
| RESEARCH ARTICLE

Forecasting Unregistered Demand: A Behavioral Framework for Enterprise Predictive Analytics

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| ABSTRACT

The emergence of innovation-driven markets has exposed critical limitations in traditional demand forecasting methodologies that rely on historical consumption patterns and established statistical models. Contemporary e-commerce environments demonstrate how technological advancements create entirely new consumption behaviors that cannot be predicted through conventional time series analysis or regression-based approaches. The behavioral indicator framework represents a paradigmatic shift from retrospective demand analysis to real-time consumer intent signal monitoring, addressing the phenomenon of "unregistered demand" where technological improvements unlock previously constrained market opportunities. The glance view conversion methodology exemplifies this approach by capturing consumer engagement patterns that precede actual purchase decisions, enabling organizations to predict demand transformations before manifestation in sales data. Global adoption patterns of quick commerce models reveal consistent behavioral changes across diverse economic environments, with delivery speed improvements generating measurable shifts in consumer engagement metrics, including browsing duration, interaction frequency, and abandonment rates. Enterprise-scale implementation requires sophisticated machine learning architectures capable of processing real-time behavioral data streams while integrating seamlessly with existing supply chain management systems. Hybrid forecasting models that combine traditional demand signals with behavioral indicators demonstrate superior accuracy compared to single-methodology approaches, particularly for scenarios involving product innovations or service enhancements. The technical challenges encompass real-time data processing capabilities, behavioral pattern recognition algorithms, and advanced feature engineering techniques that transform raw behavioral data into actionable predictive signals for supply chain decision-making.

| KEYWORDS

Behavioral indicators, Demand Forecasting, Unregistered Demand, Quick Commerce, Enterprise-scale Implementation

| ARTICLE INFORMATION

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1. Introduction

Traditional demand forecasting methodologies in supply chain management have long depended on established statistical models and historical consumption patterns to predict future market behavior. Time series analysis, exponential smoothing, and regression-based approaches form the cornerstone of most enterprise forecasting systems, operating under the fundamental assumption that past demand patterns provide reliable indicators for future consumption trends. However, these conventional methodologies encounter significant limitations when applied to scenarios where technological innovations fundamentally alter consumer behavior patterns. The e-commerce sector has witnessed particular challenges in this regard, as digital platforms experience rapid shifts in consumer expectations and purchasing behaviors that traditional forecasting models struggle to capture effectively [1]. Research demonstrates that when new product features or service capabilities create previously non-existent consumption opportunities, conventional forecasting accuracy experiences substantial degradation, highlighting the inadequacy of historical-pattern-based prediction models in innovation-driven markets.

The concept of "unregistered demand" represents a critical gap in current forecasting literature, describing latent market opportunities that emerge when technological improvements remove constraints that previously limited consumer behavior. This phenomenon occurs when innovations do not merely satisfy existing demand more efficiently, but instead unlock entirely new consumption patterns that were previously impossible or impractical to fulfill. Unlike traditional demand elasticity, which measures consumer response to price or availability changes within existing behavioral frameworks, unregistered demand represents fundamental shifts in consumer capability and expectation [2]. The emergence of digital platforms has accelerated this phenomenon, as technological capabilities enable new forms of consumer engagement and transaction patterns that have no historical precedent. Studies of digital transformation initiatives across various industries demonstrate that unregistered demand can create substantial market expansion opportunities within relatively short timeframes, far exceeding what traditional forecasting models would predict based on historical data alone.

The evolution of e-commerce delivery speed provides a compelling paradigm for understanding forecasting challenges in innovation-driven markets. The transformation from standard delivery timeframes to same-day delivery, and subsequently to quick commerce models with ultra-fast fulfillment, represents a fundamental shift in consumer purchasing behavior rather than simply an improvement in existing service quality. This evolution has created new consumption categories, such as impulse grocery purchases and emergency retail fulfillment, that had no historical precedent for forecasting purposes [1]. The behavioral changes associated with improved delivery speed demonstrate how technological improvements can unlock latent demand that was previously constrained by logistical limitations. Data from major e-commerce platforms indicates that reducing delivery timeframes creates measurable increases in purchase frequency and significant reductions in cart abandonment rates, behavioral changes that were invisible to traditional demand forecasting models.

The proposed behavioral indicator framework addresses these forecasting challenges by shifting focus from historical demand patterns to real-time consumer intent signals. Rather than relying on completed transaction data, this approach monitors engagement metrics such as product views, browsing duration, and interaction patterns to predict demand changes before manifestation as actual purchases. Early implementations of glance view conversion methodologies demonstrate significant improvements in forecasting accuracy for innovation-driven scenarios compared to traditional approaches [2]. This framework enables organizations to capture demand transformation events in real-time, providing the predictive capability necessary for effective supply chain planning in rapidly evolving markets. The methodology recognizes that consumer behavior changes occur along measurable engagement metrics that can be captured and analyzed before conversion into actual purchases, offering a more responsive approach to demand prediction in dynamic market environments.

2. Traditional Forecasting Limitations in Innovation-Driven Markets

Existing supply chain intelligence methodologies in contemporary enterprise environments operate under deeply entrenched assumptions that future demand patterns will fundamentally mirror historical trends with predictable statistical variations. The prevailing forecasting paradigms rely heavily on established mathematical models, including moving averages, seasonal decomposition techniques, and regression analysis that have evolved through decades of industrial application. These traditional approaches have demonstrated remarkable consistency in stable market environments, particularly for mature product categories where consumer behavior patterns exhibit predictable cyclical variations [3]. However, the mathematical foundations of these methodologies create inherent limitations when market dynamics deviate substantially from established historical patterns. The dependence on retrospective data analysis as the primary foundation for future predictions generates systematic vulnerabilities when technological innovations introduce unprecedented variables into market ecosystems. Advanced demand forecasting research demonstrates that conventional methodologies experience progressive deterioration in accuracy when confronted with scenarios involving disruptive technological implementations or novel service delivery mechanisms.

The academic literature reveals a pronounced deficiency in addressing what contemporary research identifies as "demand transformation events" - critical junctures where technological advancements transcend incremental improvements to create fundamentally new consumption paradigms. These transformation events represent more than simple market evolution; instead, they signify complete restructuring of consumer expectation frameworks and purchasing behavior patterns that have no precedent in historical data sets [4]. The existing body of forecasting research has predominantly concentrated on optimizing prediction accuracy within established market structures, devoting insufficient attention to developing analytical frameworks capable of anticipating demand patterns that emerge from technological discontinuities. This research gap becomes particularly acute in contexts involving artificial intelligence integration and predictive analytics implementations, where the velocity of technological change consistently outpaces the adaptive capacity of traditional forecasting models. Contemporary studies examining the intersection of emerging technologies and consumer behavior patterns consistently reveal that existing forecasting methodologies fail to capture the comprehensive scope of demand fluctuations that occur when technological barriers undergo removal.

The scholarly literature demonstrates limited exploration of predictive frameworks specifically engineered for scenarios where innovation unlocks previously dormant market potential that had been constrained by technological or logistical barriers. The

predominant focus of existing forecasting research addresses demand variability within established market parameters, rather than investigating methodologies for predicting entirely novel consumption behaviors that emerge from technological breakthroughs [3]. This research limitation carries significant implications for organizations attempting to forecast demand for innovative products or services that lack direct historical precedents. The challenge intensifies when considering that traditional market research methodologies, including consumer surveys and demographic analysis, frequently fail to accurately predict behavioral responses when consumers encounter fundamentally new capabilities or service offerings. Academic investigation in this domain has been constrained by the inherent difficulty of obtaining comprehensive data on demand transformation events, as organizations typically maintain confidentiality regarding forecasting failures or unexpected demand pattern emergences.

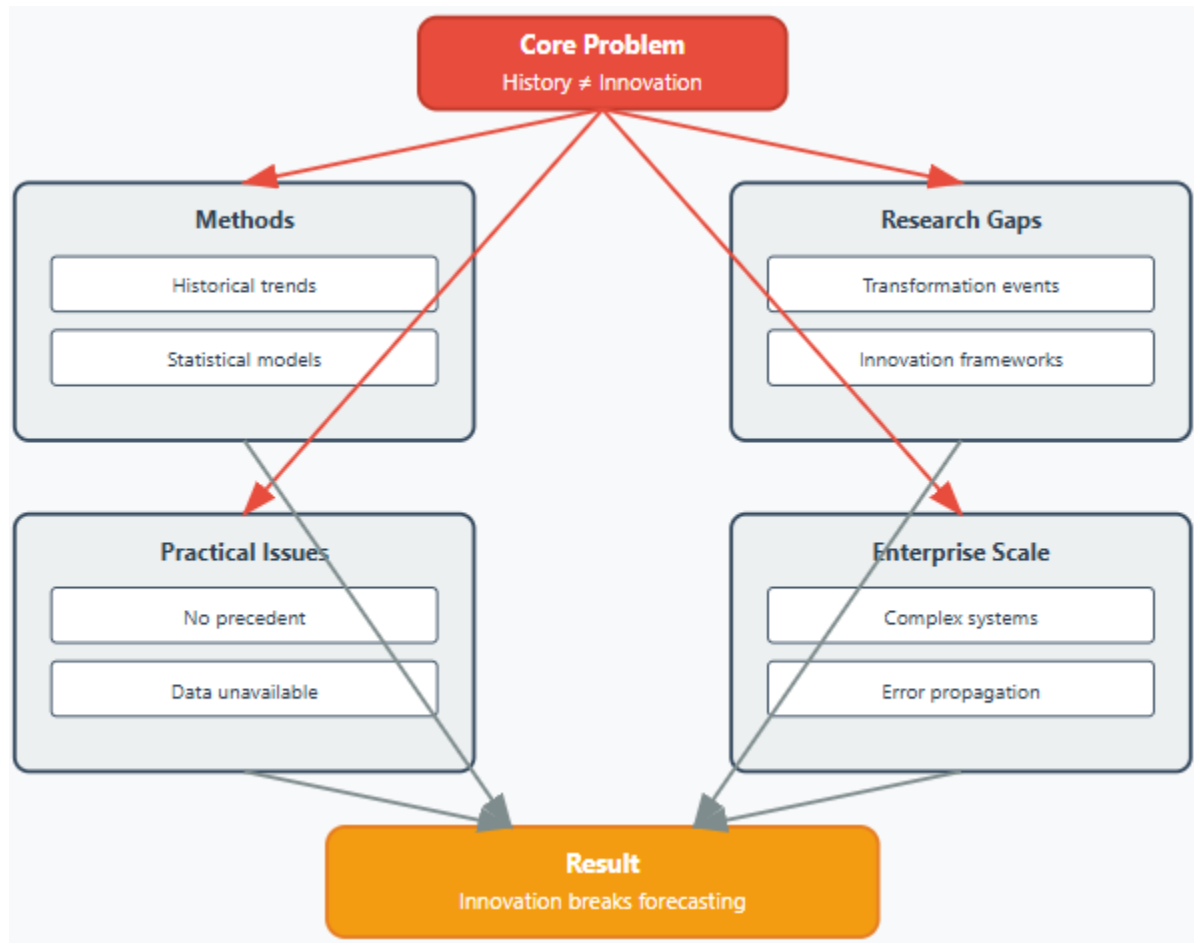


Fig 1: Traditional Forecasting Limitations [3, 4]

Enterprise-scale systems encounter exponentially amplified forecasting challenges due to the intricate operational complexity and substantial resource commitments characteristic of large-scale supply chain management infrastructures. The implications of forecasting inaccuracy escalate dramatically in enterprise environments, where prediction errors can precipitate substantial financial consequences through inventory misalignment, capacity planning failures, and resource allocation inefficiencies [4]. The multifaceted nature of enterprise supply chains, encompassing diverse stakeholder networks, geographic distribution centers, and product category portfolios, introduces additional uncertainty layers that traditional forecasting models struggle to address comprehensively. Research indicates that enterprise-scale forecasting systems experience cascading error propagation when confronting innovation-driven demand patterns, as the interconnected architecture of large supply chains amplifies the impact of prediction inaccuracies across multiple operational domains and decision-making hierarchies.

3. The Behavioral Indicator Framework

The behavioral indicator framework represents a revolutionary departure from conventional demand forecasting methodologies, establishing a new paradigm that prioritizes real-time consumer intent signals over historical demand pattern analysis. This transformative approach recognizes that modern digital ecosystems generate continuous streams of behavioral data that offer superior predictive capabilities compared to traditional retrospective analysis methods. The framework operates on the fundamental principle that consumer purchasing decisions follow identifiable digital pathways that can be monitored and analyzed

to predict future demand patterns with enhanced accuracy [5]. Unlike traditional forecasting systems that depend on completed transaction histories, behavioral indicator frameworks capture intermediate engagement signals that provide earlier warning systems for demand fluctuations. The implementation of these advanced analytical approaches in contemporary business environments has demonstrated consistent improvements in forecasting precision, particularly when addressing scenarios involving product innovations or service enhancements where historical precedent provides limited guidance. Research indicates that organizations adopting behavioral indicator frameworks experience measurable improvements in demand prediction accuracy, enabling more effective resource allocation and inventory management strategies.

Consumer behavior transformation occurs through systematic progression along measurable engagement metrics that manifest consistently before actual purchase completion, creating observable patterns that can be quantified and leveraged for predictive analytics purposes. The digital interaction environment generates comprehensive behavioral data streams encompassing browsing patterns, search behaviors, content engagement duration, and interaction frequency that collectively provide insights into consumer purchasing intentions [6]. These engagement metrics function as leading indicators of demand changes, offering temporal advantages over traditional lagging indicators such as completed sales transactions or historical purchase patterns. The behavioral progression from initial interest expression to purchase completion follows identifiable trajectories that can be mapped and analyzed to predict conversion probabilities under varying market conditions and service scenarios. Advanced analytics platforms demonstrate that engagement metric analysis can identify demand pattern shifts substantially earlier than conventional forecasting methods, providing organizations with enhanced planning capabilities for inventory management and operational resource allocation. The correlation between engagement metrics and subsequent purchasing behavior exhibits consistent patterns across diverse product categories and consumer demographic segments, suggesting the broad applicability of behavioral indicator methodologies across multiple industry verticals.

The glance view conversion methodology represents a sophisticated analytical approach focused on monitoring how service improvements and operational enhancements affect consumer engagement patterns and subsequent purchasing behavior trajectories. This methodology concentrates on analyzing the relationship between brief consumer interactions with products or services and the probability of conversion under different operational scenarios and service quality conditions [5]. The glance view metric captures initial consumer interest expressions that may not progress to detailed examination but indicate latent demand potential that can be activated through strategic service enhancements or operational improvements. Research demonstrates that glance view patterns provide valuable insights into consumer response mechanisms to service quality improvements, particularly in scenarios involving delivery speed enhancements, user interface optimizations, or customer service improvements. The methodology enables organizations to quantify the impact of operational improvements on consumer engagement levels, providing measurable feedback mechanisms for investment effectiveness evaluation and strategic decision-making processes. Implementation of glance view conversion analysis has demonstrated particular effectiveness in digital commerce environments where consumer attention spans are constrained and initial impressions significantly influence purchasing decision outcomes.

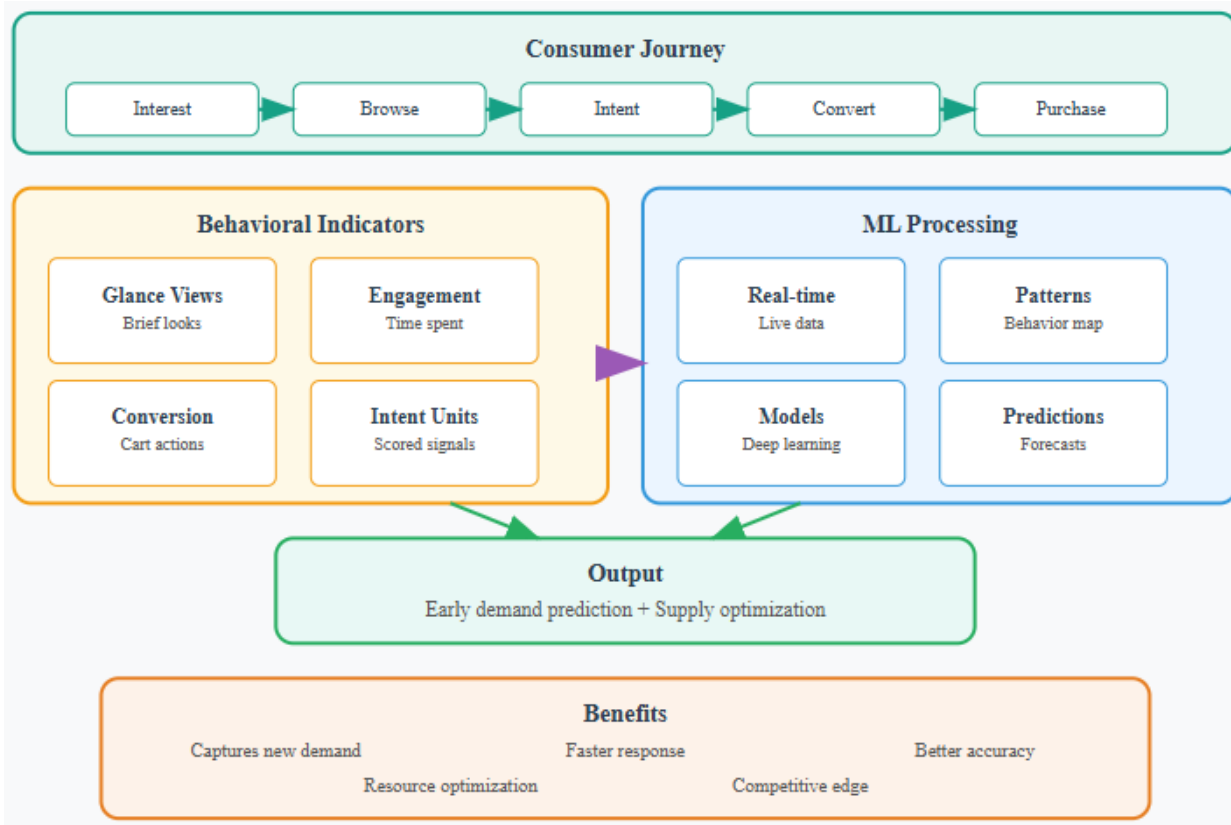


Fig 2: Behavioral Indicator Framework [5, 6]

Every measured increment of consumer engagement represents quantifiable units of consumer intent that can be systematically correlated with conversion probability under different service scenarios and operational conditions. The granular measurement of consumer interactions enables precise calibration of demand forecasting models to account for varying levels of service quality and operational efficiency across different business contexts [6]. This approach recognizes that consumer intent exists along a continuous spectrum of engagement intensity, with different interaction levels corresponding to varying conversion probabilities that can be mathematically modeled and predicted through advanced analytics techniques. The correlation between engagement metrics and conversion outcomes provides organizations with actionable insights for optimizing service delivery mechanisms and operational performance to maximize demand capture efficiency. Advanced behavioral analytics platforms demonstrate that engagement-based forecasting methodologies can achieve superior accuracy compared to traditional approaches, particularly for scenarios involving service innovations or operational enhancements that lack historical precedent or comparable market benchmarks.

4. Quick Commerce Evolution and Global Market Transformation

The e-commerce delivery transformation represents a paradigmatic shift in consumer commerce behavior that has fundamentally altered the relationship between service speed and purchasing patterns across global markets. This transformation extends far beyond simple operational improvements, representing a comprehensive restructuring of consumer expectations and engagement behaviors that has created entirely new categories of demand forecasting challenges. The evolution from traditional multi-day delivery models to rapid fulfillment systems operating within hours demonstrates how technological capabilities can unlock latent consumer behaviors that were previously constrained by logistical limitations [7]. The case study reveals that delivery speed enhancements generate cascading effects throughout the consumer journey, influencing everything from initial product discovery behaviors to final purchase completion rates. Research demonstrates that the transition to rapid delivery models has created measurable changes in consumer decision-making processes, with shorter delivery windows reducing the psychological barriers associated with impulse purchasing and enabling new consumption patterns that were previously impractical. The delivery speed revolution has established natural experiments in consumer behavior modification, providing unprecedented insights into how operational improvements can activate dormant market segments and create demand patterns that traditional forecasting methodologies would have been unable to anticipate or quantify accurately.

Global adoption patterns of rapid delivery systems demonstrate remarkably consistent behavioral transformations across diverse economic environments, suggesting universal consumer responses to delivery speed improvements that transcend traditional market boundaries and cultural contexts. The implementation of accelerated fulfillment models has generated similar engagement pattern modifications across developed and developing markets, with consumers consistently exhibiting increased platform utilization rates, higher session frequencies, and expanded product category exploration when delivery timeframes are compressed [8]. These behavioral changes operate independently of traditional demographic segmentation variables, with both urban and rural consumers demonstrating comparable response patterns to delivery speed enhancements, though with varying intensity depending on existing infrastructure capabilities and market maturity levels. The consistency of behavioral transformations across different economic development stages suggests that the relationship between delivery speed and consumer engagement operates according to fundamental psychological principles that remain largely invariant across diverse market conditions. Research indicates that emerging markets often experience more pronounced behavioral modifications in response to delivery speed improvements, as these enhancements represent greater relative service quality improvements compared to previously available alternatives. The global adoption patterns demonstrate that rapid delivery implementation creates predictable sequences of consumer behavior modification that can be systematically anticipated and leveraged for advanced demand forecasting applications.

Observable engagement metrics, including browsing duration, interaction frequency, and abandonment behaviors, have consistently preceded actual sales performance improvements in rapid delivery implementations, creating measurable leading indicators of demand transformation events that provide temporal advantages for supply chain optimization. The systematic analysis of pre-purchase engagement behaviors reveals consistent patterns that emerge before conversion rate improvements become apparent in transactional data, offering valuable prediction windows for inventory planning and resource allocation strategies [7]. Research demonstrates that engagement metrics begin exhibiting significant changes within relatively short timeframes following delivery speed improvements, while actual sales increases typically manifest over extended periods, creating actionable prediction intervals for supply chain optimization. The correlation between engagement metric fluctuations and subsequent sales performance has proven remarkably robust across different product categories and consumer segments, suggesting stable predictive relationships that can be systematically leveraged for forecasting applications. Abandonment behavior patterns, in particular, have demonstrated strong predictive capabilities for rapid delivery success, with reductions in abandonment rates serving as reliable early indicators of impending demand increases. The systematic nature of engagement metric changes preceding sales improvements provides organizations with actionable intelligence for optimizing inventory levels and resource allocation in anticipation of demand pattern shifts.

The competitive landscape surrounding delivery speed optimization has demonstrated the strategic imperative of behavioral indicator forecasting, as organizations require predictive capabilities to anticipate demand changes before manifestation in actual sales data becomes apparent. The rapid proliferation of accelerated delivery models across global markets has created intense competitive pressures, with delivery speed becoming a primary competitive differentiator that significantly impacts market positioning and consumer retention rates [8]. Organizations implementing behavioral indicator forecasting methodologies have demonstrated superior capacity to capitalize on delivery speed improvements, achieving enhanced inventory positioning and resource allocation efficiency compared to competitors utilizing traditional forecasting approaches. The competitive dynamics have revealed that organizations capable of predicting demand changes from engagement metrics can achieve substantial first-mover advantages in market expansion and customer acquisition initiatives. Research indicates that companies utilizing behavioral forecasting approaches have achieved superior performance metrics in rapid delivery implementations, with enhanced inventory

turnover rates and reduced stockout incidents compared to traditional forecasting methodologies, demonstrating the tangible business value of advanced predictive analytics in dynamic market environments.

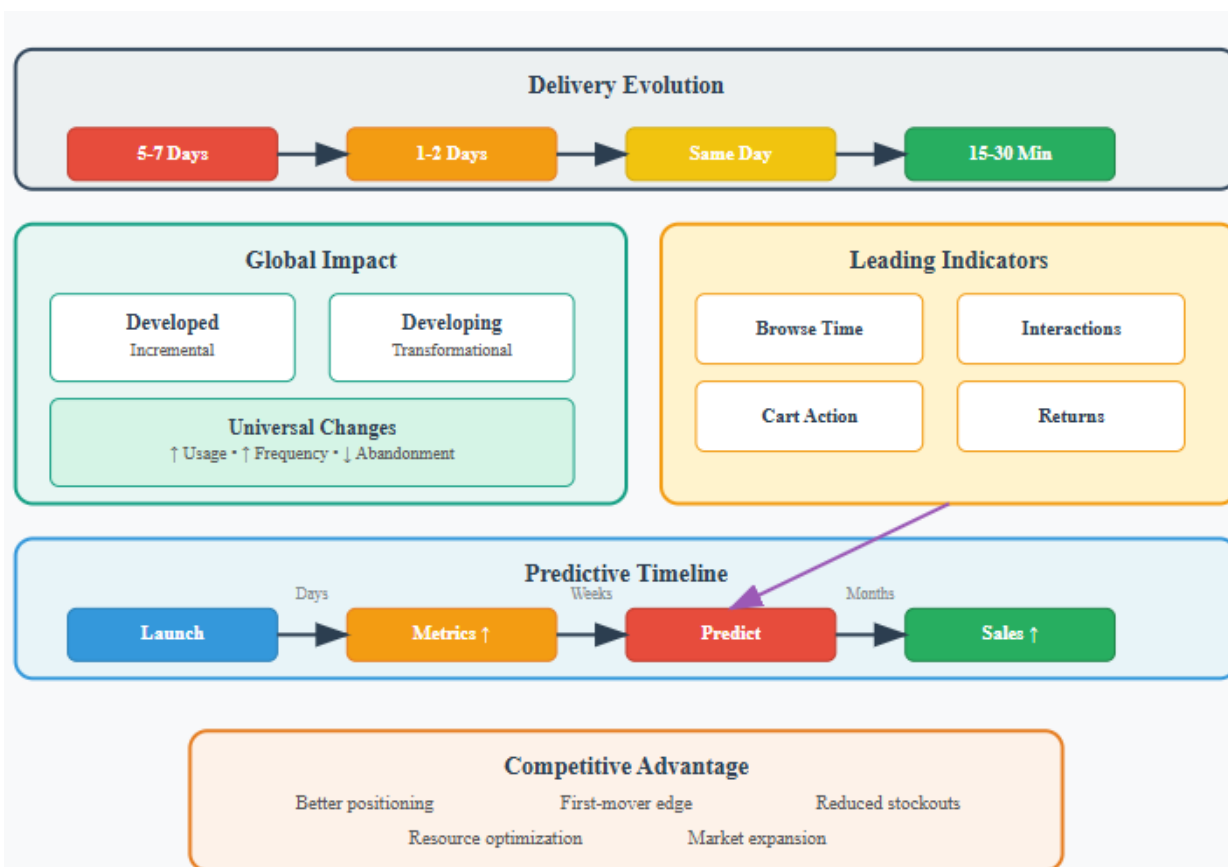


Fig 3: Quick Commerce Evolution [7, 8]

5. Enterprise-Scale Implementation

The implementation of sophisticated machine learning systems architecture for processing real-time behavioral data streams demands unprecedented computational infrastructure capabilities that far exceed traditional enterprise forecasting requirements. Modern behavioral forecasting systems necessitate complex technological frameworks capable of managing massive volumes of streaming data while maintaining the operational reliability and scalability essential for enterprise-scale supply chain operations. The architectural requirements encompass distributed computing environments, advanced data pipeline management systems, and sophisticated stream processing capabilities that can handle continuous data ingestion from diverse sources, including web analytics platforms, mobile applications, customer interaction systems, and Internet of Things devices [9]. The technical complexity of behavioral data processing significantly surpasses conventional forecasting systems, requiring dynamic computational resource allocation to accommodate varying data volumes and processing demands that fluctuate throughout operational cycles. Research demonstrates that enterprise-scale behavioral forecasting systems must incorporate robust fault tolerance mechanisms, redundancy protocols, and disaster recovery capabilities to ensure continuous operation in mission-critical supply chain environments. The architecture must also address data quality management challenges, as behavioral data streams frequently contain inconsistencies, missing values, and noise that can compromise forecasting accuracy without proper preprocessing and validation protocols. The implementation of real-time behavioral analytics requires careful consideration of latency constraints, data consistency requirements, and system reliability standards that are fundamental to enterprise-scale operational effectiveness.

Hybrid forecasting models that systematically combine traditional demand signals with behavioral indicators represent a significant advancement in predictive analytics methodologies, offering enhanced accuracy while maintaining the operational stability required for enterprise decision-making processes. These sophisticated systems integrate historical sales patterns, seasonal variations, and market trend analysis with real-time behavioral metrics to generate comprehensive demand predictions that capture both established consumption patterns and emerging market dynamics [10]. The technical implementation of hybrid modeling approaches requires advanced algorithms capable of dynamically weighting different input sources based on predictive value under varying market conditions, with machine learning techniques enabling automatic adjustment of model parameters in response to changing business environments. Research indicates that hybrid forecasting methodologies can achieve substantially

improved prediction accuracy compared to single-source approaches, particularly in scenarios involving product innovations or market disruptions where behavioral indicators provide early detection capabilities for demand pattern changes. The integration of behavioral and traditional forecasting signals requires sophisticated calibration mechanisms to ensure that real-time behavioral data enhances rather than overwhelms established forecasting methodologies that have proven effective in stable market conditions. Advanced ensemble learning techniques enable the systematic combination of multiple forecasting models with complementary strengths and weaknesses, creating robust prediction systems that can adapt effectively to diverse market conditions and product category variations.

The technical challenges inherent in enterprise-scale behavioral forecasting implementation encompass real-time data processing capabilities, sophisticated behavioral pattern recognition algorithms, and seamless integration with existing enterprise resource planning infrastructures. Real-time data processing requirements demand high-performance computing systems capable of managing continuous data streams with minimal latency while preserving data integrity and processing accuracy throughout the analytical pipeline [9]. Behavioral pattern recognition algorithms must possess the capability to identify subtle changes in consumer engagement patterns that precede demand fluctuations, requiring advanced machine learning techniques, including deep neural networks, natural language processing capabilities, and computer vision systems. The integration with established ERP systems presents additional complexity layers, as behavioral forecasting outputs must be seamlessly incorporated into existing supply chain planning workflows without disrupting operational continuity or requiring extensive system modifications. Research demonstrates that successful implementation requires comprehensive consideration of data governance frameworks, security protocols, and organizational change management strategies to ensure effective adoption and operational integration. The technical architecture must accommodate varying data formats, processing requirements, and output specifications across different business units and operational contexts while maintaining consistent performance standards.

Advanced feature engineering techniques are fundamental for transforming raw behavioral data into actionable predictive signals that can effectively inform supply chain decision-making processes and operational planning activities. The conversion of behavioral data streams into meaningful forecasting inputs requires sophisticated data transformation algorithms capable of extracting relevant patterns from complex, multi-dimensional behavioral datasets encompassing user interactions, engagement metrics, and purchasing journey analytics [10]. Feature engineering for behavioral forecasting involves creating derived metrics that capture consumer intent indicators, engagement intensity measurements, and purchasing probability assessments from raw interaction data, including browsing behaviors, session characteristics, search patterns, and navigation sequences. The process demands domain expertise to identify behavioral indicators that demonstrate strong correlation with future purchasing behavior while avoiding spurious relationships that could compromise forecasting reliability and accuracy. Research indicates that effective feature engineering can dramatically improve forecasting performance, with carefully designed behavioral features providing superior predictive capabilities compared to raw data inputs. The feature engineering process must also account for temporal dynamics and seasonality effects, as behavioral patterns often exhibit time-dependent relationships that require sophisticated modeling techniques to capture accurately and reliably.

Element	Description	Focus Area
Infrastructure	Scalable systems for real-time behavioral data	Performance & Reliability
Data Pipelines	Continuous data ingestion and stream processing	Latency & Data Quality
Hybrid Models	Combines traditional and behavioral forecasting signals	Accuracy & Adaptability
Feature Engineering	Extracts predictive signals from behavioral interactions	Signal Strength & Relevance
ERP Integration	Embeds forecasts into existing planning systems	Workflow Compatibility

Table 1: Key Elements of Enterprise-Scale ML Architecture for Behavioral Demand Forecasting [9, 10]

Conclusion

Innovation-driven demand patterns necessitate fundamental evolution in supply chain intelligence methodologies as traditional forecasting approaches prove inadequate when technological improvements create entirely new consumption behaviors. The behavioral indicator framework offers a viable pathway for enterprise-scale systems to capture demand transformation events through real-time consumer intent signal monitoring rather than historical pattern analysis. The success of glance view conversion methodology in e-commerce environments demonstrates practical viability and strategic importance for organizations seeking competitive advantages in rapidly evolving markets. Global implementation patterns reveal consistent behavioral transformations across diverse economic contexts, suggesting universal applicability of engagement metric analysis for predicting demand changes before sales data manifestation. Enterprise-scale deployment requires sophisticated machine learning architectures capable of

processing massive behavioral data streams while maintaining operational reliability and seamless integration with existing supply chain management infrastructures. Future developments should focus on expanding the framework to additional industry verticals and developing more sophisticated algorithms for real-time behavioral pattern recognition. The integration of artificial intelligence and predictive analytics capabilities will enable more accurate demand forecasting for innovation-driven scenarios where historical precedent provides limited guidance. Organizations adopting behavioral forecasting methodologies can achieve superior performance in inventory management, resource allocation, and strategic planning compared to traditional approaches, demonstrating tangible business value in dynamic market environments.

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