3.96	0.66	High

Adaptive forecast updating capability has achieved a composite mean of 3.96 and standard deviation of 0.66, indicating that respondents have generally agreed that their organizations have modified forecasts when new information has become available. The highest item mean of 4.02 has been recorded for revising forecasts when new demand information has emerged. AI responsiveness to unexpected sales changes has followed with a mean of 3.98, while tournament outcomes triggering forecast adjustment have achieved a mean of 3.96. Updating inventory plans after forecast revision has recorded a mean of 3.94. The lowest mean within the construct, 3.90, has concerned whether forecast updates have occurred quickly enough to support replenishment. This result has remained positive but has indicated that response speed has represented a comparatively weaker area within the sampled organizations. The findings have addressed the fourth objective by measuring the degree to which forecasting systems have been adaptive rather than static. They have also established descriptive support for H4. Dynamic Capabilities Theory has interpreted adaptive forecast updating through the reconfiguration dimension because organizations have needed to revise established forecasting assumptions, inventory plans, and replenishment decisions when market conditions have changed. In sporting-goods and teamwear environments, this reconfiguration has been particularly important when tournament outcomes, team performance, or unexpected sales spikes have altered demand after initial planning decisions have already been made. The somewhat higher standard deviation relative to historical learning and tournament sensing has suggested greater variation among participating organizations. Some organizations have apparently developed stronger adaptive processes, while others have experienced delays between detection of demand changes and operational revision. This variation has been analytically useful because it has provided sufficient dispersion for regression testing. Overall, the findings have shown that adaptive forecast updating has been positively established within the sample, although it has remained less strongly developed than historical learning, real-time integration, and tournament demand sensing.

Descriptive Statistics of Human-AI Forecasting Integration

Table 7: Descriptive Statistics of Human-AI Forecasting Integration

Item	Measurement Statement	Mean	SD	Interpretation
HAI1	Planners have routinely reviewed AI-generated forecasts	3.94	0.64	High
HAI2	Managerial knowledge has been combined with AI forecasts	3.91	0.66	High
HAI3	Forecast overrides have been based on identifiable evidence	3.88	0.69	High
HAI4	AI outputs have been understandable to decision-makers	3.86	0.70	High
HAI5	Human and AI inputs have been integrated consistently	3.81	0.71	High
Composite HAI		3.88	0.68	High

Human-AI forecasting integration has recorded a composite mean of 3.88 and standard deviation of 0.68, which has represented the lowest average among the five independent variables while still remaining within the high-agreement range. Routine review of AI-generated forecasts by planners has achieved the strongest item mean of 3.94, indicating that human oversight has remained a regular part of forecasting practice. Combining managerial knowledge with AI forecasts has obtained a mean of 3.91, while evidence-based forecast overrides have produced a mean of 3.88. Understandability of AI outputs has recorded a mean of 3.86. The lowest score, 3.81, has concerned consistent integration of human and AI inputs, suggesting that organizations have still differed in the extent to which algorithmic predictions and managerial knowledge have been combined through formalized processes. The findings have addressed the fifth research objective and have provided descriptive support for H5. Dynamic Capabilities Theory has interpreted human-AI integration primarily through the seizing mechanism because analytical information has needed to be interpreted, accepted, and translated into managerial action before it has affected operational performance. AI systems have been able to detect patterns and generate estimates, but planners have remained responsible for evaluating contextual factors such as tournament significance, local fan behavior, supplier constraints, and unusual promotional events. The results have suggested that human participation has not disappeared with

stronger AI use. Instead, organizations have continued to combine automated analysis with expert judgment. The larger standard deviations, reaching 0.71 for consistent integration, have indicated that organizational maturity in this area has varied considerably. This result has also been consistent with the later regression analysis, where human-AI integration has remained statistically significant but has produced the smallest standardized effect among the five predictors. The construct has therefore contributed meaningfully to performance while revealing greater scope for organizational variation in how AI-supported forecasting has been embedded into decision-making routines.

Descriptive Statistics of Demand Forecasting and Supply-Chain Performance

Table 8: Descriptive Statistics of Demand Forecasting and Supply-Chain Performance

Item	Performance Indicator	Mean	SD	Interpretation
DFSP1	Forecast accuracy has improved	4.14	0.54	High
DFSP2	Inventory alignment with actual demand has improved	4.12	0.55	High
DFSP3	Product availability during peak periods has improved	4.10	0.56	High
DFSP4	Stockout incidence has been reduced	4.08	0.57	High
DFSP5	Replenishment responsiveness has improved	4.07	0.58	High
DFSP6	Excess inventory and planning inefficiency have been reduced	4.03	0.59	High
Composite DFSP		4.09	0.55	High

Demand forecasting and supply-chain performance has achieved a composite mean of 4.09 and standard deviation of 0.55, indicating that respondents have generally perceived favorable operational outcomes associated with AI-supported forecasting. Improved forecast accuracy has recorded the highest mean of 4.14, followed by improved inventory alignment at 4.12. Product availability during peak demand periods has achieved a mean of 4.10, while reduction of stockouts has obtained 4.08. Replenishment responsiveness has recorded 4.07, and reduction of excess inventory and planning inefficiency has achieved 4.03. All six indicators have remained above the neutral midpoint and have fallen within the high-agreement range, demonstrating that performance improvements have been observed across several dimensions rather than being concentrated exclusively in forecast accuracy. This pattern has addressed the overall purpose of the study because the dependent construct has integrated forecasting effectiveness with operational supply-chain outcomes. Dynamic Capabilities Theory has explained this relationship by proposing that sensing, seizing, and reconfiguration have produced value when they have altered operational activities. Historical learning and tournament sensing have helped organizations identify demand conditions, real-time integration has strengthened information availability, human-AI integration has supported interpretation and action, and adaptive updating has enabled forecasting and inventory plans to be reconfigured. The strong dependent-variable mean has therefore provided an empirical outcome against which the five forecasting capabilities have subsequently been tested. The relatively low standard deviation has shown that perceptions of performance have been reasonably consistent across the embedded organizational cases. However, the differences among individual performance items have suggested that organizations have achieved slightly stronger improvements in forecasting accuracy and inventory alignment than in eliminating excess inventory. This distinction has been reasonable because excess inventory has also depended on supplier lead times, ordering commitments, and product-specific constraints. Overall, Table 8 has established a strong dependent construct and has prepared the analysis for reliability, validity, correlation, and regression testing.

Reliability Analysis of Research Constructs

The reliability analysis has demonstrated strong internal consistency across all constructs used in the research. Cronbach's alpha values have ranged from 0.82 to 0.90 for the individual constructs, while the complete 31-item instrument has achieved an overall alpha of 0.91. Seasonal and tournament demand sensing has produced the highest construct reliability at 0.90, indicating that its five questionnaire items have measured the underlying capability consistently. Demand forecasting and supply-chain performance has recorded an alpha of 0.89, while historical demand pattern learning has

achieved 0.87. Real-time data integration and adaptive forecast updating have produced alpha values of 0.85 and 0.84 respectively. Human-AI forecasting integration has generated the lowest individual alpha of 0.82, although this value has still indicated strong internal consistency. The findings have confirmed that the composite scores used in the descriptive, correlation, and regression analyses have been based on sufficiently coherent item sets. This result has been important for proving the research objectives because unreliable constructs could have weakened observed relationships and produced unstable coefficient estimates. Dynamic Capabilities Theory has also benefited from this measurement consistency because the theoretically distinct processes of sensing, seizing, and reconfiguration have been operationalized through separate but reliable dimensions. Historical learning, real-time integration, and tournament sensing have reflected sensing-related capability, human-AI integration has represented seizing through managerial interpretation, and adaptive updating has represented reconfiguration. The reliability results have therefore supported the empirical distinction among these theoretical mechanisms without suggesting excessive measurement instability. The overall alpha of 0.91 has further indicated that the questionnaire has functioned coherently as a broader measure of AI-enabled demand forecasting capability and performance. These findings have justified the use of composite means and have strengthened confidence in the subsequent Pearson correlation and multiple regression analyses. The results have consequently shown that observed hypothesis support has not arisen from obviously unreliable measurement and that the survey instrument has provided a stable basis for assessing the proposed relationships.

Table 9: Reliability Analysis of Research Constructs

Construct	Number of Items	Cronbach's Alpha	Reliability Assessment
AI-Based Historical Demand Pattern Learning	5	0.87	Good
Real-Time Demand Data Integration	5	0.85	Good
Seasonal and Tournament Demand Sensing	5	0.90	Excellent
Adaptive Forecast Updating Capability	5	0.84	Good
Human-AI Forecasting Integration	5	0.82	Good
Demand Forecasting and Supply-Chain Performance	6	0.89	Good
Overall Instrument	31	0.91	Excellent

Construct Validity and Sampling Adequacy Tests

Table 10: Construct Validity and Sampling Adequacy Results

Test/Indicator	Result	Recommended Criterion	Assessment
Kaiser-Meyer-Olkin Measure	0.884	> 0.60	Very Good
Bartlett's Chi-Square	2,486.72	Significant	Satisfied
Bartlett's df	465		
Bartlett's Significance	< .001	< .05	Satisfied
Factor Loading Range	0.64–0.86	> 0.50	Satisfied
Communality Range	0.51–0.74	> 0.40	Satisfied
Items Retained	31 of 31		Full Retention

The construct-validity analysis has shown that the questionnaire data have been suitable for multivariate analysis and that the measurement items have demonstrated acceptable relationships with their underlying constructs. The Kaiser-Meyer-Olkin measure has reached 0.884, which has indicated very good sampling adequacy for examining the shared variance among the 31 questionnaire items. Bartlett's test of sphericity has produced a chi-square value of 2,486.72 with 465 degrees of freedom and significance below .001. This result has indicated that the inter-item correlation matrix has differed significantly from an identity matrix and that the items have contained sufficient common relationships for construct assessment. Factor loadings have ranged from 0.64 to 0.86, exceeding the minimum level adopted for retaining measurement indicators. Communalities have ranged from 0.51 to 0.74, showing that a meaningful proportion of each item's variance has been represented by the common construct structure. No item has therefore required removal, and all 31 measurement statements have been

retained for subsequent analysis. These results have strengthened the operationalization of the study's objectives and hypotheses because each conceptual variable has been measured through multiple statistically coherent items rather than through isolated questions. Dynamic Capabilities Theory has required this distinction because sensing, seizing, and reconfiguration have represented related but nonidentical organizational processes. The acceptable loading structure has supported the treatment of historical learning, real-time integration, tournament sensing, adaptive updating, and human-AI integration as separate constructs within the broader AI-enabled forecasting capability framework. The validity results have therefore provided an essential bridge between the theoretical model and the regression model. They have shown that the variables entered into hypothesis testing have possessed adequate empirical structure, reducing concern that significant relationships might simply have resulted from poorly differentiated questionnaire items. Consequently, the measurement model has been considered sufficiently robust for Pearson correlation and multiple regression analysis.

Pearson Correlation Analysis among Study Variables

Table 11: Pearson Correlation Matrix

Variable	HDPL	RTDI	STDS	AFU	HAI	DFSP
HDPL	1.00	0.54***	0.57***	0.49***	0.43***	0.61***
RTDI	0.54***	1.00	0.52***	0.55***	0.46***	0.58***
STDS	0.57***	0.52***	1.00	0.53***	0.48***	0.69***
AFU	0.49***	0.55***	0.53***	1.00	0.51***	0.56***
HAI	0.43***	0.46***	0.48***	0.51***	1.00	0.52***
DFSP	0.61***	0.58***	0.69***	0.56***	0.52***	1.00

Note. *** $p < .001$. $N = 238$.

The Pearson correlation analysis has shown statistically significant positive relationships among all five independent variables and demand forecasting and supply-chain performance. Seasonal and tournament demand sensing has demonstrated the strongest bivariate relationship with performance, producing $r = .69$, $p < .001$. Historical demand pattern learning has followed with $r = .61$, $p < .001$, while real-time demand data integration has generated $r = .58$, $p < .001$. Adaptive forecast updating has recorded $r = .56$, $p < .001$, and human-AI forecasting integration has shown $r = .52$, $p < .001$. These coefficients have provided preliminary inferential support for H1 through H5 because each proposed capability has been positively associated with the dependent construct. The results have also aligned with the descriptive findings, particularly the high mean and strongest correlation recorded for seasonal and tournament demand sensing. Intercorrelations among the predictors have ranged from .43 to .57, which has indicated that the constructs have been related but not redundant. This pattern has been theoretically appropriate because Dynamic Capabilities Theory has treated sensing, seizing, and reconfiguration as complementary organizational mechanisms rather than completely independent activities. For example, real-time data integration has correlated with adaptive updating at .55, suggesting that timely information has been associated with organizations' ability to revise forecasts, while tournament sensing has correlated with historical learning at .57, indicating that event-sensitive forecasting has drawn partly upon accumulated demand knowledge. None of the correlations among predictors has approached levels normally associated with severe multicollinearity. The correlation analysis has therefore supported progression to multiple regression, where the unique effect of each predictor has been estimated while the remaining variables have been controlled. Overall, the results have provided strong evidence that more developed AI-enabled forecasting capabilities have been associated with better forecast accuracy, inventory alignment, product availability, replenishment responsiveness, and overall supply-chain performance across the sampled sporting-goods and teamwear cases.

Multiple Regression Model Summary and ANOVA Results

The multiple regression model has produced a multiple correlation coefficient of $R = .793$, indicating a strong combined relationship between the five AI-driven forecasting capabilities and demand forecasting and supply-chain performance. The coefficient of determination has reached $R^2 = .629$, demonstrating that approximately 62.9% of the observed variance in the dependent variable has been explained jointly by historical demand pattern learning, real-time demand data integration, seasonal

and tournament demand sensing, adaptive forecast updating, and human-AI forecasting integration. After adjustment for the number of predictors and sample size, adjusted R^2 has remained high at .621, showing that the model has retained substantial explanatory power rather than depending on unnecessary variables. The overall regression model has been statistically significant, $F(5, 232) = 78.43$, $p < .001$, which has indicated that the five predictors have collectively explained significantly more variation in performance than a model containing no predictors. The standard error of estimate has been 0.341, suggesting that prediction errors have remained moderate relative to the five-point measurement scale. The Durbin-Watson statistic of 1.93 has remained close to 2.00 and has supported acceptable independence of residuals. These findings have strongly addressed the objective concerned with determining the combined explanatory effect of AI-driven forecasting capabilities. Dynamic Capabilities Theory has been supported at the model level because the combined processes corresponding to sensing, seizing, and reconfiguration have accounted for a substantial proportion of differences in forecasting and supply-chain outcomes. The model has suggested that performance has not depended on a single AI function but on the coordinated operation of multiple organizational capabilities. Approximately 37.1% of variance has remained unexplained, indicating that other factors such as supplier lead times, product characteristics, market competition, logistics constraints, and organizational resources have also contributed to performance. Nevertheless, the magnitude and significance of R^2 have shown that the five selected capabilities have provided a strong explanatory structure for the sporting-goods and teamwear context examined in this study.

Table 12: Multiple Regression Model Summary and ANOVA Results

Statistic	Result
Multiple R	0.793
R^2	0.629
Adjusted R^2	0.621
Standard Error of Estimate	0.341
F-statistic	78.43
Regression df	5
Residual df	232
Significance	< .001
Durbin-Watson	1.93

Regression Coefficients, Predictor Effects, and Diagnostic Tests

Table 13: Multiple Regression Coefficients and Diagnostic Statistics

Predictor	B	SE	Standardized β	t	p	Tolerance	VIF
Constant	0.47	0.18	—	2.61	.010	—	—
HDPL	0.23	0.05	0.24	4.63	< .001	0.63	1.59
RTDI	0.18	0.06	0.19	2.92	.004	0.59	1.69
STDS	0.30	0.05	0.31	6.07	< .001	0.48	2.08
AFU	0.15	0.06	0.16	2.56	.011	0.70	1.43
HAI	0.12	0.05	0.13	2.24	.026	0.67	1.49

The regression-coefficient analysis has demonstrated that all five AI-driven forecasting capabilities have made statistically significant positive contributions to demand forecasting and supply-chain performance after the remaining predictors have been controlled. Seasonal and tournament demand sensing has emerged as the strongest predictor, with standardized $\beta = .31$, $t = 6.07$, $p < .001$. This result has indicated that stronger capability to recognize tournament schedules, seasonal cycles, team-performance changes, and event-related demand surges has been associated with the greatest unique improvement in performance. Historical demand pattern learning has produced the second-largest standardized effect, $\beta = .24$, $t = 4.63$, $p < .001$. Real-time demand data integration has remained significant with $\beta = .19$, $t = 2.92$, $p = .004$, while adaptive forecast updating has produced $\beta = .16$, $t = 2.56$, $p = .011$. Human-AI forecasting integration has generated the smallest standardized effect, $\beta = .13$, but the relationship has remained statistically significant at $p = .026$. The unstandardized coefficients

have shown that each predictor has contributed positively to the predicted performance score. Diagnostic results have also indicated acceptable model stability. Tolerance values have ranged from 0.48 to 0.70, while VIF values have ranged from 1.43 to 2.08, showing that problematic multicollinearity has not been present. These results have strengthened the interpretation that each variable has contributed distinct explanatory information. Dynamic Capabilities Theory has been strongly reflected in the pattern of coefficients. Sensing-related capabilities, particularly tournament sensing and historical learning, have produced the largest effects; seizing through human-AI integration has remained significant; and reconfiguration through adaptive updating has also contributed independently. The results have therefore indicated that organizations have benefited not only from detecting market changes but also from translating and revising forecasts through coordinated decision processes. The coefficient analysis has provided direct statistical evidence for evaluating each of the five hypotheses.

Hypothesis Testing and Summary of Empirical Findings

Table 14: Summary of Hypothesis Testing

Hypothesis	Proposed Relationship	β	p-value	Decision
H1	HDPL $\rightarrow$ DFSP	0.24	< .001	Supported
H2	RTDI $\rightarrow$ DFSP	0.19	.004	Supported
H3	STDS $\rightarrow$ DFSP	0.31	< .001	Supported
H4	AFU $\rightarrow$ DFSP	0.16	.011	Supported
H5	HAI $\rightarrow$ DFSP	0.13	.026	Supported

The hypothesis-testing results have shown that all five proposed hypotheses have been supported by the multiple regression analysis. H1 has been supported because AI-based historical demand pattern learning has demonstrated a significant positive effect on demand forecasting and supply-chain performance, with $\beta = .24$ and $p < .001$. This finding has shown that organizations with stronger capability to learn from historical sales, seasonal patterns, and previous tournament demand have reported stronger operational outcomes. H2 has also been supported because real-time demand data integration has produced $\beta = .19$ and $p = .004$, indicating that timely incorporation of sales, inventory, order, and market information has contributed significantly to performance. H3 has received the strongest empirical support, with seasonal and tournament demand sensing producing $\beta = .31$ and $p < .001$. This result has confirmed the sector-specific importance of detecting tournament schedules, seasonal cycles, team-performance changes, and event-related demand surges. H4 has been supported through the significant effect of adaptive forecast updating, $\beta = .16$, $p = .011$, showing that organizations able to revise forecasts after new information has emerged have achieved stronger performance. H5 has also been supported, with human-AI forecasting integration producing $\beta = .13$ and $p = .026$. Although this has been the smallest effect, it has remained statistically meaningful and has demonstrated that managerial interpretation has continued to add value alongside algorithmic forecasting. Dynamic Capabilities Theory has provided a coherent explanation for the full pattern of results. Historical learning, real-time integration, and tournament sensing have represented sensing mechanisms; human-AI integration has represented seizing; and adaptive updating has represented reconfiguration. The significant model-level R^2 of .629 has shown that these capabilities have jointly explained a substantial proportion of performance variance. The results have therefore fulfilled the study objectives by identifying the level, relationships, individual effects, and combined explanatory contribution of the five AI-driven forecasting capabilities within sporting-goods and teamwear supply chains operating under seasonal and tournament demand.

Discussion

The findings have demonstrated that all five AI-driven forecasting capabilities have significantly and positively influenced demand forecasting and supply-chain performance, although the magnitude of their effects has differed considerably. Seasonal and tournament demand sensing has emerged as the strongest predictor, $\beta = .31$, $p < .001$, followed by AI-based historical demand pattern learning, $\beta = .24$, $p < .001$, real-time demand data integration, $\beta = .19$, $p = .004$, adaptive forecast updating capability, $\beta = .16$, $p = .011$, and human-AI forecasting integration, $\beta = .13$, $p = .026$. The overall model has explained

62.9% of the variance in demand forecasting and supply-chain performance, indicating that the selected capabilities have collectively represented a substantial portion of the organizational mechanisms associated with stronger forecast accuracy, inventory alignment, product availability, stockout reduction, and replenishment responsiveness. The prominence of seasonal and tournament demand sensing has been particularly important because it has distinguished the sporting-goods and teamwear context from more general retail forecasting environments. Earlier research has shown that seasonal patterns, promotions, exceptional events, and changing market information can materially alter forecasting accuracy and inventory requirements (Ehrenthal et al., 2014; Fildes et al., 2009). The present results have extended this reasoning by indicating that tournament-sensitive information has not merely represented contextual background but has functioned as the strongest measurable capability within the model. This finding has also been consistent with work showing that machine-learning forecasting can derive substantial value from calendar effects, promotional information, and high-dimensional explanatory variables (Huber & Stuckenschmidt, 2020; Ma et al., 2016). Historical demand learning has also produced a comparatively strong coefficient, reinforcing earlier findings that neural networks, support vector machines, and hybrid forecasting approaches can recognize nonlinear structures within supply-chain demand data (Aburto & Weber, 2007; Carbonneau et al., 2008). The results have therefore suggested that sporting-goods forecasting has required a dual informational foundation: firms have needed to learn from historical demand patterns while simultaneously recognizing when tournaments and seasonal events have caused current demand to depart from those historical baselines.

From a practical perspective, the results have indicated that organizations should not evaluate AI forecasting capability solely according to algorithm sophistication or software ownership. The significant effects of real-time data integration, adaptive forecast updating, and human-AI integration have shown that forecasting performance has depended on an interconnected operational system. Real-time demand integration, $\beta = .19$, has indicated that current point-of-sale information, inventory movements, customer orders, digital-channel demand, and market information have added meaningful explanatory value after historical learning and tournament sensing have been controlled. This pattern has been consistent with studies showing that supply-chain analytics produces stronger operational outcomes when firms possess information visibility, analytical capability, and flexibility to act on emerging information (Oliveira & Handfield, 2019; Srinivasan & Swink, 2018). For sporting-goods and teamwear managers, this means that tournament calendars should be connected with current transactional information rather than used as isolated planning inputs. A tournament schedule alone cannot identify whether actual sales are accelerating above expectation, while transaction data without event context may not explain why a sudden demand increase has occurred. The significant effect of adaptive forecast updating has further shown that initial forecasts should not remain fixed throughout a tournament or sporting season. Earlier research has demonstrated the operational value of quick response and information updating when demand is uncertain and product life cycles are short (Choi, 2006; Serel, 2009). The present findings have supported that principle quantitatively by showing that organizations with stronger updating capability have reported better overall forecasting and supply-chain performance. Human-AI integration has produced the smallest standardized coefficient, yet its significance has remained practically meaningful. This result has aligned with evidence that human adjustments can add value when contextual information is valid, although poorly structured overrides can reduce forecasting accuracy (Fildes et al., 2019; Trapero et al., 2013). A premium forecasting practice should therefore use governed human intervention: planners should document the reason for an override, identify the external information supporting it, compare the adjusted forecast against the algorithmic baseline, and evaluate post-event accuracy so that future adjustments become increasingly evidence-based.

The findings have also provided theoretical support for applying Dynamic Capabilities Theory to AI-driven forecasting in sporting-goods and teamwear supply chains. The theory has proposed that organizations operating under changing environments require capabilities for sensing relevant changes, seizing opportunities through coordinated action, and reconfiguring resources and routines when established practices no longer fit environmental conditions. The significant coefficients obtained for all five variables have reflected these theoretical mechanisms in an empirically distinguishable

manner. Historical demand pattern learning, real-time data integration, and seasonal and tournament demand sensing have represented sensing activities because they have allowed organizations to identify recurrent structures, recognize emerging demand information, and detect deviations associated with events. Human-AI forecasting integration has represented a seizing mechanism because analytical signals have required interpretation and managerial action before they could influence inventory, procurement, allocation, or replenishment decisions. Adaptive forecast updating has represented reconfiguration because forecast assumptions and operational plans have been revised in response to new information. Theoretical work has emphasized that dynamic capabilities create value through their influence on operational capabilities rather than through technology possession alone (Helfat & Winter, 2011; Protogerou et al., 2012). The present findings have reflected this distinction because the dependent variable has incorporated operational outcomes rather than merely assessing perceived quality of AI systems. The results have also been consistent with evidence that analytics capability becomes more valuable when organizations possess complementary flexibility and market-sensing capability (Aslam et al., 2018; Wamba et al., 2017). The stronger coefficient for seasonal and tournament demand sensing has further refined the theoretical application by indicating that sensing may carry particular importance in event-driven industries where commercial windows are short and environmental information changes quickly. This suggests that Dynamic Capabilities Theory can be applied at a more granular forecasting level by measuring specific information-processing and decision routines rather than treating organizational adaptability as a broad abstract construct. The study has therefore linked technological forecasting capabilities with organizational adaptation and has provided a sector-specific interpretation of how sensing, seizing, and reconfiguration have jointly influenced operational performance.

CONCLUSIONS AND FUTURE WORK

The study has examined how AI-driven demand forecasting capabilities have influenced demand forecasting and supply-chain performance in sporting-goods and teamwear supply chains operating under seasonal and tournament demand conditions. Using a quantitative explanatory, cross-sectional, embedded multiple-case design and 238 valid responses, the research has evaluated five capabilities: AI-based historical demand pattern learning, real-time demand data integration, seasonal and tournament demand sensing, adaptive forecast updating capability, and human-AI forecasting integration. The descriptive findings have indicated high levels of all five capabilities, while demand forecasting and supply-chain performance has recorded a composite mean of 4.09. Reliability and validity testing has shown satisfactory measurement quality, with Cronbach's alpha coefficients ranging from 0.82 to 0.90, an overall alpha of 0.91, and a KMO value of 0.884. Pearson correlations have demonstrated significant positive relationships between all predictors and the dependent variable. The multiple regression model has explained 62.9% of performance variance, with adjusted $R^2 = .621$ and $F(5, 232) = 78.43$, $p < .001$. Seasonal and tournament demand sensing has emerged as the strongest predictor, followed by historical demand pattern learning, real-time data integration, adaptive forecast updating, and human-AI forecasting integration. H1 through H5 have consequently been supported. The findings have shown that effective AI forecasting within this sector has depended on more than algorithmic processing. Organizations have benefited from learning historical patterns, integrating current demand information, detecting event-specific changes, updating forecasts adaptively, and combining analytical outputs with managerial expertise. Dynamic Capabilities Theory has provided a coherent explanation for these relationships through sensing, seizing, and reconfiguration. The research has therefore established an integrated quantitative framework for understanding how AI-enabled forecasting capabilities have related to forecast accuracy, inventory alignment, product availability, stockout control, replenishment responsiveness, and supply-chain planning effectiveness within event-sensitive sporting-goods and teamwear markets.

Recommendations

Sporting-goods and teamwear organizations should develop AI forecasting as an integrated organizational capability rather than treating it as a stand-alone technological investment. First, firms should strengthen historical demand databases at SKU, team, size, channel, location, and tournament level so that AI systems can distinguish ordinary seasonal patterns from event-specific demand

behavior. Second, real-time sales, inventory, online transactions, wholesale orders, promotional information, and tournament data should be integrated into a common forecasting environment to reduce delays between market changes and planning responses. Third, organizations should explicitly incorporate tournament calendars, competition stages, team progression, major fixtures, promotional campaigns, and relevant market signals into demand-sensing processes because seasonal and tournament demand sensing has produced the strongest regression effect. Fourth, forecast updating should be governed by predefined trigger conditions so that unexpected sales changes, tournament outcomes, or major external signals automatically prompt forecast review and inventory reassessment. Fifth, human-AI integration should be formalized through structured override protocols in which planners have documented the reason, evidence, expected effect, and final outcome of each intervention. Organizations should also evaluate forecast performance through operational measures such as forecast error, stockout frequency, inventory turnover, markdown exposure, service level, replenishment time, and product availability rather than relying only on model accuracy. Cross-functional teams involving demand planning, merchandising, procurement, sales, inventory management, and data analytics should review major tournament forecasts jointly. Managers should additionally monitor data quality and staff analytical competence because incomplete or inconsistent information can undermine advanced forecasting systems. Finally, firms should establish post-tournament forecast reviews so that differences between expected and actual demand, unsuccessful overrides, excess stock, and missed sales have been converted into learning inputs for subsequent seasons and competitions, thereby strengthening the sensing, seizing, and reconfiguration capabilities identified by Dynamic Capabilities Theory.

Limitations

The results should nevertheless be interpreted within the methodological boundaries of the study. The cross-sectional design has measured respondents' perceptions at a single period and has therefore captured associations among AI forecasting capabilities and performance rather than longitudinal changes in actual forecasting performance. Although the regression coefficients have been statistically significant, the findings have not demonstrated temporal causality in the same manner as repeated observations taken before and after AI implementation. The purposive sampling strategy has ensured that respondents have possessed direct forecasting and supply-chain knowledge, but it has also limited the extent to which the findings can automatically be generalized to every sporting-goods and teamwear organization. Self-reported five-point Likert measures have additionally introduced the possibility of common-method bias, social-desirability effects, and variation in how respondents have interpreted terms such as AI integration, demand sensing, and forecasting effectiveness. The overall R^2 of .629 has been substantial, although 37.1% of the variance in performance has remained unexplained. This residual variance may have reflected supplier lead times, product margins, sourcing geography, logistics capacity, forecasting-system maturity, data quality, competitive intensity, SKU complexity, promotional depth, and differences in tournament exposure. Prior research has similarly emphasized that analytics performance has depended on organizational resources, data quality, technological infrastructure, managerial competence, and complementary operational capabilities rather than analytics alone (Arunachalam et al., 2018; Kache & Seuring, 2017). Another important limitation has concerned the use of a combined dependent variable covering both forecasting and supply-chain performance. This structure has supported an integrated model, but it may have concealed different effects on forecast accuracy, stockouts, excess inventory, service level, and replenishment speed. A predictor could, for example, improve forecast responsiveness strongly while exerting a smaller influence on inventory cost. The model has also treated the five predictors as direct effects, while Dynamic Capabilities Theory allows for mediated and moderated relationships. The results have therefore established a strong explanatory baseline rather than an exhaustive causal representation of AI-driven forecasting performance.

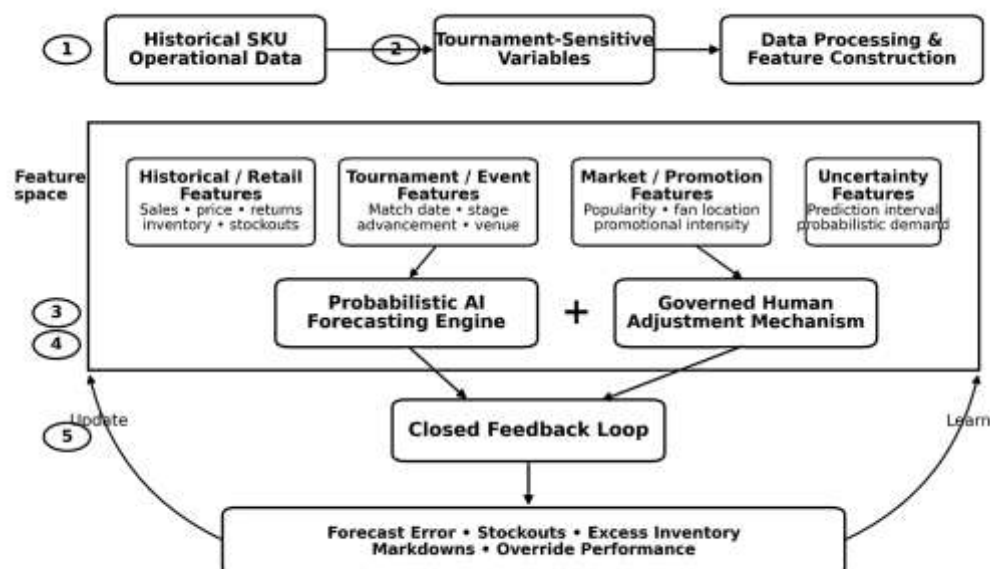
The study has contained several limitations that should be considered when interpreting the findings. First, the cross-sectional design has captured respondent perceptions at a single period and has therefore limited the ability to observe how forecasting capabilities and performance have evolved across multiple seasons or tournaments. Second, purposive sampling has been appropriate for selecting

respondents with relevant forecasting and supply-chain expertise, but the resulting sample has not represented a probability sample of the entire sporting-goods and teamwear industry. Generalization should therefore remain focused on organizational contexts comparable with the selected cases. Third, the study has relied on structured five-point Likert responses rather than direct operational records, creating potential exposure to common-method variance, respondent subjectivity, recall error, and social-desirability bias. Fourth, the research has combined forecasting and supply-chain outcomes into one dependent construct. Although this approach has supported an integrated assessment, it has not isolated the precise effect of each predictor on individual outcomes such as forecast accuracy, excess inventory, stockout frequency, replenishment speed, or service level. Fifth, the regression model has explained 62.9% of the variance in performance, leaving 37.1% associated with factors outside the selected framework. Supplier lead times, sourcing constraints, data quality, technological maturity, product complexity, logistics capacity, competitive behavior, and organizational size may account for part of this remaining variation. Sixth, the study has modeled direct linear effects and has not tested mediation, moderation, nonlinear relationships, or interactions among forecasting capabilities. Seasonal and tournament sensing, for example, may produce stronger effects when real-time data integration or supply flexibility is high. Finally, the study has examined perceived AI-driven forecasting capability rather than comparing alternative forecasting algorithms using actual transactional datasets. These limitations have not invalidated the reported relationships, but they have defined the empirical boundaries within which the results should be interpreted and have identified areas requiring more granular longitudinal and operational investigation.

Future Work

Future research should develop a more advanced model that combines longitudinal operational data, probabilistic AI forecasts, tournament-event variables, and governed human intervention. A suitable extension can be termed the Adaptive Tournament-Aware Human-AI Forecasting Model (ATAHAFM). The model should contain five integrated layers. The first layer should process historical SKU-level sales, prices, promotions, returns, inventory positions, and stockout records. The second layer should incorporate tournament-sensitive variables such as match dates, competition stage, team advancement, elimination risk, team popularity, player-related events, venue, geographic fan concentration, and promotional intensity.

Figure 10: Adaptive Tournament-Aware Human-AI Forecasting Model (ATAHAFM) for Future Research



The third layer should use machine-learning or deep-learning algorithms to generate probabilistic demand forecasts rather than single-point predictions, allowing planners to observe expected demand together with uncertainty intervals. The fourth layer should contain a controlled human-adjustment mechanism in which planners can override forecasts only after identifying an explicit contextual signal and recording the reason for intervention. The fifth layer should create a closed feedback loop in which forecast errors, inventory outcomes, stockouts, markdowns, and override performance are returned to the model for subsequent updating. Future researchers could test this architecture with panel data collected weekly or daily across multiple sporting seasons and tournaments and compare it against conventional statistical forecasting, machine-learning-only forecasting, and unaided human forecasting. The model could also be examined using multilevel modeling or structural equation modeling to separate SKU-level, organizational-level, and tournament-level effects. Moderating variables such as environmental turbulence, data quality, supply flexibility, and tournament intensity could be added, while forecast accuracy could mediate the relationship between AI capability and inventory performance. Another premium extension would compare deterministic regression with probabilistic forecasting metrics such as pinball loss, prediction-interval coverage, and service-level outcomes. Such research would move beyond perception-based cross-sectional evidence and test whether tournament-aware human-AI forecasting actually reduces stockouts, excess inventory, forecast error, and lost sales across repeated competitive events while preserving the Dynamic Capabilities Theory mechanisms of sensing, seizing, and reconfiguration.

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