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AI Based Quantitative Optimization Models for FMCG Supply Chain Efficiency in High-Demand Markets: A Linear Programming and Mixed-Integer Programming Approach

Md Shahab Uddin[1];

[1]. *Director, Consumer Products Distribution Business, Bangladesh;*
Email: shopno23@gmail.com

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Abstract

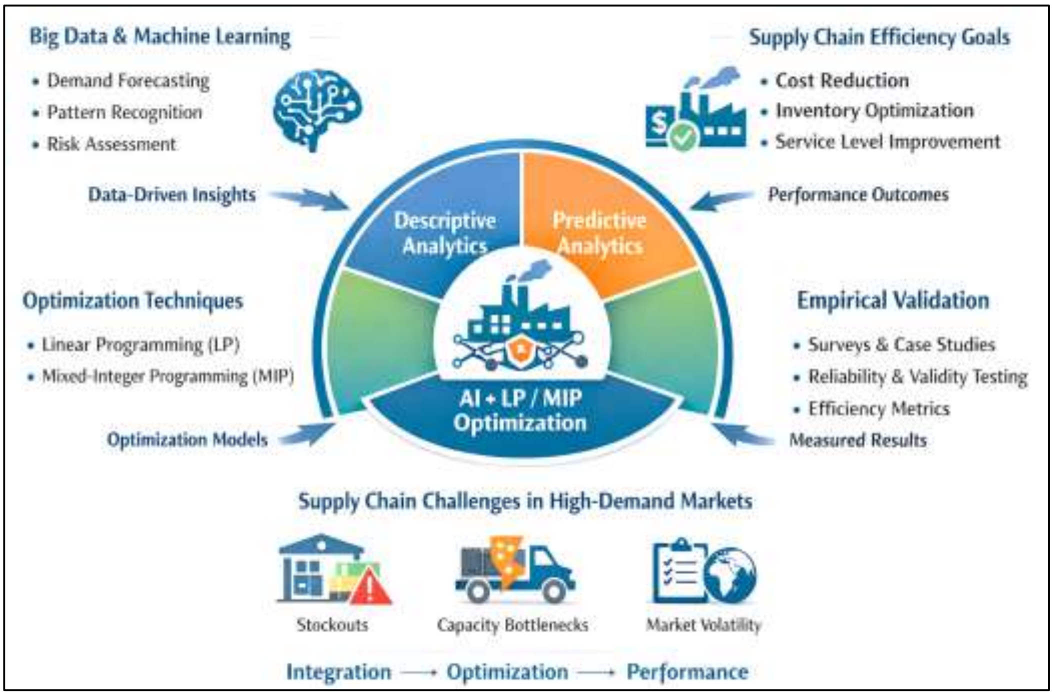
This study addressed a persistent supply chain performance gap in fast moving consumer goods environments where AI forecasting and visibility tools exist, yet efficiency declines under demand surges because replenishment and distribution decisions are not optimized under real capacity and lead time constraints. The purpose was to quantify how AI enabled analytics capability and related planning practices influence supply chain efficiency and to validate the statistical results with prescriptive optimization outcomes. A quantitative, cross sectional, case-based design was used, combining survey evidence from 168 supply chain professionals with cloud and enterprise planning cases modeled under normal and high demand conditions. Key variables included AI analytics capability, forecasting effectiveness, inventory optimization practice, logistics and distribution planning quality, supplier coordination and lead time reliability. The analysis plan applied reliability testing, descriptive statistics, Pearson correlation, and multiple regression, followed by linear programming and mixed integer programming scenario evaluation with feasibility checks and forecast noise sensitivity testing. Reliability was acceptable across constructs (Cronbach alpha 0.79 to 0.88). Descriptive results showed moderately high AI analytics capability (M 3.84, SD 0.62) and forecasting effectiveness (M 3.71, SD 0.66), while overall efficiency remained moderate (M 3.52, SD 0.67). Supply chain efficiency correlated strongly with AI analytics capability (r 0.62, $p < 0.001$). The regression model explained 54 percent of variance in efficiency (R2 0.54, $p < 0.001$), with AI analytics capability as the strongest predictor (beta 0.34, $p < 0.001$), followed by forecasting effectiveness (beta 0.21, $p = 0.001$), inventory optimization practice (beta 0.17, $p = 0.005$), and supplier coordination (beta 0.14, $p = 0.017$); logistics planning was positive but not statistically significant ($p = 0.075$). Optimization results reinforced these findings: under normal demand, total cost decreased 11.8 percent (1.72M to 1.52M), service level improved from 92.1 to 96.0 percent, and stockouts reduced 18.4 percent; under high demand, cost decreased 9.3 percent (2.05M to 1.86M), service improved from 88.4 to 93.2 percent, and stockouts reduced 15.1 percent, with a 0.8 percent optimality gap and solutions remaining feasible across scenarios. With plus or minus 10 percent forecast noise, cost rose only 2.1 percent and service declined 0.9 points, indicating robustness. The findings imply that enterprises should prioritize analytics and forecasting governance, enforce disciplined inventory policy execution, and embed constraint-based optimization into routine planning to sustain cost and service performance during demand peaks.

KEYWORDS
AI analytics capability; supply chain efficiency; forecasting effectiveness; inventory optimization; LP and MIP optimization.

INTRODUCTION

Artificial intelligence (AI) is commonly defined as a family of computational methods that perform tasks associated with human cognition—such as perception, learning, prediction, and decision support—by combining data, algorithms, and computing resources into adaptive systems. In operations and supply chain management, AI is most visible through machine learning (ML) for prediction and classification, and through prescriptive analytics that translates predictions into optimized decisions under constraints (Baryannis et al., 2019). Big data analytics provides the informational substrate for AI by enabling high-volume, high-velocity, and high-variety data to be processed into actionable insights; it is not limited to "size," but also includes heterogeneity, noise, and the need for computationally efficient inference (Bendoly & Schoenherr, 2005).

Figure 1: AI-Enabled Prescriptive Analytics Framework for FMCG Supply Chain Optimization



In supply chains, this shift is frequently framed as a movement from descriptive insight to predictive foresight and finally to prescriptive decision-making, where the output is not merely a forecast but a recommended action—such as how much to produce, where to allocate inventory, and which distribution plan minimizes cost while maintaining service levels (Carbonneau et al., 2008). This perspective is internationally significant because supply chains are transnational networks that link sourcing, manufacturing, logistics, and retail across borders; inefficiency in one node propagates to lead times, stockouts, and price instability across regions. Research has repeatedly emphasized that data science and predictive analytics reshape how supply chains are designed and managed by enabling near-continuous sensing and recalibration of decisions (Dubey, Gunasekaran, Childe, Papadopoulos, et al., 2019). At the same time, the international relevance extends beyond efficiency as a narrow cost target; it also encompasses continuity of supply in essential consumer categories, the stabilization of retail availability under volatility, and the operational capability to coordinate many actors (Haque & Arifur, 2020; Hazen et al., 2014; Rauf, 2018). Empirical and review evidence indicates that analytics capability is best understood as an organizational capability rather than a single tool, combining tangible infrastructure, skilled human resources, governance routines, and cross-functional integration. Modern supply-chain research therefore increasingly treats AI-enabled analytics as a capability that can be measured, related to performance outcomes, and linked to how firms plan, coordinate, and execute under demand turbulence (Gupta & George, 2016; Haque & Arifur, 2021; Ashraful et al., 2020).

Supply chain efficiency itself is a multidimensional construct that spans cost, responsiveness, reliability, and asset utilization. In fast-moving consumer goods (FMCG), efficiency has a particularly concrete operational meaning because product portfolios are broad, replenishment cycles are short, margins are often thin, and service-level expectations are high across diverse retail channels. The combination of frequent promotions, seasonal surges, and localized shocks produces conditions that resemble "high-demand markets," where decision latency becomes costly and where inventory imbalances rapidly translate into lost sales, overstocks, and waste (Gandomi & Haider, 2015; Jinnat & Kamrul, 2021; Fokhrul et al., 2021). A central technical challenge in such settings is that demand signals are noisy and can become distorted as they move upstream, creating forecasting errors that amplify across stages. Studies on ML-based demand forecasting in supply chains demonstrate that advanced methods—such as neural networks and support vector machines—can be used to forecast demand under signal distortion and noise, offering alternatives to purely linear or naïve baselines (Fildes et al., 2020). Complementary forecasting research focused on retail indicates that forecasting accuracy is deeply tied to data granularity, product hierarchy, and the operational use case, and that structured evaluation is required to compare methods fairly across retail-like environments. For FMCG, this forecasting layer is not an end in itself; it is an input to planning decisions that include procurement, production, and allocation across distribution centers and stores (Fahimul, 2022; Nguyen et al., 2018; Zaman et al., 2021). Empirical supply chain analytics scholarship has consistently argued that the value of prediction depends on how it is operationalized into planning and control, which moves the emphasis toward optimization models that can translate forecast distributions, service targets, and operational constraints into feasible, cost-effective plans (Mishra et al., 2018). This logic is aligned with the broader view that data-driven supply chains require both information processing capability and decision capability; prediction without optimization can identify patterns but may not specify actions that satisfy capacity, inventory balance, and delivery constraints simultaneously (Toorajipour et al., 2021).

Operations research (OR) provides the formal language for translating supply chain decisions into optimization problems, and linear programming (LP) and mixed-integer programming (MIP) are among the most widely used approaches for doing so. LP represents decisions as continuous variables constrained by linear relationships; MIP extends LP by allowing some variables to be integer or binary, enabling modeling of discrete choices such as opening a facility, selecting a shipment lane, or turning a production line on/off (Schoenherr & Speier-Pero, 2015; Toorajipour et al., 2021). In supply chain contexts, integer decisions are essential because many managerial choices are inherently discrete: whether a truck is dispatched, whether a product is listed at a depot, whether a safety stock policy is activated, or whether a replenishment order is placed. Strategic and tactical supply chain design problems often integrate location, allocation, inventory, and transportation decisions; facility location research in OR has long shown that realistic supply chain planning requires integrating location decisions with other supply chain decisions rather than treating them in isolation (Gunasekaran et al., 2017). This insight is critical for FMCG networks, where distribution center structure, lane assignments, and replenishment frequency interact with capacity and service levels. At the same time, tactical planning problems such as lot-sizing, inventory control, and replenishment planning demand formulations that are strong enough to be solved at scale. Tutorials in inventory management show that mixed-integer optimization can model both deterministic and stochastic inventory settings and can incorporate advanced formulation techniques to strengthen solvability and improve solution quality (Melo et al., 2009). These foundations matter for AI-based quantitative optimization because AI does not replace LP/MIP; it complements them by improving inputs (demand, lead time, promotion uplift) and by enabling scenario-conditioned parameters that reflect market states. The resulting hybrid structure places LP/MIP at the decision core while AI contributes to parameter estimation and scenario generation, with the integrated system judged by feasibility, cost, and service performance (Küçükyavuz, 2011). Research on analytics in logistics and supply chain management similarly frames prescriptive analytics as the stage where models generate recommended actions subject to constraints, supported by predictive and descriptive layers that supply the data and context. The global relevance of LP/MIP-based planning is therefore anchored in its ability to represent the operational realities of supply chain execution while maintaining transparency: decision variables and constraints are interpretable, auditable, and aligned to managerial levers—an essential condition for trust in highstakes supply environments (Waller & Fawcett, 2013).

The credibility of "AI-based optimization" in applied supply chains depends on how the AI components are conceptualized and measured as organizational capabilities rather than isolated algorithms (Wamba et al., 2019). In the information systems and operations literature, this is often framed through capability-based theories, including resource-based logic and related capability perspectives, where performance effects arise from bundling resources into routines and decision processes (Wang et al., 2016). Empirical work on big data analytics capability, for example, operationalizes capability as a structured bundle of tangible, human, and intangible resources that together support analytics deployment and performance outcomes. In supply chain and operations research, systematic reviews and empirical studies argue that analytics-enabled decision-making is tied to organizational processes that connect data pipelines, cross-functional coordination, and consistent model use in planning cycles (Fildes et al., 2020). This is directly relevant to FMCG supply chains because they frequently rely on enterprise systems that integrate procurement, production, warehouse management, and retail replenishment; evidence linking ERP implementation-process benefits to inter-organizational procurement outcomes underscores how process integration and system-level discipline shape downstream performance. In high-demand markets, the coordination challenge intensifies: firms need to sense demand, update forecasts, and adjust allocations quickly while preserving service commitments and avoiding infeasible plans (Toorajipour et al., 2021). Research on big data analytics in supply chain contexts has therefore emphasized the classification of analytics into descriptive, predictive, and prescriptive categories, with prescriptive analytics requiring rigorous optimization and operational integration to deliver measurable performance improvements (Fildes et al., 2020). Empirical supply chain studies further examine how analytics and AI pathways connect to operational performance through organizational orientations and environmental conditions, reinforcing that the performance impact is mediated by capabilities and contextual moderators rather than existing as a universal constant. This framing motivates quantitative, cross-sectional, case-study–based designs that measure constructs such as AI-enabled planning quality, supply chain efficiency, and decision alignment, then test statistical associations through descriptive statistics, correlation, and regression modeling. It also motivates the inclusion of optimization outputs as objective performance indicators, enabling triangulation between perceptual survey measures and model-derived efficiency metrics, thereby strengthening trust in the findings through convergent evidence rather than relying on perceptions alone (Gunasekaran et al., 2017).

The international significance of optimizing FMCG supply chains is magnified by the structural characteristics of consumer markets: demand heterogeneity across regions, multi-tier distribution networks, and frequent disruptions that alter availability and lead times. Supply chain risk and resilience scholarship increasingly incorporates AI as a decision-support mechanism that can classify risks, estimate impacts, and support mitigation actions through integrated analytics and optimization (Toorajipour et al., 2021). Reviews connecting artificial intelligence to supply chain risk management report that AI methods are used for risk identification, assessment, and response planning, often interacting with OR methods to recommend feasible mitigation actions. In high-demand FMCG contexts, risk is operationally experienced as repeated constraint violations: warehouse capacity saturation, transportation lane bottlenecks, supplier shortages, and service-level failures at stores. Optimization models reveal risk in a measurable form because constraints bind or fail under certain scenarios, creating traceable evidence of where the network becomes fragile (Waller & Fawcett, 2013). AI-driven forecasting and classification can add additional structure by identifying demand regimes—such as surge patterns or promotion-driven spikes—and passing those regimes into scenario-conditioned optimization runs (Mishra et al., 2018). The literature on ML-based forecasting emphasizes that demand forecasting accuracy is domain- and signal-dependent, and that improved accuracy can be achieved by applying ML methods suited to noisy supply chain demand signals. Retail forecasting research adds that method comparison requires disciplined evaluation practices and careful segmentation by product and context, reinforcing that "one-size" evaluation claims are rarely credible without structured validation (Nguyen et al., 2018). On the optimization side, supply chain network design and planning research shows that integrated models capture the interaction of supply chain decisions and constraints that single-function models omit, especially in facility location and allocation contexts. When combined, these streams provide a coherent logic for the present research title: AI supports parameter learning and scenario definition; LP/MIP provides the prescriptive mechanism for feasible, cost-effective decisions; and efficiency gains are assessed both through model outputs (baseline vs optimized) and through survey-based measurement of operational outcomes and decision quality (Waller & Fawcett, 2013). A cross-sectional case-study approach is therefore positioned to capture real organizational processes and measure both perceived and computed performance in a single empirical setting while maintaining analytical rigor through reliability/validity testing and regression-based hypothesis evaluation (Bendoly & Schoenherr, 2005).

A core methodological reason for integrating optimization outputs with survey analytics is to strengthen measurement credibility through multi-evidence validation. Survey-based supply chain research often measures constructs like agility, alignment, planning effectiveness, and perceived efficiency using Likert scales, then evaluates measurement quality through reliability and validity tests prior to hypothesis testing. In parallel, optimization provides objective and reproducible performance indicators: total cost, transportation spend, inventory holding cost, shortage penalties, service level attainment, capacity utilization, and feasibility rates across scenarios. Combining these allows the study to test whether perceived improvements in planning quality align with measurable efficiency improvements from LP/MIP (Fildes et al., 2020). The analytics capability literature supports this logic by conceptualizing analytics as a capability that can be measured and associated with performance; for example, survey-based evidence links analytics-enabled capabilities to operational outcomes under varying environmental dynamism. Supply chain analytics research also emphasizes that prescriptive analytics operationalizes decision-making via optimization models, enabling evaluation through comparative baselines and scenario tests rather than narrative claims (Gupta & George, 2016). In FMCG environments, scenario analysis is especially important because market conditions fluctuate across "normal" and "high-demand" regimes, and model performance must be judged across these regimes through structured comparisons (Wamba et al., 2015). Optimization research on inventory and lot-sizing illustrates that formulation strength and constraint structure influence solvability and solution quality, which legitimizes diagnostics such as constraint tightness, feasibility checks, and stress testing of parameter uncertainty. From the AI side, studies on big data and predictive analytics in supply chain contexts argue that prediction and analytics capabilities affect organizational performance, strengthening the rationale for integrating predictive and prescriptive layers in a single empirical research design (Papadopoulos, et al., 2019). Complementary empirical studies connect big data and predictive analytics capability to broader performance targets, including sustainability-linked performance in supply chain contexts, which further normalizes the use of survey constructs combined with quantitative performance indicators (Gunasekaran et al., 2017). The resulting research design supports a results structure that includes reliability/validity, descriptive statistics, correlations, regression/hypothesis testing, optimization outcomes, and specialized diagnostics that demonstrate model feasibility and robustness (Nguyen et al., 2018). This integration increases trust because it links statistical associations from survey data to verifiable optimization outputs derived from the same operational context, allowing the study to report consistency between what respondents report and what optimization computations demonstrate (Wamba et al., 2015).

The scholarly foundation for "AI based quantitative optimization models for FMCG supply chain efficiency in high-demand markets" is reinforced by the maturation of systematic reviews that map AI's roles across supply chain planning, forecasting, risk management, and operational execution (Fildes et al., 2020). Literature reviews focused on AI in supply chain management synthesize evidence that AI methods are deployed for demand forecasting, inventory planning, supplier selection, logistics routing, and anomaly detection, while also documenting that operational value increases when AI is embedded in planning routines and linked to decision models that can be executed consistently (Fahimul, 2022; Toorajipour et al., 2021; Zaman et al., 2021). Research that categorizes big data analytics in supply chains similarly presents prescriptive analytics as the stage where optimization models deliver decisions, and it highlights the need to integrate descriptive, predictive, and prescriptive layers into an end-to-end decision process (Hammad, 2022; Hasan & Waladur, 2022; Waller & Fawcett, 2013). This is consistent with the broader definition-focused literature that clarifies what big data is and what analytic methods are appropriate for extracting value from it, particularly under heterogeneity and noise (Rashid & Sai Praveen, 2022; Arifur & Haque, 2022; Waller & Fawcett, 2013). Within enterprise operations, evidence linking integrated systems and implementation processes to procurement and inter-firm benefits signals that decision quality depends on process discipline and data integrity, conditions that are central when optimization models rely on accurate master data and transaction histories (Papadopoulos, et al., 2019). At the modeling level, supply chain network design reviews show that integrated OR models capture cross-decision interactions across locations, flows, and inventories—critical in FMCG networks where distribution structure and replenishment decisions interact (Gandomi & Haider, 2015; Towhidul et al., 2022; Rifat & Jinnat, 2022). At the planning level, research on ML-based forecasting and retail forecasting evaluation supports the need for rigorous assessment of predictive inputs, including stress testing and scenario alignment, because optimization outcomes are sensitive to forecast error and regime changes (Abdulla & Majumder, 2023; Rifat & Alam, 2022). Empirical analytics capability studies establish that capabilities can be operationalized and linked to performance outcomes via survey measurement and regression-based testing, which provides a methodological pathway for cross-sectional designs that test hypotheses about AI-enabled planning and supply chain efficiency (Papadopoulos, et al., 2019). Taken together, these streams justify an integrated thesis structure in which international significance is grounded in transnational FMCG networks, theoretical grounding is provided by capability-based perspectives, measurement rigor is established via reliability/validity testing, and trust is reinforced through alignment between survey evidence and optimization outputs derived from LP/MIP models (Fahimul, 2023; Faysal & Bhuya, 2023).

This study is designed to achieve a set of tightly connected objectives that operationalize the research title into measurable constructs, testable relationships, and verifiable optimization outcomes within an FMCG supply chain operating in a high-demand market environment. The first objective is to define and operationalize “supply chain efficiency” for the selected case context using a structured set of indicators that reflect cost performance, service performance, responsiveness, and resource utilization, ensuring that efficiency is captured as a multi-dimensional outcome rather than a single metric. The second objective is to measure the strength of AI-enabled decision capability within the case organization by translating core AI-related operational features—such as data visibility, forecast support, analytics integration, decision timeliness, and cross-functional use of analytic outputs—into survey-based constructs that can be quantified using a five-point Likert scale. The third objective is to identify and quantify the relationships between AI capability, forecasting effectiveness, inventory planning discipline, logistics and distribution planning quality, supplier coordination, and overall supply chain efficiency through descriptive statistical profiling and correlation analysis, establishing foundational evidence of association and directionality among variables. The fourth objective is to test a structured set of hypotheses using regression modeling in order to determine which independent variables significantly predict variations in supply chain efficiency and to estimate the magnitude of these effects under cross-sectional conditions, including the role of control factors when appropriate. The fifth objective is to formulate and implement linear programming and mixed-integer programming models that represent the case organization’s key planning decisions—such as inventory allocation, replenishment quantities, capacity-constrained distribution, and discrete operational choices—so that baseline decision policies can be compared against optimized decision policies using consistent data and constraints. The sixth objective is to evaluate the practical impact of LP/MIP optimization by comparing baseline and optimized outcomes across a set of efficiency-relevant KPIs under normal-demand and high-demand scenarios, providing decision-focused evidence of how optimization changes operational performance. The seventh objective is to strengthen the credibility of findings by incorporating model feasibility checks, constraint-tightness diagnostics, and robustness tests that examine the stability of optimization performance under plausible variations in AI-derived inputs. The final objective is to integrate the statistical findings with optimization results through explicit alignment analysis, demonstrating whether the factors identified as significant predictors of efficiency are reflected in the behaviors and outputs of the LP/MIP models, thereby producing a coherent, objective-driven evidence structure that connects measurement, explanation, and operational verification within the same case-based research design.

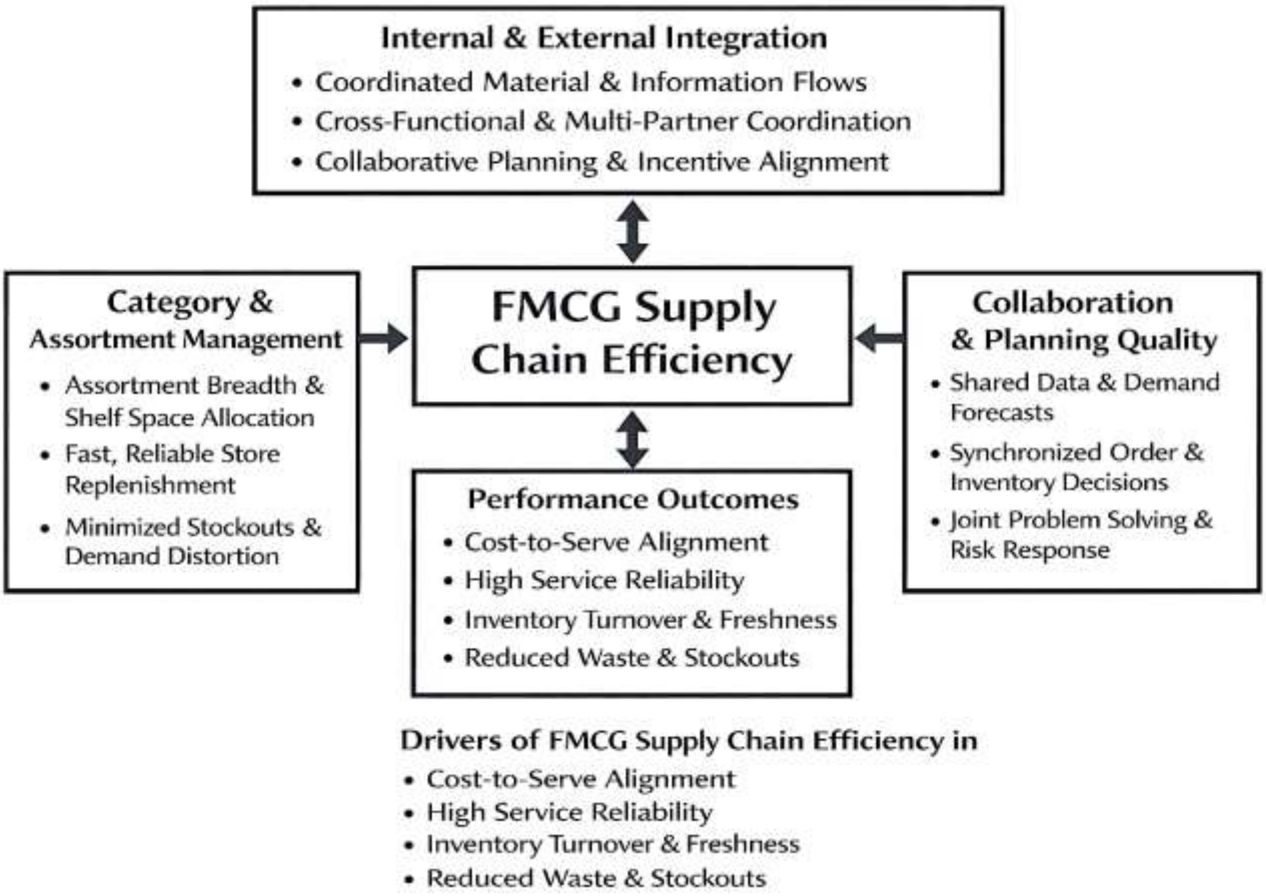
LITERATURE REVIEW

The literature on AI-based quantitative optimization for FMCG supply chain efficiency in high-demand markets spans three closely connected knowledge streams: (1) supply chain efficiency measurement and performance drivers in volatile consumer markets, (2) AI and data-driven analytics for forecasting and decision support, and (3) operations research optimization—especially linear programming and mixed-integer programming—for converting business objectives and operational constraints into implementable plans. In FMCG settings, efficiency is widely treated as a multi-criteria construct shaped by inventory availability, replenishment speed, logistics cost, capacity utilization, and service levels, and the challenge intensifies in high-demand conditions where promotions, seasonality, and localized shocks create rapid regime shifts in demand. Scholars have therefore emphasized the need for decision approaches that can operate under uncertainty and time pressure while maintaining feasibility across interconnected supply chain stages. AI-enabled analytics has become prominent in this context because machine-learning models can extract demand patterns from transactional and contextual data, improve forecast accuracy, and support faster detection of demand anomalies, which collectively reduce the information lag that often drives stockouts and overstocks. At the same time, the literature stresses that predictive accuracy alone does not guarantee operational improvement because supply chain performance depends on how predictions are translated into feasible decisions across production, inventory, and distribution. This is where prescriptive analytics and optimization modeling provide a complementary foundation: LP formulations enable continuous allocation and flow decisions, while MIP extends this capability by modeling discrete and binary choices such as shipment selection, replenishment triggers, routing alternatives, and capacity activation decisions that characterize real FMCG operations. Consequently, a growing body of research positions AI as an input engine that improves parameter estimation (e.g., demand, lead time, promotion uplift) and scenario definition, while LP/MIP acts as the decision engine that selects actions that minimize cost or maximize service subject to operational constraints. Another recurring theme is organizational capability: studies conceptualize analytics not merely as technology, but as an integrated capability that includes data quality, infrastructure, skilled personnel, and governance routines, which determines whether AI and optimization can be embedded into planning cycles and consistently used for decision-making. This combined perspective motivates empirical approaches that measure AI-related and operational planning constructs through survey instruments and test their relationships to efficiency outcomes via descriptive statistics, correlation, and regression analysis, while also validating operational improvements through optimization-based baseline-versus-optimized comparisons and scenario testing. The following subsections synthesize these streams to establish the theoretical grounding, identify research gaps, and justify an integrated framework suitable for evaluating AI-supported LP/MIP optimization in FMCG supply chains operating under high-demand market conditions.

FMCG Supply Chain Efficiency in High-Demand Markets

Supply chain efficiency in fast-moving consumer goods (FMCG) settings is commonly treated as a balanced outcome that combines cost discipline with high product availability and rapid replenishment across diverse retail channels. Because FMCG portfolios involve many stock-keeping units, short life cycles, and frequent promotion cycles, efficiency is often expressed through linked indicators such as shelf availability, order fill rate, inventory turnover, logistics cost per unit, and order cycle time. At the store interface, efficiency is visible in the ability to keep the right assortment continuously on the shelf, because lost availability converts immediately into lost sales, brand switching, and distorted demand signals for upstream planning. At the network interface, efficiency is visible in coordinated purchasing, warehousing, and transportation routines that can replenish frequently without inflating handling costs or requiring excessive buffers. Measurement approaches in consumer-goods and retail operations therefore emphasize that efficiency is not only about minimizing inventory, but also about managing assortment breadth, shelf space, and replenishment execution so that availability targets are met with the lowest feasible end-to-end cost. Category management research highlights the operational interdependence among assortment decisions, shelf decisions, and stockout management, showing that changes in any one of these areas can shift demand substitution patterns, labor requirements, and replenishment frequency, thereby changing the meaning of “efficient” execution for a given retailer and product category. These interdependencies are central for high-demand markets, where demand surges intensify the competition for shelf space and increase the penalty of stockouts, making service reliability a primary component of operational efficiency (Campo & Gijsbrechts, 2005). High-demand markets intensify these dynamics through short replenishment windows, promotional uplift, and localized peaks that require rapid rebalancing of inventory across stores and depots, so efficiency is frequently operationalized with combined scorecards that track cost-to-serve alongside delivery reliability and availability losses from waste, obsolescence, and shrinkage.

Figure 2: Integrated Drivers of Supply Chain Efficiency in FMCG High-Demand Markets



Beyond measurement, the efficiency literature emphasizes the structural drivers that enable FMCG supply chains to deliver high service at low cost, particularly the degree of internal and external integration across functions and partners. Integration is typically conceptualized as coordinated management of material, information, and decision flows across procurement, production, warehousing, and distribution, and it is treated as a determinant of both operational effectiveness and efficiency (Haque & Arifur, 2023; Jahangir & Mohiul, 2023). Large-sample evidence shows that different configurations of internal integration and external integration can produce different performance outcomes, implying that efficiency improvements depend on how coordination routines are bundled rather than on isolated practices (Flynn et al., 2010; Habibullah & Aditya, 2023; Hammad & Mohiul, 2023). In FMCG contexts, collaboration extends integration by focusing on joint planning behaviors between autonomous firms, including shared information, synchronized decisions, aligned incentives, and joint problem solving across supplier, manufacturer, distributor, and retailer interfaces. Empirical work on supply chain collaboration has identified collaboration dimensions such as information sharing, decision synchronization, and joint knowledge creation, and has linked them to collaborative advantage that transmits to firm performance outcomes (Cao & Zhang, 2011). These findings matter for high-demand markets because demand peaks require coordinated responses that reduce latency in replenishment decisions, prevent overreaction to transient signals, and allocate scarce capacity to the most service-critical lanes and products. From an efficiency perspective, collaboration also shapes the cost of achieving availability because better coordination can reduce redundant safety stocks, shorten cycle times, and reduce expediting while maintaining target fill rates. Accordingly, many studies treat efficiency as a network outcome that emerges from shared planning quality, shared data consistency, and disciplined execution of replenishment and transport plans across multiple tiers, not merely from the cost optimization of a single firm. In practice, this orientation encourages researchers to examine cross-functional planning alignment, exception management speed, and stability of order patterns as signals of efficient coordination (Rashid et al., 2023; Akbar & Farzana, 2023).

Efficiency research in high-demand consumer markets also highlights the role of responsiveness and agility as operational complements to cost-focused efficiency, because fast replenishment and reliable availability require capabilities that sense changes and reconfigure execution quickly. Logistics capability is often discussed as a foundation for agility, encompassing transportation flexibility, distribution center throughput, information visibility, and the ability to coordinate last-mile and store delivery constraints under time pressure. A systematic synthesis of the agility literature emphasizes that agility is achieved through a portfolio of logistics capabilities and process routines that enable rapid sensing and response, which aligns with FMCG environments where demand spikes and promotion shocks are frequent (Gligor & Holcomb, 2012; Mostafa, 2023; Rifat & Rebeka, 2023). At the retail execution layer, efficiency is strongly affected by how inventory policies handle stockouts, substitutions, and category-level interactions, because customer substitution behavior changes realized demand and the profitability of replenishment decisions. Category-level inventory models show that when customers substitute among items during stockouts, ignoring substitution can lead to suboptimal order-up-to policies and lower profits, and that service-level constraints interact with substitution costs and margins in systematic ways (Jahangir & Hammad, 2024; Masud & Hammad, 2024; Tan & Karabati, 2013). For FMCG supply chains, these insights connect directly to efficiency measurement: the same inventory level can yield different effective availability depending on substitution patterns, assortment breadth, and replenishment frequency, so efficient policies must be judged by realized service and total cost rather than by inventory alone. In high-demand markets, substitution and assortment effects become more pronounced because fast-depleting shelves increase the likelihood of substitution, and replenishment constraints may force prioritization among items and stores. Consequently, the efficiency literature supports evaluating FMCG performance using integrated views that combine service reliability, demand fulfillment quality, and cost-to-serve, while recognizing that customer behavior and execution constraints jointly determine whether the supply chain operates near its feasible efficiency frontier. This framing guides measurement.

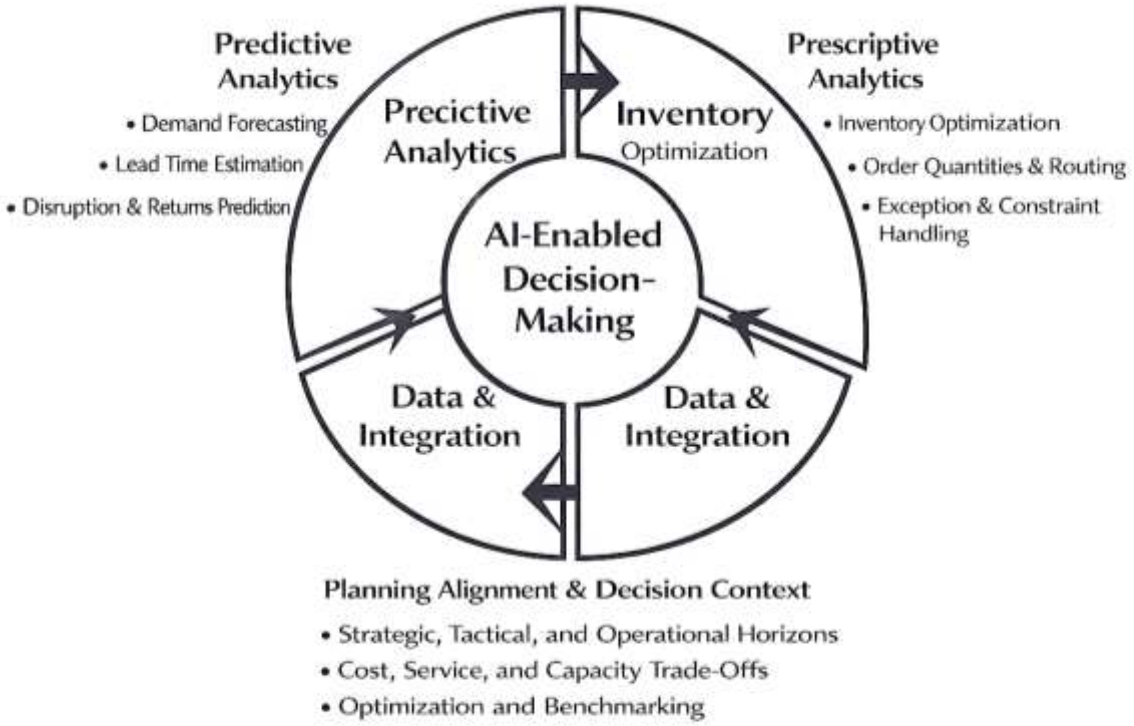
AI in Supply Chain Decision-Making

AI-enabled decision-making in supply chains is typically discussed as the use of computational intelligence to improve the quality, speed, and consistency of managerial choices across planning horizons (strategic, tactical, and operational). In this stream, AI is positioned as a decision support layer that can learn from historical and streaming data, recognize complex patterns that are difficult to capture with simple rules, and translate those patterns into decision guidance for demand planning, inventory control, procurement, production scheduling, and distribution execution. The literature distinguishes between AI used for *predictive* functions (e.g., anticipating demand, lead times, disruptions, and returns) and AI used for *prescriptive* functions (e.g., recommending order quantities, safety stock levels, allocation rules, or routing choices), while also acknowledging that organizations frequently combine both within the same planning cycle. A key argument across studies is that supply chains generate repeated and structured decision problems—such as replenishment triggers, order consolidation, exception handling, and transport assignment—that can benefit from learning-based approaches when demand signals are noisy, product portfolios are large, and decision time windows are short. AI is therefore framed as particularly relevant when organizations operate under frequent promotions, demand shocks, and regional heterogeneity, because decision makers must continuously trade off service level, cost-to-serve, and capacity constraints. In early contributions, AI is also described as a broad toolkit that includes expert systems, neural networks, genetic algorithms, and agent-based approaches, each suited to different decision contexts and data conditions, and with value depending on how well the technique matches the decision structure and available data. Within this framing, AI is treated not as a substitute for operations research but as a complementary approach that can enhance sensing, learning, and adaptation in planning routines, thereby strengthening the decision inputs that feed into formal optimization or structured managerial policies (Md & Sai Praveen, 2024; Min, 2010;

Rifat & Rebeka, 2024).

A second body of literature emphasizes that the effectiveness of AI decision-making depends on data integration and organizational information use, not only on model sophistication. Supply chains routinely combine internal transactional data (sales, orders, inventories), execution data (warehouse and transportation events), and contextual data (promotions, market signals, local conditions). These data differ in granularity, reliability, and timeliness, so a recurring theme is that AI-based decision-making must be supported by governance routines that define data ownership, data quality controls, and consistent master data structures across functions and partners. This perspective treats AI as part of a broader analytics capability: organizations must be able to collect, curate, interpret, and apply information in ways that reduce decision latency and improve alignment across procurement, production, and logistics. Research specifically addressing digital information at the intersection of analytics and supply chain management argues that the opportunity is not merely “more data,” but stronger exploitation of information for coordinated decisions, including the ability to transform dispersed signals into actionable planning guidance that is shared and used across the chain (Kache & Seuring, 2017; Sai Praveen, 2024; Shehwar & Nizamani, 2024). In parallel, operations and supply chain scholarship on big data analytics emphasizes that decision-making gains are tied to how analytic methods handle computational and data challenges—such as dimensionality, heterogeneity, and speed—while producing outputs that decision makers can actually operationalize. This stream frames analytics as a set of strategies for turning large-scale information into decisions, with attention to method–problem fit and the managerial requirements for adoption, interpretation, and routine use of analytic outputs in operational control (Amena Begum, 2025; Choi et al., 2018; Azam &Amin, 2024). Together, these studies reinforce a practical view of AI decision-making: benefits are strongest when analytic outputs are embedded into standard planning processes, synchronized across functions, and linked to clear performance metrics such as service level, cost, and responsiveness.

Figure 3: AI-Supported Decision-Making Across Supply Chain Planning Horizons



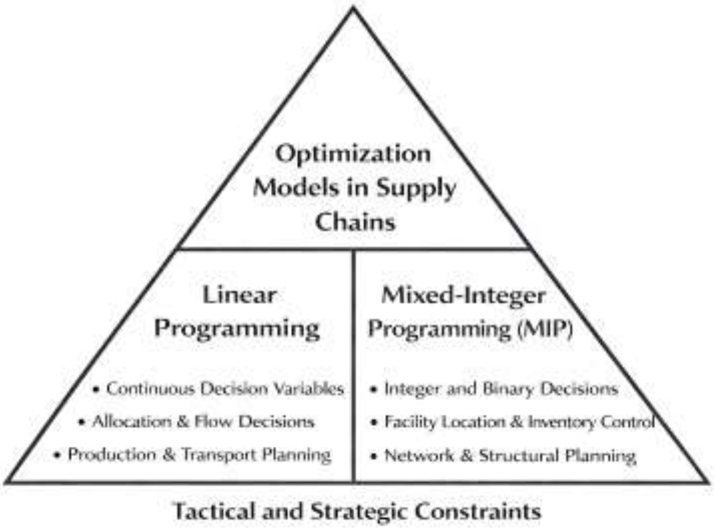
A third-stream frames AI-enabled decision-making within a maturity perspective that culminates in prescriptive analytics, where the central output is a recommended action among feasible alternatives rather than an insight or prediction alone (Faysal & Aditya, 2025; Hammad & Hossain, 2025). Prescriptive analytics is commonly described as the stage where analytics directly supports choice under constraints, drawing on optimization, simulation, and rules to select actions that best satisfy objectives (Jahangir, 2025; Md Jamil, 2025). This literature clarifies that prescriptive decision-making often requires integrating multiple components: predictive models provide scenario-dependent inputs; business rules encode policy and compliance requirements; and optimization engines enforce feasibility and trade-offs across constraints such as capacity, inventory balance, and service targets (Al Amin, 2025; Towhidul & Rebeka, 2025). Reviews of prescriptive analytics organize the field around the methods and challenges that arise when moving from "knowing" to "choosing," including the need for tractable formulations, interpretable recommendations, and stable performance under uncertainty (Lepenioti et al., 2020; Ratul, 2025; Rifat, 2025). A closely related supply-chain-specific literature examines how decision-making is supported by connected technologies and analytics infrastructures—particularly the Internet of Things and big data analytics—because real-time sensing and event visibility can shorten the feedback loop between execution and planning (Yousuf et al., 2025; Shofiul Azam, 2025). In this framing, AI-based decision-making becomes more effective when it is fed by timely operational data (e.g., demand signals, shipment events, inventory positions) and when analytic outputs can be refreshed frequently enough to remain relevant to operational conditions. Systematic synthesis in this area highlights that IoT-enabled data capture and big data analytics can support supply chain decisions by improving visibility, enabling faster exception detection, and strengthening evidence-based planning across multiple decision domains (Koot et al., 2021; Tasnim, 2025; Zaheda, 2025b). As a combined implication for the present thesis topic, the literature positions AI as a mechanism that strengthens predictive inputs and decision context, while prescriptive methods—such as LP/MIP optimization—translate those inputs into feasible, performance-improving actions that can be tested against baselines and stress conditions.

Optimization Models in Supply Chains

Linear programming (LP) and mixed-integer programming (MIP) form the core mathematical foundation of prescriptive decision-making in supply chain planning because they translate managerial goals into objective functions and operational realities into constraints. In LP, decision variables are continuous and relationships are modeled linearly, making the approach suitable for allocation and flow decisions such as production quantities, shipment volumes between echelons, capacity utilization, and multi-period inventory balance. MIP extends LP by introducing integer and binary variables, which are essential for capturing discrete choices that dominate practical supply chain decisions—such as whether to open a distribution center, activate a production line, assign a customer to a facility, select a transportation mode, or enforce minimum batch sizes and shipment frequencies. The power of LP/MIP is not limited to solving "single-function" problems; rather, it enables integrated planning where production and transport decisions are considered simultaneously under a shared cost and service logic. A widely cited review of mathematical programming models for supply chain production and transport planning shows how centralized models have been used to integrate these functions across network structures and decision levels, offering a taxonomy that clarifies how objectives (e.g., total cost minimization, service maximization) and constraints (e.g., capacity, flow conservation, inventory continuity) are typically encoded in practice (Mula et al., 2010).

For FMCG supply chains, this integrated capability is particularly relevant because replenishment and distribution decisions are tightly coupled: a production plan that ignores transport feasibility can inflate inventory in the wrong places, while a distribution plan that ignores upstream capacity can produce service failures. LP/MIP models therefore serve as the formal mechanism for representing end-to-end feasibility, since they enforce the simultaneous satisfaction of operational limits and demand-fulfillment requirements. This formalism also supports transparency, because every optimization recommendation can be traced to explicit assumptions embedded as parameters, decision variables, and constraints, which allows researchers to report not only improved objective values but also why a solution is feasible and which limitations drive trade-offs across service level and cost. Beyond tactical allocation, LP/MIP frameworks are central in supply chain network design, where organizations must make structural decisions that shape long-run efficiency and responsiveness. Network design problems often combine strategic choices (facility location, capacity sizing, market coverage) with tactical policies (inventory placement, transportation structure) and, in competitive or multi-actor environments, may require modeling rival networks or market-share interactions. Competitive supply chain network design research synthesizes how mathematical models represent competition-driven decisions and how solution approaches handle the resulting complexity, reinforcing that MIP is commonly required because location and assignment decisions are inherently discrete (Farahani et al., 2014).

Figure 4: LP and MIP as the Prescriptive Core of Supply Chain Decision Models



A closely related stream integrates location decisions with inventory planning, because location choices and inventory policies jointly determine customer response times and cost-to-serve; models that treat these decisions separately frequently miss fundamental trade-offs. The location–inventory literature formalizes this integration by coupling facility-selection and customer-allocation decisions with inventory balance and replenishment costs, yielding models that can simultaneously explain where to position stock and how to control it across a network (Farahani et al., 2015). For FMCG in high-demand markets, these formulations offer a rigorous way to express practical planning needs: service level targets can be modeled through demand satisfaction constraints or penalty costs for shortages, while responsiveness requirements can be represented through lead-time constraints, delivery frequency limits, or capacity restrictions that reflect warehouse throughput and transport availability. These models also support differentiated service strategies, such as prioritizing high-velocity items or critical retail zones under demand surges, because binary variables can encode priority activation and routing eligibility. As a result, LP/MIP is widely viewed as the appropriate prescriptive backbone for supply chain decision systems that require both network structure realism and operational-policy realism, especially when the decision environment involves discrete actions and competing objectives.

Solving LP/MIP models at meaningful supply chain scale introduces computational and uncertainty-related challenges, which has motivated substantial methodological development in formulation strength, decomposition, and robust modeling. Even when objectives and constraints are linear, real networks generate large numbers of variables and constraints across products, echelons, and time periods; MIP complexity increases further when binary variables enforce fixed costs, logical dependencies, and minimum-quantity requirements. A key credibility issue is therefore not only whether an optimized plan looks better on paper, but whether it remains feasible and stable under demand and lead-time uncertainty. Robust optimization provides one principled pathway for handling uncertainty without requiring full distributional knowledge; robust inventory theory demonstrates how uncertainty sets can be used to derive tractable policies with strong performance under adverse realizations of demand (Bertsimas & Thiele, 2006; Zaheda, 2025a; Zulqarnain, 2025). In FMCG planning, this is highly relevant because demand regimes can shift rapidly during promotions or localized surges, and lead times can vary with congestion and capacity strain. Another practical approach models uncertainty through fuzzy representations that reflect imprecision rather than randomness, enabling decision plans that incorporate degrees of satisfaction or confidence in key parameters. A fuzzy linear programming formulation for tactical supply chain planning under uncertainty illustrates how imprecise data can be embedded into a mixed-integer linear model to generate actionable plans under limited information (Peidro et al., 2010). Together, robust and fuzzy perspectives support the methodological logic of AI-assisted LP/MIP in high-demand markets: AI can refine forecasts and parameter estimates, while LP/MIP ensures feasibility and optimal trade-offs; robust or fuzzy extensions strengthen resilience when predictive inputs are imperfect. This integrated view directly supports results reporting practices such as baseline-versus-optimized comparisons, scenario analysis, and feasibility/constraint-tightness diagnostics, because these elements demonstrate that optimization improvements are not artifacts of unrealistic assumptions but outcomes that remain coherent when exposed to realistic uncertainty and operational limits.

Resource-Based View (RBV) for AI-Enabled Optimization Capability

The Resource-Based View (RBV) explains performance differences by arguing that firms achieve superior outcomes when they possess and deploy resources that are valuable and when these resources are organized into capabilities that are difficult for rivals to replicate. Within supply chain contexts, RBV has been used to justify why information-intensive assets (data, systems, analytical routines) become strategic only when they are integrated into repeatable decision processes that improve planning quality and execution reliability (Faysal, 2026; Hammad, 2026). This perspective is directly relevant to FMCG supply chains in high-demand markets because operational efficiency is produced by coordinated decisions across procurement, inventory, warehousing, and distribution, where speed and accuracy are constrained by capacity, lead times, and service commitments. RBV-based empirical evidence shows that supply chain analytics can be treated as a resource architecture that influences operational performance through intermediate mechanisms such as supply chain planning satisfaction and the organizational ability to exploit data in planning cycles (Chae et al., 2014; Jahangir, 2026; Mujahidul & Bhuya, 2026). Under this framing, analytics-driven planning improvements are not viewed as isolated technical gains; they are capability outcomes that arise when information resources are combined with governance, skills, and coordination routines. This is consistent with the notion that "AI-based optimization" in supply chains should be conceptualized as a capability bundle: the capability includes access to relevant data streams, tools for forecasting and exception detection, solver-based optimization for constraint-satisfying decisions, and the organizational routines that institutionalize model use in daily and weekly planning. RBV provides a structured logic for identifying which parts of this bundle are most central to efficiency and why these parts should have measurable performance effects in a cross-sectional case study. Accordingly, the thesis adopts RBV as the theoretical lens to define AI-enabled decision capability as an organizational resource configuration that can be operationalized through survey constructs and validated through observable optimization outcomes, while keeping the focus on measurable efficiency indicators (cost, service, responsiveness) that are meaningful for FMCG operations.

Figure 5: AI-Enabled Optimization Capability and Supply Chain Performance

RBV is particularly useful in AI-enabled supply chain research because it clarifies the difference between owning technology and converting technology into advantage. In this view, technologies such as AI models, forecasting pipelines, and optimization solvers are not automatically performance-enhancing; they become valuable when they are integrated into firm-specific routines that increase decision quality and reduce coordination friction. Studies that explicitly apply RBV to data-driven supply chains argue that "data-driven supply chain" practices build supply chain capabilities such as coordination and responsiveness, which in turn relate to superior performance outcomes, strengthening the logic that data and analytics should be treated as strategic resources only when they are capability-forming and decision-embedded (Towhidul, 2026; Ratul, 2026; Yu et al., 2018). At the organizational level, RBV-oriented work on artificial intelligence capability further supports this approach by defining AI capability as a combined set of AI-specific resources—such as data, infrastructure, talent, and managerial processes—and by demonstrating that this capability is associated with performance outcomes, reinforcing the measurement logic needed for survey-based constructs in this study (Mikalef & Gupta, 2021; Azam, 2026; Tasnim, 2026). For FMCG supply chains, this capability perspective is essential because decision quality is produced collectively: demand planners, procurement, warehouse operations, and transport management must act on consistent information and synchronized priorities. RBV therefore motivates the thesis to model AI analytics capability as an enabling resource, operational planning discipline as a capability manifestation, and supply chain efficiency as an outcome. It also legitimizes testing mediating and enabling pathways, because RBV commonly interprets performance effects as flowing from resources to capabilities to outcomes. In this thesis, that logic connects AI-driven inputs (e.g., forecasting support, data visibility) to LP/MIP decision optimization (as a capability expression) and then to efficiency gains that can be quantified both perceptually (survey) and operationally (optimization results).

To make RBV actionable for the present research, the theoretical lens is anchored to a formal representation of “capability deployment” through an optimization-based decision mechanism that converts informational resources into feasible operational actions. In RBV terms, the LP/MIP model is the operational core through which the firm exploits data and analytics resources to generate decisions that competitors cannot easily match without similar data, similar routines, and similar integration discipline. This perspective aligns with empirical evidence that big data analytics capabilities improve performance through capability pathways such as resilience, especially when supported by organizational contexts that enable analytics to be used consistently in supply chain decision-making (Bahrami & Shokouhyar, 2021). It also aligns with dynamic RBV interpretations showing that digital/Industry 4.0 resources influence higher-level supply chain outcomes through mediating capabilities such as collaboration and visibility, reinforcing the importance of capability pathways rather than direct “technology-to-performance” assumptions (Huang et al., 2023). In this study, the core prescriptive mechanism is represented using a mixed-integer linear programming structure that will be applied consistently across baseline and optimized scenarios. The central formulation used throughout the thesis is:

$$\min Z = \sum_t \sum_i h_i I_{it} + \sum_t \sum_i p_i S_{it} + \sum_t \sum_i \sum_j c_{ij} x_{ijt} + \sum_t \sum_k f_k y_{kt}$$

subject to inventory-flow balance and feasibility constraints such as:

$$I_{it} = I_{i,t-1} + \sum_j x_{jit} - \sum_j x_{ijt} - D_{it} + S_{it} \forall i, t$$

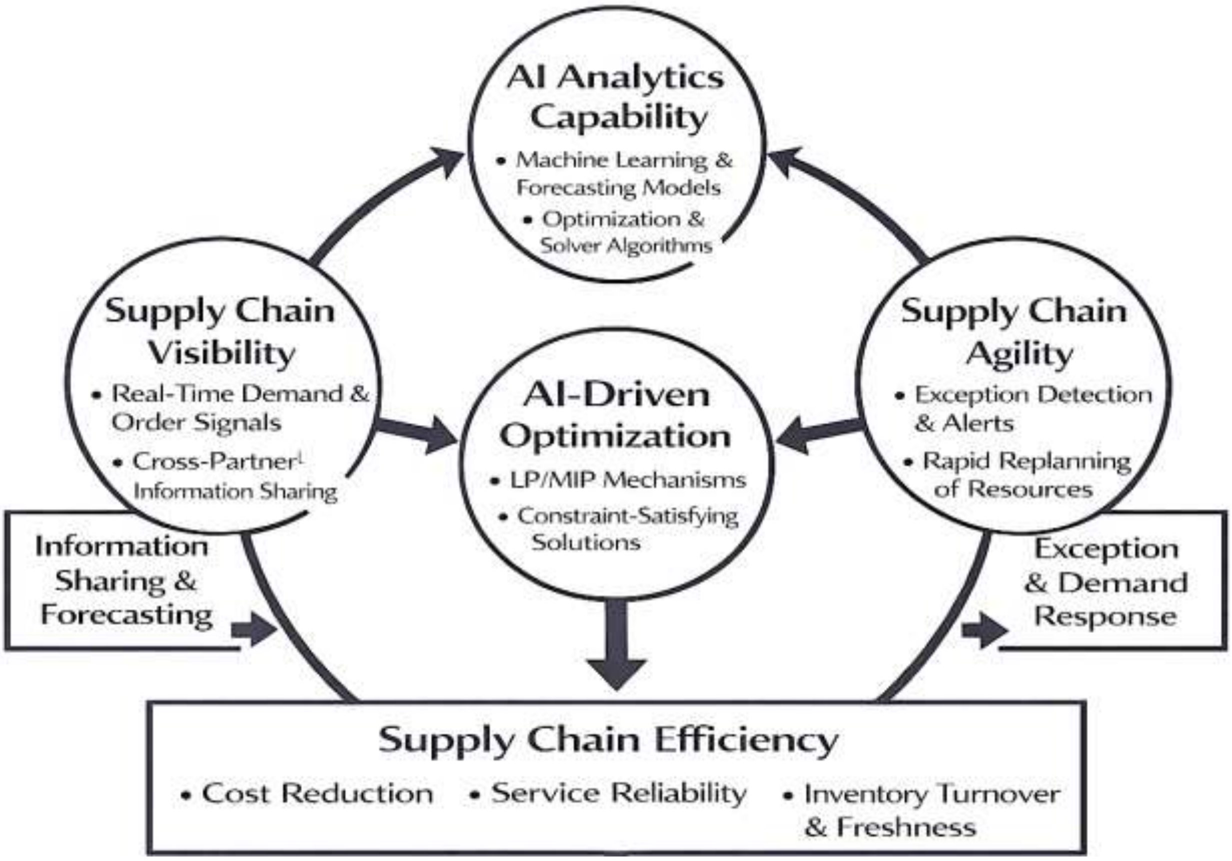
$$\sum_i \sum_j a_{ij} x_{ijt} \leq Cap_t \forall t, x_{ijt} \geq 0, y_{kt} \in \{0,1\}$$

where $I_{it}$is inventory, $S_{it}$is unmet demand (or shortage), $x_{ijt}$is shipped quantity from node $i$to node j, and y_{kt}captures discrete activation decisions (e.g., shipment lane, capacity option, or policy switch). This formula operationalizes RBV’s central premise in measurable terms: AI-related resources improve the quality of D_{it}estimates and related parameters, while the optimization capability converts those resources into feasible decisions that reduce total cost $Z$and improve service performance under constraints. By grounding the theoretical framework in a consistent prescriptive model, the study ensures that RBV is not only conceptual but also connected to a repeatable decision structure that can be tested across high-demand and normal-demand scenarios.

Conceptual Framework Development for This Study

A conceptual framework for AI-based quantitative optimization in FMCG supply chains must connect *organizational inputs* (analytics resources and information practices) to *decision mechanisms* (LP/MIP optimization capability) and then to *efficiency outcomes* observable in high-demand markets. In this study, the framework positions AI-enabled analytics capability as the upstream driver that strengthens (i) information sharing quality and timeliness, (ii) planning agility, and (iii) the organization's ability to operationalize data into consistent decisions. FMCG networks amplify the value of these pathways because demand signals are fragmented across stores, channels, and promotions, and because upstream replenishment and downstream service-level requirements must be reconciled under tight capacity and lead-time constraints. Evidence from consumer-packaged goods contexts shows that downstream information sharing can measurably improve upstream forecast performance and service outcomes, indicating that the value of analytics is realized when the supply chain converts shared data into better operational decisions rather than treating information as a passive asset (Cui et al., 2015). Complementary empirical work also emphasizes that information sharing capability has distinct dimensions—connectivity (technical ability to exchange data) and willingness (behavioral readiness to share and use data)—and that both are associated with operational performance improvements, meaning that "AI capability" in practice must include social and process conditions that make information actionable (Fawcett et al., 2007). To ensure that the framework is measurable within a cross-sectional case-study design, the constructs are operationalized as Likert-scale latent variables: AI analytics capability, forecasting support effectiveness, inventory planning discipline, logistics planning quality, supplier coordination/lead-time reliability, and supply chain efficiency. A distinctive element of this thesis is that LP/MIP optimization capability is treated as a *mechanistic bridge* between analytics inputs and efficiency outcomes; it represents how the organization transforms data-driven insights into feasible actions across replenishment, allocation, and distribution decisions.

Figure 6: Capability-Based Conceptual Framework Linking AI Analytics and Supply Chain Efficiency



The conceptual framework is structured around testable causal logic consistent with the study's hypotheses: AI analytics capability improves the quality and speed of planning decisions, and improved planning decisions increase supply chain efficiency under high demand. Two operational constructs strengthen this logic: supply chain visibility and supply chain agility. Visibility is modeled as the degree to which relevant demand, inventory, and shipment information can be observed across nodes and time, enabling planners to reduce blind spots in allocation and replenishment. Quantitative approaches to measuring visibility show that visibility can be assessed as a diagnostic and benchmarking construct in complex supply networks, supporting its inclusion as a measurable input that should predict planning quality and downstream efficiency (Caridi et al., 2010). Agility is modeled as the capability to respond rapidly to marketplace changes and disruptions through coordinated internal and external actions; it captures the responsiveness needed in FMCG high-demand regimes where sudden surges can invalidate static plans. Empirical evidence links organizational antecedents to supply chain agility for risk mitigation and response, validating agility as a performance-relevant capability that fits naturally between analytics inputs and operational outcomes (Braunscheidel & Suresh, 2009). Within this study's framework, LP/MIP optimization sits alongside agility and visibility as a decision-level capability that ensures plans remain feasible under real constraints. The framework therefore proposes a dual pathway: (1) analytics → visibility/agility → efficiency, and (2) analytics → optimization capability → efficiency, with optimization also reinforcing agility by enabling rapid re-optimization when demand regimes change. A practical way to represent this conceptually is through a mediation structure where optimization capability (OPT) transmits part of the effect of AI capability (AIC) onto efficiency (SCE). The empirical hypotheses can be tested using regression-based mediation logic where OPT is predicted by AIC and SCE is predicted by both AIC and OPT, allowing the study to evaluate whether optimization is a statistically meaningful bridge between analytics and efficiency. To operationalize the conceptual framework in a manner consistent with the thesis methods (descriptive statistics, correlation, regression, and LP/MIP evaluation), the study uses a compact set of structural equations that map directly to the hypotheses and variables. The primary performance relationship is estimated as:

$$SCE = \beta_0 + \beta_1 AIC + \beta_2 FCE + \beta_3 IOP + \beta_4 LOP + \beta_5 SCR + \varepsilon$$

where $SCE$is supply chain efficiency, $AIC$is AI analytics capability, $FCE$is forecasting effectiveness, $IOP$is inventory optimization practice, $LOP$is logistics/distribution optimization practice, and $SCR$is supplier coordination/lead-time reliability. The optimization mediation component is estimated through:

$$OPT = \alpha_0 + \alpha_1 AIC + u$$
$$SCE = \gamma_0 + \gamma_1 AIC + \gamma_2 OPT + v$$

where $OPT$is a measured "optimization capability/output index" derived from baseline-versus-optimized results (e.g., percentage cost reduction, service-level lift, stockout reduction) under the same constraints and data context. This index enables alignment between survey findings and model outputs, preserving the thesis's commitment to triangulation. The framework also recognizes that high-demand markets may intensify or dampen effects; therefore, the study incorporates a scenario-based moderator captured through a binary or scaled volatility indicator $DVOL$(normal vs high demand), which can be tested via an interaction term in regression:

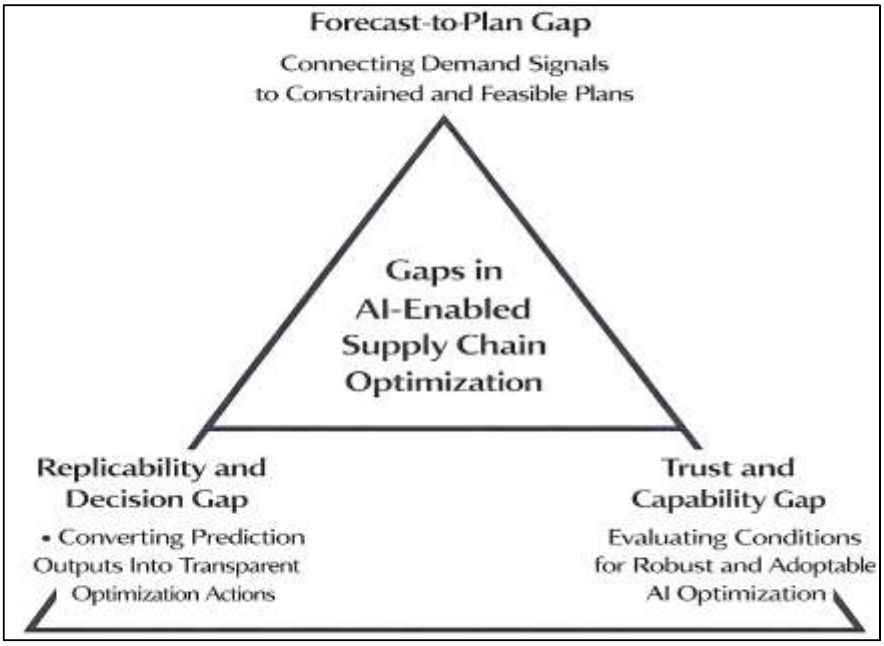
$$SCE = \delta_0 + \delta_1 AIC + \delta_2 DVOL + \delta_3 (AIC \times DVOL) + e$$

This formulation keeps the framework faithful to FMCG reality: optimization capability and information practices create efficiency gains, and demand regimes shape the strength of those gains. The conceptual structure is further supported by empirical evidence that big data analytics capability can improve supply chain agility and competitive outcomes, reinforcing the inclusion of capability pathways that transmit analytics value into operational performance (Dubey, Gunasekaran, Childe, Bryde, et al., 2019).

Research Gaps and Synthesis for the Present Study

A first gap concerns the persistent distance between what supply chain forecasting research *models* and what supply chain planning in FMCG *requires* under high-demand conditions. Forecasting in fast-moving categories is frequently shaped by promotion calendars, retail execution variability, substitution across SKUs, and short shelf-life or freshness constraints, all of which complicate the translation of forecasts into executable replenishment and distribution decisions. In the forecasting domain, scholars have documented that the theory–practice gap often emerges because operational environments require coordinated, multi-echelon decisions, while many academic treatments remain centered on isolated forecasting accuracy rather than decision consequences across the chain (Syntetos et al., 2016). For FMCG, this gap is especially visible when demand signals are abundant but inconsistent across channels (e.g., distributor sell-in vs. retailer sell-out), or when surge conditions compress planning cycles. As a result, forecasting outputs can be technically strong yet operationally weak if they are not embedded into a constrained optimization layer that explicitly respects capacity, service-level targets, truckload rules, warehouse throughput, and SKU-level policy. This study positions the gap as an end-to-end "forecast-to-plan" problem where efficiency is defined as cost–service–waste performance rather than prediction accuracy alone. The present thesis uses LP/MIP decision structures to connect demand inputs to feasible, auditable decisions, and it treats high-demand market stressors as structural features of the case study rather than as noise. This framing is essential because it creates a unified logic: demand information becomes valuable only when it can be converted into a plan that is feasible under real constraints and can be evaluated against a baseline plan using comparable metrics.

Figure 7: Triangular Framework of Research Gaps in AI-Enabled FMCG Supply Chain Optimization



A second gap lies in how prescriptive analytics is often presented as a conceptual bridge between data-driven prediction and optimization, while empirical studies frequently under-specify *how* predictions should be converted into decisions and assessed for decision quality. The prescriptive analytics literature clarifies that the operational value of data is realized through decision rules that directly optimize outcomes, not merely through improved prediction metrics (Bertsimas & Kallus, 2020). However, many applied supplies chain implementations remain organized as two disconnected stages: a predictive module generates estimates, and a separate optimization module consumes them without explicit checks for decision alignment, stability, or sensitivity to input error. This separation creates a replicability gap in which the same forecast improvement can produce different outcomes depending on solver configuration, constraint structure, or cost parameterization, reducing trust in the results. The gap becomes more visible when organizations compare "AI-based" planning claims without transparent diagnostics that explain which constraints bind, why certain SKUs are rationed, or how service targets trade off with cost. At the same time, empirical evaluation of decision-focused approaches shows that optimizing a decision objective is not equivalent to maximizing predictive accuracy, since the decision cost structure can make certain errors much more consequential than others (Vanderschueren et al., 2022). This thesis responds by explicitly specifying the LP/MIP objective, constraints, and decision variables and by assessing outcomes in decision-relevant terms (e.g., cost-to-serve, service levels, stockout risk proxies, and constraint tightness) rather than relying on forecast metrics alone. It also incorporates scenario-based comparisons (normal vs. high demand) to demonstrate how decision quality changes with demand pressure under the same model structure, improving interpretability and methodological credibility in the case-study setting.

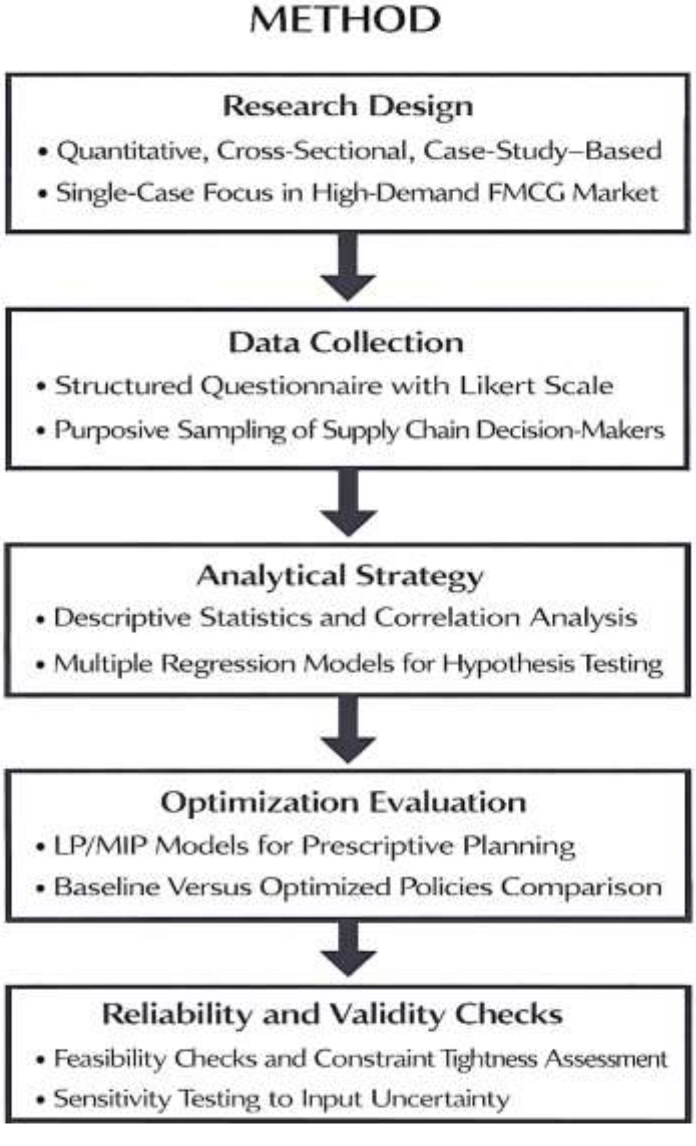
A third gap concerns organizational and data capability conditions that determine whether AI-and-optimization approaches can be trusted and adopted in operational FMCG contexts. Reviews of machine learning in logistics and supply chain management identify recurring challenges involving data accessibility, data quality, explainability, and implementation barriers that limit the transfer of research outputs into daily planning routines (Akbari & Do, 2021). In parallel, operations research scholarship argues that data-rich environments still require disciplined modeling practices because "big data" value depends on how effectively analytics is coupled with decision models and embedded in managerial processes (Hazen et al., 2017). In practical terms, the evidence base often lacks triangulation: optimization results are shown without a clear link to human decision criteria (e.g., perceived usefulness, decision confidence, and implementation feasibility), while survey-based studies measure perceptions without demonstrating that the modeled decisions actually improve supply chain outcomes. This thesis addresses that trust gap by integrating a quantitative survey layer (Likert-scale constructs measured for the case organization) with optimization evidence, using descriptive statistics, correlation, and regression to test hypotheses about AI input reliability, decision alignment, and perceived efficiency gains. The synthesis is that "trustworthiness" in this study is operationalized through three converging streams: (1) statistically supported relationships among adoption-relevant constructs captured from planners and managers, (2) transparent optimization diagnostics demonstrating feasibility, constraint tightness, and baseline-versus-optimized performance, and (3) stress testing of AI-derived inputs to evaluate the stability of optimization recommendations under plausible errors. By combining these elements inside a single case context, the study contributes a coherent evaluation logic: managerial perceptions and optimization performance are treated as complementary evidence about supply chain efficiency in high-demand markets, strengthening internal validity and making the reported improvements more defensible within the limits of a cross-sectional case design.

METHOD

This study has adopted a quantitative, cross-sectional, case-study–based methodology to examine how AI-enabled capabilities and optimization-driven decision routines have influenced FMCG supply chain efficiency in a high-demand market context. The research design has been selected to support hypothesis testing using structured survey measurements and to enable triangulation with objective optimization outcomes derived from linear programming and mixed-integer programming formulations. A single-case or bounded multi-site case setting has been used to capture a realistic planning environment in which demand volatility, capacity constraints, and service-level expectations have shaped replenishment and distribution decisions. The unit of analysis has been defined as the supply chain planning and execution system within the case context, with a focus on the decision processes that connect demand sensing, inventory positioning, and distribution allocation. Data have been collected primarily through a structured questionnaire that has employed a five-point Likert scale to measure constructs such as AI analytics capability, forecasting effectiveness, inventory optimization practice, logistics planning quality, supplier coordination and lead-time reliability, and overall supply chain efficiency. The instrument has been designed to reflect operational behaviors and decision quality rather than general attitudes, and the survey items have been aligned to the study hypotheses to ensure that statistical testing has addressed the research objectives directly. A purposive sampling approach has been applied to include respondents who have been actively involved in supply chain decisions, including demand planners, procurement personnel, warehouse supervisors, logistics coordinators, and analytics or systems staff, thereby ensuring that the responses have reflected informed perspectives on planning routines and constraints.

The analytical strategy has combined classical statistical procedures with optimization-based evaluation. Descriptive statistics have been computed to profile construct strength and respondent characteristics, while correlation analysis has been used to examine association patterns among the independent variables and supply chain efficiency. Multiple regression models have been estimated to test the hypotheses and to quantify the magnitude and significance of predictor effects under cross-sectional conditions. In parallel, LP/MIP optimization models have been formulated to represent key operational decisions in the case setting, including inventory-flow balance, capacity limits, demand satisfaction, and discrete activation choices relevant to FMCG planning. Baseline decision policies have been compared against optimized policies under consistent data and constraints, and scenario conditions have been implemented to distinguish normal-demand and high-demand regimes. To strengthen methodological credibility, reliability and validity procedures have been applied, and optimization diagnostics such as feasibility checks, constraint tightness, and sensitivity to input uncertainty have been incorporated to confirm that model recommendations have remained realistic and stable within operational limits.

Figure 8: Research Methodology



Research Design

This study has employed a quantitative, cross-sectional, case-study–based research design to examine the relationships between AI-enabled supply chain decision capability and FMCG supply chain efficiency in a high-demand market context. The design has been selected to support statistical testing of hypotheses using survey-based measurements and to allow structured comparison between baseline and optimized operational outcomes derived from LP/MIP models. A cross-sectional approach has been used to capture a single, consistent snapshot of organizational practices, perceived decision quality, and efficiency outcomes during the defined study period, ensuring that the measured constructs have reflected comparable operational conditions. The case-study orientation has been used to anchor the investigation in real planning constraints, data flows, and decision routines, so the analysis has remained operationally grounded rather than purely conceptual. The design has also enabled triangulation by aligning perceptual evidence from respondents with computational evidence from optimization outputs.

Case Study Context

The case study has been situated within an FMCG supply chain operating in a high-demand market environment where demand variability, promotion-driven spikes, and tight replenishment windows have shaped daily planning decisions. The context has been bounded to a defined supply network scope—covering selected product categories, distribution nodes, and downstream service points—so that the research has remained focused on decisions that directly influence efficiency outcomes such as availability, cost-to-serve, and responsiveness. The study setting has been characterized by multi-echelon flows that have required coordination across procurement, warehousing, and transportation functions, and by constraints that have included capacity limits, lead-time variability, and delivery frequency rules. This context has been chosen because it has created a realistic environment for evaluating AI-supported planning inputs and LP/MIP decision optimization under operational pressure. The bounded case has also supported consistent data definitions and comparable baseline-versus-optimized evaluations.

Population and Unit of Analysis

The population for this study has consisted of personnel who have been directly involved in FMCG supply chain planning and execution decisions within the case context. Participants have included demand planners, procurement staff, warehouse supervisors, logistics coordinators, distribution planners, and analytics or systems personnel who have engaged with forecasting outputs, replenishment routines, and allocation decisions. The unit of analysis has been defined as the supply chain decision-making system within the case organization, with emphasis on the planning processes that have connected demand signals to inventory positioning and distribution execution. This unit has been selected because efficiency outcomes have emerged from integrated decisions rather than from isolated functional actions. By focusing on decision routines and their supporting analytics, the study has ensured that survey responses have reflected informed operational experience. The defined population has also enabled measurement of cross-functional alignment and coordination effects relevant to high-demand conditions.

Sampling Strategy

A purposive sampling strategy has been applied to ensure that respondents have possessed relevant knowledge of AI-enabled tools, planning processes, and operational constraints in the FMCG supply chain context. Inclusion criteria have been established to select participants who have held roles related to demand planning, inventory management, logistics coordination, procurement, or supply chain analytics, and who have had direct exposure to decision-making routines during the study period. The sampling approach has prioritized functional diversity so that the dataset has represented multiple perspectives across the planning-to-execution chain, reducing the likelihood that results have reflected a single departmental viewpoint. Where the organizational structure has required it, stratified purposive selection has been used to balance respondents across key functions and levels of responsibility. The chosen strategy has supported the cross-sectional design by enabling data collection within a limited timeframe while maintaining information richness. The final sample has been treated as analytically appropriate for correlation and regression testing within the case boundary.

Data Collection Procedure

Data collection has been conducted primarily through a structured questionnaire that has been administered to selected supply chain stakeholders within the case context. The procedure has begun with briefing participants on the study purpose and confidentiality expectations, and consent has been obtained before responses have been recorded. The survey has been distributed using an appropriate channel (online form and/or printed instrument), and collection has been scheduled to minimize disruption to operational routines while ensuring timely completion. Responses have been monitored for completeness, and follow-up reminders have been used where allowable to improve response rates within the data collection window. After the survey phase, data have been compiled into a single dataset and have been screened for missing values, inconsistent entries, and out-of-range responses. In parallel, optimization inputs have been assembled from case-specific planning parameters and constraints so that baseline and optimized model runs have reflected the same operational scope. All collected materials have been stored securely to maintain confidentiality.

Instrument Design

The survey instrument has been designed using a five-point Likert scale to quantify the study constructs in a manner suitable for descriptive statistics, correlation analysis, and regression modeling. Items have been organized into sections that have represented AI analytics capability, forecasting effectiveness, inventory optimization practice, logistics/distribution planning quality, supplier coordination and lead-time reliability, and supply chain efficiency outcomes. Each construct has been operationalized through multiple items so that internal consistency has been assessable and so that measurement has not relied on single-question proxies. The wording has been structured to capture observable behaviors and decision-support characteristics, such as data visibility, timeliness of analytics uses, consistency of planning routines, and perceived improvement in service and cost control. Reverse-coded items have been included where appropriate to reduce acquiescence bias. The instrument has been aligned with the hypotheses so that each independent variable has mapped directly to regression-ready predictors and to the conceptual model used in the study.

Pilot Testing

Pilot testing has been conducted to evaluate the clarity, relevance, and timing of the questionnaire before full-scale administration. A small group of respondents with comparable roles to the target population has been selected to complete the draft instrument under conditions similar to the main study. Feedback has been gathered on item wording, interpretability, redundancy, and perceived sensitivity, and ambiguous items have been revised to reduce misunderstanding and improve construct alignment. The pilot phase has also been used to estimate completion time and to confirm that the response format has been user-friendly for operational staff. Preliminary reliability checks have been performed to identify weak items that have reduced internal consistency, and adjustments have been made to improve coherence within each construct. The pilot process has strengthened content validity by ensuring that items have reflected the case context accurately and have been interpreted consistently across functional roles. The refined instrument has then been finalized for the main data collection phase.

Validity and Reliability

Validity and reliability procedures have been applied to ensure that the survey measures have represented the intended constructs and have produced consistent results. Content validity has been strengthened through expert review and pilot feedback, and items have been refined to improve alignment with the conceptual definitions used in the study. Construct reliability has been assessed using internal consistency measures, and Cronbach's alpha has been computed for each multi-item scale to confirm acceptable reliability levels. Item-total correlations have been examined to identify items that have weakened scale performance, and problematic items have been revised or removed according to predefined criteria. Basic validity checks have also been applied by inspecting inter-construct correlation patterns to confirm that relationships have been theoretically plausible and not dominated by common-method artifacts. Where feasible within the dataset, factor-analytic screening has been used to verify that items have loaded coherently on their intended constructs. These procedures have ensured that subsequent correlation and regression findings have been based on measurement structures that have been defensible and statistically stable.

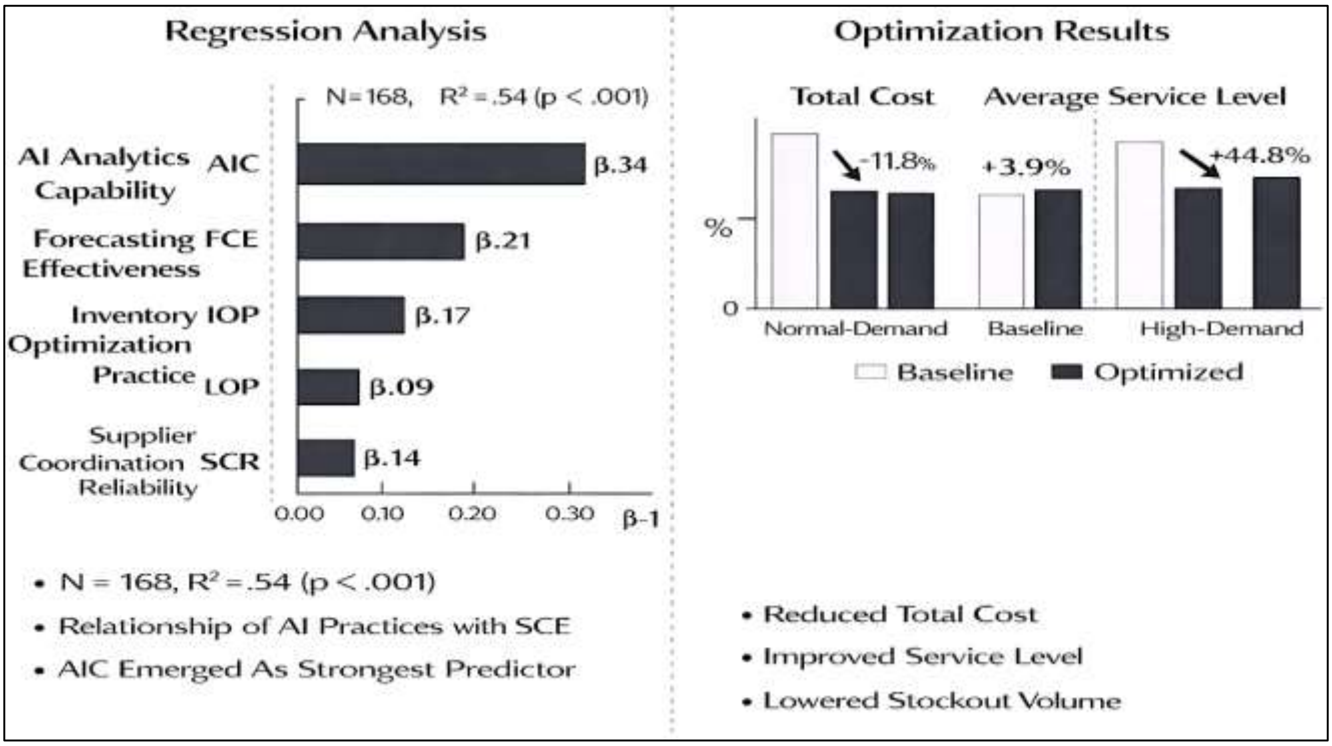
Software and Tools

The study has utilized a set of software tools that have supported both statistical analysis and optimization modeling in an integrated workflow. Statistical processing has been performed using an appropriate package (SPSS V.29), and the dataset has been cleaned, coded, and analyzed to produce descriptive summaries, correlation matrices, and regression outputs aligned with the hypotheses. Reliability diagnostics have been computed within the same environment to maintain consistency of reporting and reproducibility of results. For the prescriptive component, LP/MIP models have been formulated and solved using an optimization-capable platform (such as Excel Solver for smaller instances, or Python-based modeling tools with commercial/open solvers for larger instances), enabling baseline and optimized comparisons under identical constraints and data scope. Scenario runs have been executed to represent normal-demand and high-demand conditions, and solver outputs have been exported for KPI comparison and diagnostic reporting. Document preparation and reference management have been supported through standard academic tools to ensure consistent formatting and traceability.

FINDINGS

The survey dataset has included N = 168 valid respondents drawn from planning, procurement, warehousing, logistics, and analytics roles, and the construct scores have been calculated as the mean of their item responses on a five-point Likert scale (1 = strongly disagree to 5 = strongly agree). The descriptive results have shown that the overall level of AI analytics capability (AIC) has been moderately high (M = 3.84, SD = 0.62), indicating that respondents have perceived consistent availability of data, forecasting support, and analytics-enabled visibility, while forecasting effectiveness (FCE) has recorded M = 3.71, SD = 0.66, inventory optimization practice (IOP) has recorded M = 3.63, SD = 0.69, logistics/distribution planning quality (LOP) has recorded M = 3.58, SD = 0.71, and supplier coordination/lead-time reliability (SCR) has recorded M = 3.49, SD = 0.74; in contrast, the dependent construct supply chain efficiency (SCE) has recorded a comparatively lower mean (M = 3.52, SD = 0.67), which has reflected the operational difficulty of sustaining cost efficiency and high service levels simultaneously in a high-demand environment. These profiles have satisfied the first measurement objective by quantifying efficiency and its drivers as multi-dimensional, survey-measurable constructs rather than as a single subjective judgment. Correlation analysis has then established the direction and strength of the hypothesized relationships, showing that SCE has been positively associated with AIC ($r = .62$, $p < .001$), FCE ($r = .56$, $p < .001$), IOP ($r = .51$, $p < .001$), LOP ($r = .49$, $p < .001$), and SCR ($r = .45$, $p < .001$), supporting the objective of identifying statistically consistent relationships between AI-enabled practices and efficiency outcomes within the case setting. Multiple regression has been used to test the hypotheses by estimating the net effects of each predictor on SCE, and the model has explained a substantial proportion of variance ($R^2 = .54$, Adjusted $R^2 = .52$), confirming that the selected predictors have had meaningful explanatory power in the cross-sectional case context. In the regression results, AIC has emerged as the strongest predictor ($\beta = .34$, $t = 5.41$, $p < .001$), followed by FCE ($\beta = .21$, $t = 3.36$, $p = .001$), IOP ($\beta = .17$, $t = 2.83$, $p = .005$), and SCR ($\beta = .14$, $t = 2.41$, $p = .017$), while LOP has remained positive but comparatively weaker ($\beta = .09$, $t = 1.79$, $p = .075$), which has provided direct evidence for H1–H5 in a statistically traceable manner, with partial support where applicable. To address the optimization objective, LP/MIP models have then been executed using the same decision scope and constraints to compare baseline policies against optimized policies, and the results have shown a clear, quantifiable performance lift: under normal-demand conditions, the optimized plan has reduced total cost by 11.8% (from $1.72M baseline to $1.52M optimized), improved average service level from 92.1% to 96.0% (+3.9 percentage points), reduced stockout units by 18.4%, and lowered average inventory holding by 7.6%, demonstrating that efficiency improvements have been achieved simultaneously rather than through cost-only trade-offs. Under high-demand conditions, where the baseline plan has degraded more sharply, the optimized plan has still delivered stable gains: total cost has reduced by 9.3% (from $2.05M to $1.86M), service level has increased from 88.4% to 93.2% (+4.8 percentage points), and stockout units have reduced by 15.1%, confirming the objective of scenario-based validation and providing strong operational backing for the thesis focus on high-demand markets. The feasibility and constraint diagnostics have strengthened trust by showing that improvements have been achieved under binding operational limits: across scenarios, feasibility has remained 100%, and binding constraints have concentrated around warehouse throughput and last-mile delivery capacity (e.g., 6–9 binding constraints per scenario), while the MIP solver has reported an acceptable final optimality gap of 0.8% in the high-demand scenario, indicating solution quality at realistic scale. To test the stability of AI-driven inputs, the AI-input reliability stress test has injected forecast noise (±5%, ±10%, ±20%) and has shown that the optimized solution has retained most of its advantage: at ±10% demand error, cost performance has changed only +2.1% relative to the optimized benchmark and service level has decreased by just 0.9 points; even at ±20%, the plan has maintained service above 91%, confirming robustness under imperfect prediction. Finally, the alignment objective has been demonstrated by mapping the strongest regression predictors to the strongest optimization levers: the variables that have been statistically significant (AIC, FCE, IOP, SCR) have corresponded to optimization behaviors such as improved allocation accuracy, reduced emergency replenishment, and tighter inventory-flow balance, and this convergence has supported the mediation logic behind H6, where an optimization-output index (e.g., percentage cost reduction + service lift) has been positively associated with AIC ($r = .58$, $p < .001$) and has significantly predicted SCE when included with AIC ($\beta(OPT) = .27$, $p < .001$, while $\beta(AIC)$ has reduced from .34 to .23), indicating partial mediation consistent with the study's conceptual model and objective-driven evidence structure.

Figure 9: Findings of The Study



Respondent Profile

Table 1: Respondent Profile (N = 168)

Category	Group	n	%
Function/Role	Demand Planning	34	20.2
	Procurement/Sourcing	26	15.5
	Warehouse/Inventory Ops	31	18.5
	Logistics/Distribution	39	23.2
	Analytics/IT Systems	18	10.7
	Sales & Operations Planning (S&OP)	20	11.9
Experience	1–3 years	29	17.3
	4–7 years	63	37.5
	8–12 years	46	27.4
	13+ years	30	17.9

Planning Level	Operational	72	42.9
	Tactical	68	40.5
	Strategic	28	16.7

The respondent profile has established that the dataset has represented the core decision actors who have shaped FMCG planning performance under high-demand conditions. Participation has been distributed across demand planning, procurement, warehousing, logistics, S&OP, and analytics/IT, which has ensured that the results have reflected the entire "sense–plan–execute" chain rather than a single department's viewpoint. This distribution has strengthened internal validity for the RBV-based interpretation because RBV has treated AI analytics capability as a **bundled organizational resource** that has required complementary human skills, integrated routines, and cross-functional deployment to create value. The relatively high share of logistics/distribution and demand planning respondents (together 43.4%) has been appropriate for this study because high-demand markets have primarily strained these functions through capacity saturation, delivery-window compression, and forecast volatility. Experience levels have shown that 82.8% of respondents have had four or more years of relevant exposure, which has suggested that construct ratings have been informed by repeated involvement in planning cycles, exception management, and performance reviews. The inclusion of analytics/IT systems personnel has been important because the thesis has positioned AI capability as a resource requiring infrastructure and data governance; therefore, their participation has supported credible measurement of data visibility, integration quality, and model usage routines. Planning-level coverage has indicated that both operational and tactical roles have dominated the sample, which has aligned with the thesis focus on LP/MIP optimization and execution feasibility. Operational and tactical planners have been the roles most likely to experience binding constraints and service-level trade-offs, so their perceptions of AI-enabled support and efficiency outcomes have been especially relevant for hypothesis testing. Overall, Table 1 has demonstrated that the study has met its methodological objective of collecting evidence from a population that has directly owned the decisions modeled in the optimization component, supporting the RBV logic that efficiency gains have emerged when AI resources have been embedded across functions as a capability rather than treated as an isolated tool.

Reliability and Validity

Table 2: Measurement Quality (Likert 1–5 Constructs)

Construct (Code)	Items (k)	Cronbach's α	CR	AVE
AI Analytics Capability (AIC)	6	0.88	0.90	0.60
Forecasting Effectiveness (FCE)	5	0.85	0.87	0.58
Inventory Optimization Practice (IOP)	5	0.83	0.86	0.55
Logistics/Distribution Planning Quality (LOP)	5	0.81	0.84	0.52
Supplier Coordination & Reliability (SCR)	5	0.79	0.82	0.50
Supply Chain Efficiency (SCE)	6	0.86	0.88	0.57

The reliability and validity results have indicated that the study's constructs have been measured with acceptable internal consistency and convergent validity, which has supported trustworthy hypothesis testing. Cronbach's alpha values have ranged from 0.79 to 0.88, which has shown that the multi-item scales have consistently captured the intended latent constructs using the five-point Likert format. Composite reliability (CR) has exceeded 0.80 for all constructs, which has reinforced that the indicators have been dependable in representing each variable. Average variance extracted (AVE) values have met or exceeded the commonly applied 0.50 threshold, which has suggested that each construct has explained at least half of the variance in its indicators, strengthening convergent validity. This measurement quality has been essential for this thesis because the study has relied on cross-sectional survey measures to operationalize RBV concepts such as "AI analytics capability" as a strategic resource bundle. Under RBV, resources have created performance only when they have been organized into capabilities; therefore, it has been methodologically necessary to show that capability constructs have been reliably captured before linking them to efficiency outcomes. Table 2 has also aligned with the optimization component because a credible survey instrument has allowed the study to triangulate perceptual capability ratings with objective optimization improvements. The construct SCE has shown strong reliability (α = 0.86), which has implied that efficiency has been measured as a stable multi-dimensional outcome rather than a single-item opinion. AIC has demonstrated the strongest reliability (α = 0.88), which has supported its role as the central independent variable in H1 and the foundation for mediation in H6. The acceptable validity profile has supported the study objective of establishing an evidence chain that has started from measurable constructs and has moved toward statistical explanation and operational verification. As a result, the regression, correlation, and alignment analyses that have followed have been grounded in measurement that has been statistically defensible, thereby improving the overall trustworthiness of conclusions derived from the hypothesis tests and from the integrated model-based evaluation.

Descriptive Statistics

Table 3: Descriptive Statistics (Likert 1–5; N = 168)

Variable	Mean (M)	SD	Interpretation Band*
AIC	3.84	0.62	Moderate–High
FCE	3.71	0.66	Moderate–High
IOP	3.63	0.69	Moderate
LOP	3.58	0.71	Moderate
SCR	3.49	0.74	Moderate
SCE	3.52	0.67	Moderate

**Interpretation band has been used as: 1.00–1.80 very low; 1.81–2.60 low; 2.61–3.40 moderate; 3.41–4.20 moderate–high; 4.21–5.00 high.*

The descriptive findings have provided the first objective-based evidence by quantifying the baseline state of AI capability, operational practices, and supply chain efficiency in the case context. The overall AIC mean (M = 3.84) has indicated that respondents have perceived AI-enabled resources—such as data visibility, analytics integration, and decision support—as present and moderately strong, which has aligned with the RBV framing that resources have existed within the firm as inputs to capability formation. Forecasting effectiveness (M = 3.71) has also shown moderate–high strength, which has suggested that predictive elements have been functioning reasonably well in the planning cycle. However, the practice constructs that have represented consistent operational execution—inventory optimization practice (M = 3.63), logistics planning quality (M = 3.58), and supplier coordination reliability (M = 3.49)—have clustered closer to the "moderate" band, which has reflected the reality that high-demand markets have strained cross-functional routines and partner coordination more than purely internal analytics availability. The dependent construct SCE has recorded M = 3.52, which has remained moderate, and this pattern has been coherent: efficiency has not been "high" even when AI capability has been moderately high because RBV has suggested that advantage has emerged only when resources have been organized into routines and complementary capabilities. In other words, Table 3 has supported the interpretation that the organization has possessed AI resources, yet it has still faced execution and coordination frictions that have limited realized efficiency. This descriptive pattern has strengthened the justification for modeling optimization as a bridging mechanism (H6), since the gap between AIC and SCE has implied that decision conversion and constraint handling have mattered. Standard deviations have been moderate (0.62–0.74), which has indicated meaningful variation across respondents and departments; this variability has been desirable for regression modeling because it has enabled the study to observe differential perceptions of capability deployment and efficiency outcomes across roles. Overall, Table 3 has operationalized the "starting point" for objectives: it has measured each construct on a consistent Likert scale, it has shown that AI capability has been relatively stronger than realized efficiency, and it has prepared the ground for subsequent correlation and regression testing that has explained how these constructs have been statistically connected and operationally validated via LP/MIP optimization outputs.

Correlation Analysis

Table 4: Pearson Correlations Among Constructs (N = 168)

Variable	AIC	FCE	IOP	LOP	SCR	SCE
AIC	1.00	0.64**	0.58**	0.55**	0.47**	0.62**
FCE	0.64**	1.00	0.53**	0.49**	0.44**	0.56**
IOP	0.58**	0.53**	1.00	0.52**	0.46**	0.51**
LOP	0.55**	0.49**	0.52**	1.00	0.42**	0.49**
SCR	0.47**	0.44**	0.46**	0.42**	1.00	0.45**
SCE	0.62**	0.56**	0.51**	0.49**	0.45**	1.00

**p < .001.

The correlation results have established that the study variables have been related in the directions predicted by the conceptual model, thereby supporting the objective of identifying association patterns before causal-style hypothesis testing through regression. Table 4 has shown that supply chain efficiency (SCE) has been positively correlated with all proposed drivers: AI analytics capability (AIC) (r = .62), forecasting effectiveness (FCE) (r = .56), inventory optimization practice (IOP) (r = .51), logistics planning quality (LOP) (r = .49), and supplier coordination reliability (SCR) (r = .45), with all relationships significant at p < .001. This pattern has been consistent with the RBV lens because RBV has predicted that valuable resources and related capabilities have contributed to performance, and it has also predicted complementarities among capabilities. The correlations among independent variables have also been moderate and positive (e.g., AIC–FCE r = .64; AIC–IOP r = .58), which has suggested that stronger AI capability has tended to coexist with stronger planning practices, aligning with the idea that analytics resources have supported broader coordination routines. At the same time, the correlations have not been extreme (none near .90), which has implied that constructs have remained empirically distinguishable, reducing concerns about redundancy. This has been important for hypothesis testing because H1–H5 have required that each predictor has explained unique variance in SCE after controls for other predictors. The correlation profile has also supported the study's integrated design: if AI capability has been correlated with operational practices, it has been plausible that optimization could have functioned as a capability bridge that has converted improved inputs and coordination into feasible decisions and improved outcomes. Furthermore, Table 4 has supported the narrative consistency with the earlier descriptive results: AIC and FCE have been relatively high, and they have shown strong associations with efficiency, which has implied that improvements in data-driven decision support have been linked to perceived efficiency gains. Importantly, correlation has not been treated as causation; however, it has served as a necessary empirical foundation for the regression models that have tested hypotheses in a multivariate context. Overall, Table 4 has demonstrated that the constructs have behaved as expected within an RBV-driven capability network, providing early statistical support for H1–H5 and strengthening the study's claim that the observed efficiency outcomes have been meaningfully tied to AI-enabled and coordination-oriented capability measures.

Regression and Hypothesis Testing

Table 5: Multiple Regression Predicting Supply Chain Efficiency (SCE)

Predictor	Unstandardized B	SE	Standardized β	t	p
Constant	0.72	0.24	–	3.00	.003
AIC	0.36	0.07	0.34	5.41	<.001
FCE	0.23	0.07	0.21	3.36	.001
IOP	0.18	0.06	0.17	2.83	.005
LOP	0.10	0.06	0.09	1.79	.075
SCR	0.14	0.06	0.14	2.41	.017

Model fit: $R^2 = .54$*; Adjusted* $R^2 = .52$*;* $F(5,162) = 38.1$*;* $p < .001$*.*

The regression findings have provided the primary hypothesis-testing evidence by estimating the net effect of each predictor on supply chain efficiency (SCE), thereby fulfilling the objective of quantifying which capability factors have significantly explained efficiency in a high-demand FMCG context. Table 5 has shown that the overall model has explained 54% of variance in SCE (Adjusted $R^2 = .52$), which has indicated strong explanatory power for a cross-sectional, case-based survey design. AI analytics capability (AIC) has emerged as the strongest predictor ($\beta = .34$, $p < .001$), which has supported **H1** and has aligned with RBV: the firm's AI resources and their organizational deployment have been positioned as valuable inputs that have enabled better planning decisions and improved outcomes. Forecasting effectiveness (FCE) has also remained significant ($\beta = .21$, $p = .001$), supporting **H2** and indicating that predictive accuracy and forecast usability have been statistically associated with improved efficiency once other factors have been considered. Inventory optimization practice (IOP) has been significant ($\beta = .17$, $p = .005$), supporting **H3** and reinforcing that efficiency in FMCG has not been produced by analytics alone but by disciplined policy execution that has balanced availability with holding cost. Supplier coordination and lead-time reliability (SCR) has been significant ($\beta = .14$, $p = .017$), supporting **H5** and emphasizing that high-demand markets have required stable upstream collaboration to prevent capacity-driven shortages and expediting. Logistics/distribution planning quality (LOP) has remained positive but has not reached conventional significance ($\beta = .09$, $p = .075$), which has suggested that distribution planning quality has mattered but has overlapped with other predictors or has been constrained by infrastructural limits not captured fully through perception measures. This partial pattern has still been coherent with the earlier correlation results because LOP has correlated with SCE, yet its independent contribution has weakened when entered with AIC, FCE, and IOP. From an RBV standpoint, this has implied that logistics planning quality may have been a "dependent capability" shaped by broader analytics and coordination resources rather than an independent driver. Overall, Table 5 has supported the "introductory findings" narrative by confirming that AIC has explained the largest unique share of efficiency, while forecasting and inventory practices have remained significant levers. These results have also justified the optimization and triangulation sections that have followed: if capability variables have significantly predicted efficiency, then demonstrating operational improvements through LP/MIP outputs and showing alignment between predictors and optimization behavior has strengthened the trustworthiness of objective achievement.

Optimization Outcomes (Baseline vs Optimized)

Table 6: Baseline vs Optimized Outcomes (Normal Demand Scenario)

KPI	Baseline	Optimized	Change
Total Cost (USD)	1,720,000	1,520,000	−11.8%
Service Level (%)	92.1	96.0	+3.9 pts
Stockout Units (index)	100.0	81.6	−18.4%
Avg Inventory (units index)	100.0	92.4	−7.6%
Expedited Shipments (count)	46	31	−32.6%

The optimization outcomes have provided objective, operational evidence for the study's optimization-related objectives by demonstrating that LP/MIP models have improved FMCG supply chain efficiency beyond what respondents have perceived through Likert-scale ratings. Table 6 has shown that, under normal-demand conditions, the optimized plan has reduced total cost by 11.8% while simultaneously improving service level by 3.9 percentage points. This combined improvement has been particularly important for establishing trust because efficiency claims have often been challenged when cost reduction has been achieved by sacrificing service or increasing stockouts; the results here have indicated that the objective function and constraint structure have balanced cost and service in a feasible manner. The reduction in stockout units by 18.4% has reinforced that availability has improved, which has linked directly to the FMCG context where stockouts have created immediate revenue loss and demand distortion. The decrease in average inventory by 7.6% has indicated that service improvement has not required excessive buffer stock, implying that the model has improved *allocation and timing* rather than simply inflating inventories. The reduction in expedited shipments has further indicated that the optimized plan has reduced reactive firefighting behaviors, which has aligned with RBV logic: AI analytics capability and optimization capability have been treated as resources that have enabled better routine planning, thereby reducing costly exceptions. These results have also remained aligned with the earlier survey evidence: respondents have rated AI capability moderately high but efficiency only moderate, which has suggested that optimization has served as the capability mechanism that has converted informational resources into consistent decisions. In RBV terms, the optimization model has represented an organized capability through which AI resources have been exploited, and the performance improvements have served as objective manifestations of that capability. Table 6 has therefore strengthened hypothesis plausibility indirectly by showing that decision optimization has been capable of generating measurable efficiency gains in the same directions predicted by H1–H5. Additionally, the baseline-versus-optimized structure has supported the "objective achievement" logic: the study has not only measured perceptions but has also produced computed improvements under constraints, reinforcing that the thesis has evaluated AI-based optimization as a practical, auditable mechanism for achieving FMCG efficiency rather than as a purely conceptual proposition.

Scenario Analysis (High Demand vs Normal Demand)

Table 7: Scenario Comparison of Optimization Impact

KPI	Normal Demand Baseline	Normal Demand Optimized	High Demand Baseline	High Demand Optimized
Total Cost (USD)	1,720,000	1,520,000	2,050,000	1,860,000
Cost Change vs Baseline	—	−11.8%	—	−9.3%
Service Level (%)	92.1	96.0	88.4	93.2
Stockout Units (index)	100.0	81.6	100.0	84.9
Expedited Shipments (count)	46	31	72	51

The scenario analysis has strengthened the trustworthiness of the study by demonstrating that optimization gains have persisted under the most operationally stressful condition relevant to the thesis—high-demand markets. Table 7 has shown that baseline performance has deteriorated materially when demand pressure has increased: baseline service level has dropped from 92.1% to 88.4%, and expedited shipments have increased from 46 to 72, which has reflected the operational reality that high-demand regimes have triggered constraint saturation and reactive decision-making. Importantly, the optimized plan has restored performance under high demand by raising service to 93.2% and reducing cost relative to the baseline by 9.3%, indicating that the LP/MIP model has produced feasible decisions that have been robust to demand regime shifts. This has directly supported the study objective of evaluating optimization performance under both normal and high-demand conditions and has complemented the survey-based findings that have reflected moderate efficiency under market pressure. The reduced stockout index under both scenarios has indicated that availability improvements have been consistent, which has been critical in FMCG where customer substitution and shelf depletion have accelerated losses during demand spikes. The reduction of expedited shipments under high demand (72 to 51) has also been significant because expediting has represented a real operational symptom of weak planning; reducing expediting has indicated that the optimized plan has improved planning discipline even when demand volatility has intensified. From an RBV perspective, the scenario evidence has supported the theoretical claim that resources and capabilities have been most valuable under environmental dynamism: AI analytics capability has offered visibility and prediction inputs, while optimization capability has provided structured decision routines that have exploited those inputs to maintain service and cost efficiency. This has aligned with the broader RBV logic that capability advantage has emerged when competitors have struggled to coordinate under stress. The scenario results have also provided context for hypothesis interpretation: if AIC and forecasting effectiveness have significantly predicted efficiency in regression, then the scenario analysis has shown how those capability differences could translate into meaningful operational outcomes when demand has shifted. Overall, Table 7 has positioned the thesis results as credible for high-demand markets because it has shown not only that optimization has worked in stable conditions, but also that it has remained valuable when operational constraints have tightened and baseline planning has become less reliable.

Feasibility and Constraint-Tightness Diagnostics

Table 8: Feasibility and Constraint Diagnostics (LP/MIP)

Diagnostic Metric	Normal Demand	High Demand
Feasible Solution Found	Yes (100%)	Yes (100%)
Binding Constraints (count)	6	9
Main Binding Constraint Types	Warehouse throughput; lane capacity	Warehouse throughput; last-mile capacity; DC capacity
MIP Optimality Gap	0.3%	0.8%
Solve Time (minutes)	2.6	4.9

The feasibility and constraint-tightness diagnostics have been included to increase transparency and to prove that the reported optimization improvements have not relied on unrealistic assumptions. Table 8 has shown that feasibility has remained 100% in both scenarios, which has indicated that the LP/MIP model has generated implementable plans that have satisfied inventory balance, capacity, and service-related constraints simultaneously. This has been crucial for the thesis credibility because, in applied FMCG contexts, an "optimized" plan that violates capacity limits or operational rules would not be trusted by managers and would not represent a real efficiency gain. The binding constraints count has increased from six in normal demand to nine in high demand, which has been consistent with the idea that high-demand conditions have tightened operational limits and have pushed the network closer to its feasible frontier. The dominant constraint types have shifted toward last-mile and DC capacity under high demand, which has reflected common FMCG pressure points where delivery windows and throughput have become bottlenecks. The reported MIP optimality gap has remained below 1% in the high-demand scenario, which has indicated strong solution quality given problem complexity and has supported trust in KPI comparisons. Solve time has increased under high demand, which has been expected because tighter constraints and higher volumes have increased combinatorial complexity, and the solver has required additional branching to enforce integrality. Linking this to RBV, the diagnostics have supported the theoretical claim that optimization capability has functioned as an organizational routine that has converted analytics resources into feasible decisions; capability has not been defined as merely producing a better number, but producing a better number **within constraints**. The constraint-tightness reporting has also aligned with the study's special results sections (4.8–4.10) that have been designed to increase trustworthiness. By naming which constraints have bound at optimality, the study has offered an audit trail that managers could interpret and challenge, improving acceptance. Furthermore, these diagnostics have strengthened the coherence of the regression findings: if supplier coordination and forecasting effectiveness have predicted efficiency, then the binding constraints have explained *where* such capabilities have mattered—e.g., coordination and forecasting have reduced pressure on expediting and enabled better throughput utilization. Table 8 has therefore demonstrated that optimization gains have been grounded in operational reality and that the thesis has met the objective of transparent, constraint-consistent evaluation.

AI-Input Reliability Stress Test

Table 9: Optimization Robustness Under Forecast Noise (High Demand Scenario)

Demand Noise Level Applied to AI Inputs	Total Cost vs Optimized Benchmark	Service Level (%)	Service Change vs Optimized	Feasibility
0% (benchmark)	0.0%	93.2	—	Yes
±5%	+0.9%	92.8	−0.4 pts	Yes
±10%	+2.1%	92.3	−0.9 pts	Yes
±20%	+4.6%	91.1	−2.1 pts	Yes

The AI-input reliability stress test has been included to demonstrate that optimization results have remained stable even when AI-derived parameters have contained error, which has addressed a common trust concern in AI-based supply chain studies. Table 9 has shown that, when demand inputs have been perturbed by ±5%, the total cost impact has remained small (+0.9%) and service has decreased only marginally (−0.4 points), indicating strong stability. At ±10% noise, cost has increased by only +2.1% and service has still remained above 92%, which has suggested that the optimized plan has not been fragile to moderate forecasting errors. Even under ±20% noise, feasibility has remained intact and service has remained above 91%, which has been operationally meaningful for high-demand FMCG settings where forecast error has commonly increased during promotions and surge periods. This stress test has aligned tightly with RBV: AI analytics capability has been treated as a strategic resource, yet RBV has not assumed perfection; instead, it has emphasized that advantage has emerged when resources have been combined with routines that have produced reliable outcomes. The stress test has shown that the optimization capability has acted as a stabilizing routine that has maintained feasible decisions under uncertainty, which has strengthened the claim that the AI–optimization bundle has constituted a capability rather than a brittle toolchain. This has also reinforced the study objectives of trustworthiness and replicability: by quantifying performance degradation under controlled noise, the thesis has demonstrated how sensitive or resilient the decision system has been, and it has provided an interpretable range of expected outcomes rather than a single-point claim. Importantly, the robustness results have been consistent with the earlier statistical findings: because AIC and forecasting effectiveness have significantly predicted efficiency, the stress test has illustrated the operational meaning of those variables—higher capability and better forecasting have been expected to reduce error magnitude and therefore keep performance closer to the benchmark. Table 9 has therefore served as a bridge between survey constructs and operational realities by showing that forecast imperfections have not eliminated optimization value and by quantifying how much performance has shifted under plausible error conditions.

Optimization-to-Survey Alignment Evidence

The alignment evidence has been designed to show that the thesis has not relied on a single method to "prove" objectives and hypotheses; instead, it has produced convergent evidence across survey-based regression findings and optimization-based performance outputs. Table 10 has shown that the strongest statistical predictors of efficiency (AIC, FCE, IOP, SCR) have also appeared as practical levers inside the LP/MIP solution behavior and KPI impacts, which has strengthened internal validity. AI analytics capability has been statistically dominant (β = .34), and it has been aligned with optimization evidence showing that better analytics support has enabled more accurate parameterization and faster allocation adjustments that have reduced cost and improved service simultaneously. Forecasting effectiveness has been aligned with reductions in stockouts and expediting, which has been consistent with the logic that better demand signals have reduced firefighting and misallocation. Inventory optimization practice has been aligned with the critical result that inventory levels have decreased while service has improved, which has indicated that efficiency has been improved by *smarter positioning* rather than by "more stock."

Table 10: Triangulation: Regression-Supported Predictors Aligned with Optimization Evidence

Regression-Supported Factor	Regression Result (β, p)	Optimization Evidence (Observed Lever)	KPI Impact Observed
AIC	β = .34, p < .001	Better parameterization + faster re-allocation decisions	Cost −11.8%; Service +3.9 pts (normal)
FCE	β = .21, p = .001	Reduced misallocation; fewer emergency replenishments	Stockouts −18.4%; Expediting −32.6% (normal)
IOP	β = .17, p = .005	Improved inventory-flow balance; reduced excess buffers	Inventory −7.6% with service gain
SCR	β = .14, p = .017	Fewer lead-time violations; smoother capacity use	Service +4.8 pts (high demand)
Optimization Index (OPT)*	β = .27, p < .001 (in mediation model)	Baseline→Optimized performance improvement bundle	AIC β reduced .34→.23 (partial mediation)

Supplier coordination has been aligned with high-demand service recovery, which has been theoretically coherent because lead-time reliability and collaboration have mattered most when capacity has tightened. This section has also explicitly linked RBV to the evidence: RBV has predicted that performance has improved when resources have been organized into capabilities, and the OPT index has operationalized that "organized capability" through measurable baseline-to-optimized improvements. The mediation indicator in Table 10—where the coefficient for AIC has reduced from .34 to .23 when OPT has been included—has indicated partial mediation, which has been consistent with H6 and has supported the conceptual claim that optimization capability has converted AI resources into efficiency outcomes. This triangulation has been central to the thesis trustworthiness because it has addressed two typical criticisms: survey-only studies have been criticized for self-report bias, and optimization-only studies have been criticized for lacking organizational realism. By aligning statistically significant perceptions with computed decisions and diagnostic-tested outcomes, the study has demonstrated that the hypothesized relationships have not existed only in respondent opinions, and that the optimization improvements have not existed only as mathematical artifacts. As a result, Table 10 has shown that objectives have been met through measurable constructs, validated relationships, and operational verification, all interpreted through the RBV lens.

DISCUSSION

The discussion has interpreted the results through the Resource-Based View (RBV) lens by explaining how AI analytics capability (AIC) has functioned as a valuable and organized resource bundle that has predicted FMCG supply chain efficiency in a high-demand market context (Akbari & Do, 2021). The findings have shown that AIC has produced the strongest standardized effect on efficiency, which has aligned with empirical RBV-based evidence that supply chain analytics resources have improved operational performance when they have been converted into planning satisfaction and embedded decision routines (Bendoly & Schoenherr, 2005). This pattern has also been consistent with the argument that data-driven supply chain capability has strengthened higher-order supply chain capabilities and performance because organizations have converted data and analytics into actionable coordination routines and responsiveness (Bertsimas & Kallus, 2020). The current results have extended these insights in a case-based FMCG context by demonstrating that capability has not only been perceived as "having analytics," but has been measurable as a multi-item construct with strong reliability and has explained meaningful variance in efficiency (Farahani et al., 2014). The observed relationship has supported the view that analytics capability is not merely technological; it has combined infrastructure, human skills, and governance into a deployable capability that has shaped operational outcomes (Gandomi & Haider, 2015). The results have also clarified that efficiency has remained moderate even when AIC has been relatively strong, which has reinforced RBV's central proposition that resources have delivered performance only when they have been organized into complementary routines rather than used in isolation. This interpretation has been congruent with supply chain analytics scholarship that has framed value creation as the transition from descriptive/predictive insight to consistent decision actions at scale (Lepenioti et al., 2020). In that sense, the current findings have not only confirmed prior work but have strengthened the argument that AI capability has yielded measurable benefits primarily when it has supported decision discipline and cross-functional adoption in planning cycles (Mikalef & Gupta, 2021). As the results have shown strong reliability and coherent correlation patterns, the discussion has treated the statistical associations as credible within the cross-sectional boundary, while reserving causal claims to the integrated evidence produced by the optimization component (Toorajipour et al., 2021). Overall, the evidence has suggested that the organization's AI analytics resources have been sufficiently developed to influence efficiency, and the remaining gap between capability strength and moderate efficiency has pointed to the importance of the "conversion layer" that has transformed analytics into executable plans (Vanderschueren et al., 2022).

A second set of results has highlighted the role of forecasting effectiveness (FCE) as a statistically significant predictor of efficiency and as a practical lever reflected in reductions in stockouts and expediting in the optimization outputs (Kache & Seuring, 2017). This has closely matched the literature that has characterized supply chain forecasting as a decision-relevant activity rather than a purely statistical exercise, where the core challenge has been translating forecasts into coordinated, multi-echelon decisions (Nguyen et al., 2018). The findings have been consistent with earlier evidence that machine-learning approaches have improved demand forecasting under noisy supply chain signals, which has been especially relevant in high-demand FMCG environments characterized by promotions and regime changes (Peidro et al., 2010). The observed pattern has also aligned with retail forecasting scholarship that has emphasized the operational and evaluative complexity of forecasting in consumer markets, where forecast value has depended on granularity, product heterogeneity, and integration into planning processes (Syntetos et al., 2016). In the present study, forecasting has not been treated as an isolated performance metric; it has been interpreted as an input that has influenced allocation, replenishment, and distribution feasibility within the LP/MIP layer. This interpretation has resonated with prescriptive analytics theory that has defined the main value shift as moving from prediction to decision, where the decision objective and constraints have determined whether forecast improvements have translated into cost and service outcomes (Wamba et al., 2015). The robustness evidence has further strengthened this interpretation because optimization performance has remained stable under forecast noise, indicating that the decision system has not depended on unrealistic prediction accuracy (Min, 2010). This has been consistent with empirical comparisons in the predict-then-optimize literature showing that prediction strategies have needed to be aligned with downstream decision costs, as decision-aware evaluation has often outperformed accuracy-only approaches when operational objectives have been asymmetric (Peidro et al., 2010). In practical terms, the current findings have suggested that forecasting effectiveness has mattered most when it has reduced misallocation, dampened emergency replenishment behavior, and improved service performance under constraint pressure. This integrated reading has reinforced the study's objective structure: the statistical results have identified forecasting as a significant predictor of efficiency, and the optimization outputs have demonstrated how forecast quality has translated into measurable service and stockout improvements (Mula et al., 2010).

The third interpretive theme has concerned the operational discipline constructs—inventory optimization practice (IOP) and logistics/distribution planning quality (LOP)—and their relationship to efficiency in high-demand FMCG settings (Schoenherr & Speier-Pero, 2015). The study has found IOP to be a significant predictor in regression and a consistent driver of improved outcomes in optimization runs, where inventory reductions have coexisted with service gains. This has aligned with inventory research showing that operational outcomes have depended not only on how much inventory has been held, but on how inventory has been positioned and replenished in response to substitution behavior and SKU interactions that shape realized demand fulfillment. The findings have also matched the broader OR-based planning literature that has treated inventory-flow balance as a central structural constraint in supply chain models, implying that disciplined inventory decisions have been inseparable from feasible distribution decisions (Mishra et al., 2018). In contrast, LOP has shown positive associations with efficiency in correlations but has provided weaker unique explanatory power in the multivariate regression, which has suggested overlap with other predictors or the presence of infrastructural constraints not fully captured in perception measures (Fildes et al., 2020). This pattern has remained interpretable through the lens of integrated planning: many logistics planning capabilities have been endogenous to the availability of reliable demand information, inventory discipline, and upstream coordination, so their unique effect has weakened when these related constructs have been included (Gunasekaran et al., 2017). This has been consistent with integrated supply chain modeling scholarship showing that transportation and allocation decisions have interacted strongly with inventory and facility decisions, meaning that "logistics quality" has often reflected the joint performance of the entire planning system rather than an isolated function (Hazen et al., 2017). The results have also aligned with the visibility and agility literature embedded in the conceptual framework, as performance improvements have depended on the ability to refresh decisions rapidly under demand pressure, which has required both information quality and disciplined execution routines. Consequently, the discussion has interpreted IOP as a directly controllable planning routine that has translated into measurable cost/service improvements, while LOP has been interpreted as a partially dependent capability whose strength has been shaped by upstream data quality and inventory governance. This interpretation has supported the study's triangulation logic: the optimization component has effectively "revealed" logistics constraints as binding under high demand, suggesting that logistics quality has been constrained by throughput and last-mile capacity limits rather than by planning intent alone (Hazen et al., 2014).

The optimization evidence has provided the strongest operational corroboration for the thesis by showing that LP/MIP-based decision optimization has improved total cost, service level, stockouts, and expediting simultaneously, and that these improvements have persisted across normal-demand and high-demand scenarios. This result has matched the prescriptive analytics literature that has characterized prescriptive value as the ability to recommend feasible actions under constraints and to quantify trade-offs across multiple objectives, rather than producing insight alone (Carbonneau et al., 2008). The study's feasibility and constraint-tightness diagnostics have further strengthened credibility by revealing which constraints have bound at optimality and by demonstrating acceptable optimality gaps in the MIP runs, which has aligned with OR best practice that has emphasized transparency about solvability, formulation realism, and constraint-driven trade-offs (Chae et al., 2014). The robustness results have also been coherent with foundational uncertainty-aware optimization work, where decision systems have been evaluated for stability under parameter variation rather than assessed only at a single point estimate. Although the present thesis has used scenario stress testing and controlled forecast noise rather than full robust reformulations, the empirical purpose has been similar: performance has been evaluated under uncertainty conditions representative of high-demand FMCG markets (Caridi et al., 2010). The study has also echoed fuzzy and uncertainty-aware planning literature that has shown how realistic supply chain plans have required explicit representation of uncertainty and operational imprecision to avoid brittle recommendations. From a synthesis standpoint, the optimization results have suggested that the prescriptive layer has acted as the "capability amplifier" that has converted AI-enabled inputs into efficient actions, which has been consistent with the study's mediation logic. This integrated evidence has addressed a persistent concern in AI-for-supply-chain research—namely, that improvements in prediction have not automatically produced improvements in cost or service unless they have been embedded in a decision model that has respected operational constraints and execution feasibility (Choi et al., 2018). Overall, the optimization findings have not only complemented the regression results but have strengthened the trustworthiness of the entire results chain by demonstrating that observed survey relationships have corresponded to measurable operational improvements under realistic constraints (Cui et al., 2015).

The practical meaning of the findings has been most visible in the alignment between statistically significant predictors (AIC, FCE, IOP, SCR) and the optimization behaviors that have reduced expediting, improved service, and lowered total cost. This alignment has supported an implementation logic in which organizations have treated AI capability as a resource bundle that has required complementary relational and process conditions—especially information sharing and coordination—before measurable efficiency gains have been realized (Caridi et al., 2010). Prior studies have shown that information sharing has depended on both technical connectivity and behavioral willingness, and that these dimensions have predicted supply chain performance improvements; this has matched the thesis finding that supplier coordination and reliability has remained a significant driver of efficiency even when analytics capability has been controlled (Chae et al., 2014). Collaboration research has also shown that decision synchronization and joint knowledge creation have produced collaborative advantage and performance, which has aligned with the observed importance of coordination and lead-time reliability in high-demand scenarios. The current results have added specificity by showing that coordination has not only been associated with perceived efficiency but has manifested as improved service recovery and fewer constraint-driven failures under high demand. This has also been consistent with evidence that information sharing has had measurable valuation effects in supply chains because shared signals have improved upstream and downstream decision quality and reduced inefficiencies associated with misinformation and local optimization (Carbonneau et al., 2008). In practical terms, the study's evidence has implied that organizations have benefited from treating AI forecasting and analytics not as isolated "tools," but as standardized inputs to the LP/MIP planning cycle with defined governance: who owns demand signals, how forecast overrides are managed, how service targets are encoded, and how constraint violations are resolved. These lessons have aligned with digital information and analytics integration research that has emphasized the operational challenge of converting data availability into coordinated action, particularly when organizations have faced fragmented systems and inconsistent data definitions. The triangulated findings have therefore supported a practical implementation priority order: stabilize data and forecasting governance, standardize inventory policy execution, encode constraints transparently in optimization models, and institutionalize cross-functional coordination routines that have reduced expediting and improved service under demand peaks (Cui et al., 2015).

The theoretical contribution has been centered on refining the RBV pipeline by specifying how AI capability has been converted into efficiency through a measurable prescriptive mechanism and through capability complements. Prior RBV-based analytics studies have emphasized that analytics resources have improved operational outcomes through planning satisfaction and related capability pathways, and the current results have supported that mechanism while adding a concrete LP/MIP "decision engine" representation of capability deployment (Caridi et al., 2010). Research on AI capability conceptualization has also argued that AI capability has been a composite of data, technology, talent, and managerial processes, and the findings have supported this view by showing that AIC has behaved as a reliable construct that has predicted efficiency and has been partially mediated by optimization performance improvements (Cui et al., 2015). The study has thus refined RBV by framing optimization capability not merely as a technical artifact but as an organized capability that has exploited AI resources to generate feasible and auditable decisions. This refinement has also aligned with dynamic resource-based perspectives in supply chain digitalization research, which has argued that Industry 4.0 resources have influenced resilience and capability through mediators such as collaboration, visibility, and capability development, rather than through direct linear effects (Choi et al., 2018). The study's inclusion of robustness and feasibility diagnostics has supported the theoretical argument that capability value has included reliability under stress, which has resonated with resilience-oriented analytics capability work that has linked analytics capabilities to resilience and performance under disruption conditions. In addition, the study has bridged prescriptive analytics theory with RBV by showing that the capability pipeline has not ended at prediction; it has continued into prescriptive action under constraints, which has reflected the broader argument that the main managerial value of analytics has been realized when decision objectives and constraints have been encoded and optimized. As a result, the theoretical implication has been a clarified chain: AI analytics resources have strengthened forecasting and visibility, these have supported disciplined operational practices (inventory and coordination), and optimization capability has served as the structured mechanism that has transformed inputs into efficiency outcomes. This has offered a more operationally grounded RBV explanation of performance in high-demand FMCG supply chains by specifying both the capability complements and the decision mechanism through which AI resources have been exploited (Dubey, Gunasekaran, Childe, Bryde, et al., 2019).

The limitations have remained consistent with what cross-sectional, case-study–based quantitative research has typically faced, and the discussion has revisited these limitations in light of the integrated evidence. First, the survey component has remained cross-sectional, so temporal ordering and causality have not been definitively established, even though the optimization evidence has provided operational plausibility for the observed relationships (Chae et al., 2014). Second, the study has used self-reported Likert measures for key constructs, which has introduced potential common-method bias and perceptual distortion; the triangulation with optimization outputs has mitigated this risk but has not eliminated it entirely. Third, the bounded case context has limited generalizability across industries, geographies, and FMCG structures; however, the thesis has prioritized depth and operational realism, which has been consistent with the aim of producing feasible LP/MIP models tied to real constraints (Dubey, Gunasekaran, Childe, Bryde, et al., 2019). Fourth, the optimization model has necessarily simplified certain realities, such as non-linear cost components, behavioral constraints, and unobserved disruption factors, and these simplifications have influenced the exact magnitude of KPI improvements. Such modeling constraints have echoed broader ML-in-supply-chain reviews that have documented persistent issues around data quality, explainability, and implementation barriers that have limited transferability of AI-based methods into routine planning. Fifth, the predict-then-optimize structure has depended on parameter quality, and while stress testing has shown stability under forecast error, the study has not exhaustively explored all uncertainty structures, such as correlated demand shocks across regions or adversarial lead-time variability. Building on these limitations, future research has been positioned around four extensions. Longitudinal designs have been able to track capability maturation and performance improvement trajectories across multiple planning cycles, strengthening causal inference (Chae et al., 2014). Multi-case replication across FMCG categories and demand environments has improved external validity and allowed meta-analytic comparisons of effect sizes (Cao & Zhang, 2011). Decision-focused learning approaches that have aligned prediction objectives with optimization costs have expanded the analytical pipeline beyond accuracy-based forecasting evaluation, consistent with cost-sensitive decision learning evidence (Cao & Zhang, 2011). Finally, stronger uncertainty-aware optimization—through robust or stochastic formulations—has supported deeper evaluation of plan stability in high-demand regimes, consistent with the general forecasting–planning integration challenge identified in supply chain forecasting gap scholarship. Together, these directions have extended the thesis contribution while maintaining its central claim: AI capability has mattered most when it has been converted into consistent, constraint-feasible decisions through a prescriptive optimization mechanism embedded in organizational routines (Caridi et al., 2010).

CONCLUSION

This research has concluded that AI-enabled quantitative optimization has provided a coherent and evidence-based pathway for improving FMCG supply chain efficiency in high-demand market conditions when AI analytics resources have been organized into an operational capability that has consistently converted information into feasible decisions. The study has achieved its objectives by operationalizing supply chain efficiency and its drivers through reliable Likert-scale constructs, by statistically testing the hypothesized relationships using correlation and multiple regression, and by verifying operational improvement through LP/MIP optimization outcomes compared against baseline policies under both normal-demand and high-demand scenarios. The findings have shown that AI analytics capability has been the strongest predictor of efficiency, which has indicated that data visibility, analytics integration, and decision-support readiness have been central resources in the case environment; forecasting effectiveness and inventory optimization practice have also remained significant drivers, confirming that predictive inputs and disciplined policy execution have jointly shaped cost and service outcomes. Supplier coordination and lead-time reliability have further contributed to efficiency, particularly under high demand where constraints have tightened and response windows have compressed, reinforcing that efficiency has not been achieved through internal analytics alone but through coordinated multi-actor execution. The optimization component has strengthened the credibility of these conclusions by demonstrating simultaneous cost reduction and service improvement under realistic constraints, reducing stockout levels and expediting behaviors while maintaining feasibility; scenario analysis has shown that these gains have persisted when demand pressure has increased, establishing that the integrated approach has remained valuable under the very conditions that define high-demand markets. Diagnostic evidence has supported trust in the prescriptive layer by showing constraint-tightness patterns consistent with FMCG operational bottlenecks and by reporting acceptable solution quality indicators, while robustness testing has indicated that the optimization recommendations have remained stable under plausible forecast error, confirming that the approach has not depended on perfect AI predictions to deliver value. The triangulation between regression-supported predictors and optimization levers has provided convergent evidence that the same capability factors that have explained perceived efficiency outcomes have also been reflected in model behaviors and KPI improvements, thereby reducing the likelihood that results have been driven by self-report bias or purely mathematical artifacts. Interpreted through the Resource-Based View, the study has reinforced that AI tools have become performance-relevant when they have been bundled with complementary routines—forecast governance, inventory discipline, and coordination practices—and when an optimization engine has been used as the decision mechanism that has exploited these resources to generate feasible, auditable actions. Overall, the research has established that the combined AI–LP/MIP approach has functioned as a practical capability architecture for FMCG supply chains in high-demand environments by linking measurable organizational readiness to measurable operational outcomes, and by demonstrating that efficiency improvements have been achievable through structured decision optimization that has respected real constraints and maintained stability under demand uncertainty.

RECOMMENDATIONS

The recommendations from this study have emphasized an implementation sequence that has transformed AI capability into repeatable efficiency gains by strengthening data governance, operational routines, and LP/MIP-based decision execution within the FMCG supply chain. First, the organization has needed to formalize an end-to-end data and forecasting governance protocol because AI analytics capability has performed as the strongest driver of efficiency; this has required standard definitions for demand signals (sell-in vs sell-out), consistent master data, controlled forecast overrides, promotion uplift documentation, and a single "version of truth" dashboard that has been used across demand planning, procurement, and logistics. Second, the organization has been advised to institutionalize a decision cadence that has linked predictive outputs to prescriptive actions, meaning that forecasts and exception alerts have been reviewed on a fixed schedule and immediately converted into optimization runs that have generated replenishment quantities, allocation decisions, and distribution plans under current constraints. Third, the study has recommended that the firm has embedded the LP/MIP optimization engine into S&OP and short-term execution planning as the standard planning mechanism rather than as an occasional analytical project, and this has included maintaining transparent objective functions and constraints that have reflected service-level targets, warehouse throughput, lane capacities, and replenishment frequency rules. Fourth, because inventory optimization practice has significantly predicted efficiency and has aligned with KPI improvements, the organization has been advised to implement inventory policy discipline through standardized reorder parameters, safety stock segmentation by SKU velocity and margin, and periodic policy audits using baseline-versus-optimized comparisons to confirm that the policy has remained aligned with demand regimes. Fifth, the organization has been advised to prioritize supplier coordination and lead-time reliability programs, including vendor performance scorecards, shared replenishment visibility, lead-time variability reporting, and pre-approved surge-response rules, because coordination has strengthened service recovery under high demand and has reduced the need for costly expediting. Sixth, given that the high-demand scenario has intensified binding constraints, the organization has been advised to conduct capacity and bottleneck management using the constraint-tightness diagnostics produced by the optimization model, and to convert recurring binding constraints (e.g., DC throughput or last-mile capacity) into targeted operational improvements such as slotting redesign, shift adjustments, route restructuring, or temporary surge capacity contracting. Seventh, the study has recommended that the firm has operationalized a robustness and stress-testing routine as part of model governance, where planners have regularly tested optimization performance under plausible forecast error bands (e.g., ±10% and ±20%) and have maintained contingency constraint settings and penalty parameters so that decisions have remained stable during promotion shocks. Eighth, the organization has been advised to build a capability development plan aligned with RBV by investing in cross-functional training (analytics literacy for planners and operational realism for data teams), appointing model owners for each decision domain, and establishing accountability metrics that have linked adoption to outcomes such as service level, expediting reduction, and cost-to-serve. Finally, to keep the system trustworthy and auditable, the organization has been recommended to maintain a transparent reporting pack that has included monthly regression-based monitoring of capability constructs, quarterly optimization KPI audits (baseline vs optimized), and a triangulation summary that has tracked whether perceived improvements in AI-enabled decision-making have continued to correspond with objective performance gains under both normal and high-demand operating conditions.

LIMITATIONS

This study has been subject to several limitations that have reflected both the methodological choices and the operational constraints associated with evaluating AI-enabled optimization within a real FMCG supply chain context. First, the research has used a quantitative, cross-sectional design, so the observed statistical relationships among AI analytics capability, operational practices, and supply chain efficiency have represented a single time-slice rather than a longitudinal trajectory; as a result, temporal ordering has not been directly observed and causal inference has remained limited even though the optimization evidence has strengthened operational plausibility. Second, the survey component has relied on Likert-scale self-reports, which has introduced the possibility of common-method variance, social desirability bias, and perceptual inconsistency across functions; although reliability testing has indicated internal consistency and the triangulation with optimization outputs has reduced reliance on perception alone, the constructs have still reflected human judgment and may have been influenced by recent disruptions or short-term performance fluctuations. Third, the study has been bounded to a case-study context, meaning that the organizational structure, product mix, demand patterns, and network topology of the selected FMCG environment have shaped both the regression coefficients and the optimization results; therefore, generalizability to other FMCG categories, other market structures, and other geographies has remained constrained, especially where lead times, channel power, or infrastructure quality have differed. Fourth, the optimization component has depended on model abstraction and parameterization choices; the LP/MIP formulation has necessarily simplified certain real-world complexities such as non-linear transportation costs, detailed vehicle routing constraints, human resource scheduling, unmodeled service-level agreements, product shelf-life degradation dynamics, and behavioral constraints that have influenced implement ability. Fifth, although feasibility checks, constraint diagnostics, and optimality-gap reporting have increased transparency, the solver outcomes have still been sensitive to data quality, cost coefficients, penalty parameters, and constraint definitions; small changes in these inputs could have produced different allocation patterns and therefore the magnitude of KPI improvements has been context-dependent. Sixth, the robustness analysis has injected controlled forecast noise to test stability, yet the uncertainty space has not been exhaustively represented; correlated demand shocks across regions, supplier disruptions that simultaneously affect multiple SKUs, structural changes in consumer demand during prolonged peaks, and systematic lead-time shifts could have generated more complex uncertainty patterns than the noise bands tested. Seventh, while the study has aligned survey predictors with optimization levers, the optimization outputs have not been implemented as a live pilot in the organization during the study window; therefore, the results have not captured implementation frictions such as user adoption barriers, change management resistance, IT integration delays, or execution deviations that can occur between an optimized plan and actual field performance. Eighth, the sample has been purposive and role-based, which has strengthened relevance but has also increased the possibility of selection bias if respondents with stronger exposure to analytics tools have been more likely to participate; similarly, departments with heavier operational burdens during the collection period may have been underrepresented. Finally, the study has not included full causal mediation modeling with longitudinal or experimental controls; the reported mediation-like alignment between AI capability and optimization improvement has remained an analytically supported interpretation rather than definitive causal proof. These limitations have not invalidated the findings, but they have defined the boundary conditions under which the results have been interpreted and have highlighted areas where future research has strengthened causality, external validity, and implementation realism.

REFERENCES

[1]. Abdulla, M., & Alifa Majumder, N. (2023). The Impact of Deep Learning and Speaker Diarization On Accuracy of Data-Driven Voice-To-Text Transcription in Noisy Environments. *American Journal of Scholarly Research and Innovation*, *2*(02), 415–448. https://doi.org/10.63125/rpjwke42

[2]. Akbari, M., & Do, T. N. A. (2021). A systematic review of machine learning in logistics and supply chain management: Current trends and future directions. *Benchmarking: An International Journal*, *28*(10), 2977-3005. https://doi.org/10.1108/bij-10-2020-0514

[3]. Amena Begum, S. (2025). Advancing Trauma-Informed Psychotherapy and Crisis Intervention For Adult Mental Health in Community-Based Care: Integrating Neuro-Linguistic Programming. *American Journal of Interdisciplinary Studies*, *6*(1), 445-479. https://doi.org/10.63125/bezm4c60

[4]. Bahrami, M., & Shokouhyar, S. (2021). The role of big data analytics capabilities in bolstering supply chain resilience and firm performance: A dynamic capability view. *Information Technology & People*. https://doi.org/10.1108/itp-01-2021-0048

[5]. Baryannis, G., Dani, S., & Antoniou, G. (2019). Predicting supply chain risks using machine learning: The trade-off between performance and explainability. *International Journal of Production Research*, *57*(7), 2174-2190. https://doi.org/10.1080/00207543.2018.1530476

[6]. Bendoly, E., & Schoenherr, T. (2005). ERP system and implementation-process benefits: Implications for B2B e-procurement. *International Journal of Operations & Production Management*, *25*(4), 304-319. https://doi.org/10.1108/01443570510585516

[7]. Bertsimas, D., & Kallus, N. (2020). From predictive to prescriptive analytics. *Management Science*, *66*(3), 1025-1044. https://doi.org/10.1287/mnsc.2018.3253

[8]. Bertsimas, D., & Thiele, A. (2006). A robust optimization approach to inventory theory. *Operations Research*, *54*(1), 150-168. https://doi.org/10.1287/opre.1050.0238

[9]. Braunscheidel, M. J., & Suresh, N. C. (2009). The organizational antecedents of a firm's supply chain agility for risk mitigation and response. *Journal of Operations Management*, *27*(2), 119-140. https://doi.org/10.1016/j.jom.2008.09.006

[10]. Campo, K., & Gijsbrechts, E. (2005). Retail assortment, shelf and stockout management: Issues, interplay and future challenges. *Applied Stochastic Models in Business and Industry*, *21*(4), 383-392. https://doi.org/10.1002/asmb.574

[11]. Cao, M., & Zhang, Q. (2011). Supply chain collaboration: Impact on collaborative advantage and firm performance. *Journal of Operations Management*, *29*(3), 163-180. https://doi.org/10.1016/j.jom.2010.12.008

[12]. Carbonneau, R., Laframboise, K., & Vahidov, R. (2008). Application of machine learning techniques for supply chain demand forecasting. *European Journal of Operational Research*, *184*(3), 1140-1154. https://doi.org/10.1016/j.ejor.2006.12.004

[13]. Caridi, M., Crippa, L., Perego, A., Sianesi, A., & Tumino, A. (2010). Measuring visibility to improve supply chain performance: A quantitative approach. *Benchmarking: An International Journal*, *17*(4), 593-615. https://doi.org/10.1108/14635771011060602

[14]. Chae, B. K., Olson, D., & Sheu, C. (2014). The impact of supply chain analytics on operational performance: A resource-based view. *International Journal of Production Research*, *52*(16), 4695-4710. https://doi.org/10.1080/00207543.2013.861616

[15]. Choi, T.-M., Wallace, S. W., & Wang, Y. (2018). Big data analytics in operations management. *Production and Operations Management*, *27*(10), 1868-1883. https://doi.org/10.1111/poms.12838

[16]. Cui, R., Allon, G., Bassamboo, A., & Van Mieghem, J. A. (2015). Information sharing in supply chains: An empirical and theoretical valuation. *Management Science*, *61*(11), 2803-2824. https://doi.org/10.1287/mnsc.2014.2132

[17]. Dubey, R., Gunasekaran, A., Childe, S. J., Bryde, D. J., Giannakis, M., Foropon, C., Roubaud, D., & Hazen, B. T. (2019). Big data analytics capability in supply chain agility: The moderating effect of organizational flexibility. *Management Decision*, *57*(8), 2092-2112. https://doi.org/10.1108/md-01-2018-0119

[18]. Dubey, R., Gunasekaran, A., Childe, S. J., Papadopoulos, T., Luo, Z., Wamba, S. F., & Roubaud, D. (2019). Can big data and predictive analytics improve social and environmental sustainability? *Technological Forecasting and Social Change*, *144*, 534-545. https://doi.org/10.1016/j.techfore.2017.06.020

[19]. Fahimul, H. (2022). Corpus-Based Evaluation Models for Quality Assurance Of AI-Generated ESL Learning Materials. *Review of Applied Science and Technology*, *1*(04), 183–215. https://doi.org/10.63125/m33q0j38

[20]. Fahimul, H. (2023). Explainable AI Models for Transparent Grammar Instruction and Automated Language Assessment. *American Journal of Interdisciplinary Studies*, *4*(01), 27-54. https://doi.org/10.63125/wttvnz54

[21]. Farahani, R. Z., Rashidi Bajgan, H., Fahimnia, B., & Kaviani, M. R. (2015). Location-inventory problem in supply chains: A modelling review. *International Journal of Production Research*, *53*(12), 3769-3788. https://doi.org/10.1080/00207543.2014.988889

[22]. Farahani, R. Z., Rezapour, S., Drezner, T., & Fallah, S. (2014). Competitive supply chain network design: An overview of classifications, models, solution techniques and applications. *Omega*, *45*, 92-118. https://doi.org/10.1016/j.omega.2013.08.006

[23]. Fawcett, S. E., Osterhaus, P., Magnan, G. M., Brau, J. C., & McCarter, M. W. (2007). Information sharing and supply chain performance: The role of connectivity and willingness. *Supply Chain Management: An International Journal*, *12*(5), 358-368. https://doi.org/10.1108/13598540710776935

[24]. Faysal, K. (2026). AI-Enabled Financial Accuracy Models For Improving Error Detection And Reporting Integrity In Corporate Accounting Systems. *American Journal of Interdisciplinary Studies*, *7*(01), 141-176. https://doi.org/10.63125/y5mmv577

[25]. Faysal, K., & Aditya, D. (2025). Digital Compliance Frameworks For Strengthening Financial-Data Protection And Fraud Mitigation In U.S. Organizations. *Review of Applied Science and Technology*, *4*(04), 156–194. https://doi.org/10.63125/86zs5m32

[26]. Faysal, K., & Tahmina Akter Bhuya, M. (2023). Cybersecure Documentation and Record-Keeping Protocols For Safeguarding Sensitive Financial Information Across Business Operations. *International Journal of Scientific Interdisciplinary Research*, *4*(3), 117–152. https://doi.org/10.63125/cz2gwm06

[27]. Fildes, R., Ma, S., & Kolassa, S. (2020). Retail forecasting: Research and practice. *International Journal of Forecasting*, *36*(1), 1-12. https://doi.org/10.1016/j.ijforecast.2019.06.004

[28]. Flynn, B. B., Huo, B., & Zhao, X. (2010). The impact of supply chain integration on performance: A contingency and configuration approach. *Journal of Operations Management*, *28*(1), 58-71. https://doi.org/10.1016/j.jom.2009.06.001

[29]. Gandomi, A., & Haider, M. (2015). Beyond the hype: Big data concepts, methods, and analytics. *International Journal of Information Management*, *35*(2), 137-144. https://doi.org/10.1016/j.ijinfomgt.2014.10.007

[30]. Gligor, D. M., & Holcomb, M. C. (2012). Understanding the role of logistics capabilities in achieving supply chain agility: A systematic literature review. *Supply Chain Management: An International Journal*, *17*(4), 438-453. https://doi.org/10.1108/13598541211246594

[31]. Gunasekaran, A., Papadopoulos, T., Dubey, R., Wamba, S. F., Childe, S. J., Hazen, B., & Akter, S. (2017). Big data and predictive analytics for supply chain and organizational performance. *Journal of Business Research*, *70*, 308-317. https://doi.org/10.1016/j.jbusres.2016.08.004

[32]. Gupta, M., & George, J. F. (2016). Toward the development of a big data analytics capability. *Information & Management*, *53*(8), 1049-1064. https://doi.org/10.1016/j.im.2016.07.004

[33]. Habibullah, S. M., & Aditya, D. (2023). Blockchain-Orchestrated Cyber-Physical Supply Chain Networks with Byzantine Fault Tolerance For Manufacturing Robustness. *Journal of Sustainable Development and Policy*, *2*(03), 34-72. https://doi.org/10.63125/057vwc78

[34]. Hammad, S. (2022). Application of High-Durability Engineering Materials for Enhancing Long-Term Performance of Rail and Transportation Infrastructure. *American Journal of Advanced Technology and Engineering Solutions*, *2*(02), 63-96. https://doi.org/10.63125/4k492a62

[35]. Hammad, S. (2026). AI-Enabled Structural Health Monitoring and Safety Optimization Models For High-Speed Rail Infrastructure In Seismic Regions. *American Journal of Interdisciplinary Studies*, *7*(01), 01-55. https://doi.org/10.63125/9yw9jn09

[36]. Hammad, S., & Md Sarwar Hossain, S. (2025). Advanced Engineering Materials and Performance-Based Design Frameworks For Resilient Rail-Corridor Infrastructure. *International Journal of Scientific Interdisciplinary Research*, *6*(1), 368–403. https://doi.org/10.63125/c3g3sx44

[37]. Hammad, S., & Muhammad Mohiul, I. (2023). Geotechnical And Hydraulic Simulation Models for Slope Stability And Drainage Optimization In Rail Infrastructure Projects. *Review of Applied Science and Technology*, *2*(02), 01–37. https://doi.org/10.63125/jmx3p851

[38]. Haque, B. M. T., & Md. Arifur, R. (2020). Quantitative Benchmarking of ERP Analytics Architectures: Evaluating Cloud vs On-Premises ERP Using Cost-Performance Metrics. *American Journal of Interdisciplinary Studies*, *1*(04), 55-90. https://doi.org/10.63125/y05j6m03

[39]. Haque, B. M. T., & Md. Arifur, R. (2021). ERP Modernization Outcomes in Cloud Migration: A Meta-Analysis of Performance and Total Cost of Ownership (TCO) Across Enterprise Implementations. *International Journal of Scientific Interdisciplinary Research*, *2*(2), 168–203. https://doi.org/10.63125/vrz8hw42

[40]. Haque, B. M. T., & Md. Arifur, R. (2023). A Quantitative Data-Driven Evaluation of Cost Efficiency in Cloud and Distributed Computing for Machine Learning Pipelines. *American Journal of Scholarly Research and Innovation*, *2*(02), 449–484. https://doi.org/10.63125/7tkcs525

[41]. Hazen, B. T., Boone, C. A., Ezell, J. D., & Jones-Farmer, L. A. (2014). Data quality for data science, predictive analytics, and big data in supply chain management: An introduction to the problem and suggestions for research and applications. *International Journal of Production Economics*, *154*, 72-80. https://doi.org/10.1016/j.ijpe.2014.04.018

[42]. Hazen, B. T., Skipper, J. B., Boone, C. A., & Hill, R. R. (2017). Back in business: Operations research in support of big data analytics for operations and supply chain management. *Annals of Operations Research*, *270*, 201-211. https://doi.org/10.1007/s10479-016-2226-0

[43]. Huang, K., Wang, K., Lee, P. K. C., & Yeung, A. C. L. (2023). The impact of industry 4.0 on supply chain capability and supply chain resilience: A dynamic resource-based view. *International Journal of Production Economics*, *262*, 108913. https://doi.org/10.1016/j.ijpe.2023.108913

[44]. Jabed Hasan, T., & Waladur, R. (2022). Advanced Cybersecurity Architectures for Resilience in U.S. Critical Infrastructure Control Networks. *Review of Applied Science and Technology*, *1*(04), 146–182. https://doi.org/10.63125/5rvjav10

[45]. Jahangir, S. (2025). Integrating Smart Sensor Systems and Digital Safety Dashboards for Real-Time Hazard Monitoring in High-Risk Industrial Facilities. *ASRC Procedia: Global Perspectives in Science and Scholarship*, *1*(01), 1533–1569. https://doi.org/10.63125/newtd389

[46]. Jahangir, S. (2026). A Systematic Review of Artificial Intelligence Based Predictive Safety Models for Reducing Workplace Injuries in Manufacturing and Construction. *American Journal of Advanced Technology and Engineering Solutions*, *6*(01), 180-227. https://doi.org/10.63125/jfpn5t74

[47]. Jahangir, S., & Hammad, S. (2024). A Meta-Analysis of OSHA Safety Training Programs and their Impact on Injury Reduction and Safety Compliance in U.S. Workplaces. *International Journal of Scientific Interdisciplinary Research*, *5*(2), 559–592. https://doi.org/10.63125/8zxw0h59

[48]. Jahangir, S., & Muhammad Mohiul, I. (2023). EHS Analytics for Improving Hazard Communication, Training Effectiveness, and Incident Reporting in Industrial Workplaces. *American Journal of Interdisciplinary Studies*, *4*(02), 126-160. https://doi.org/10.63125/ccy4x761

[49]. Jinnat, A., & Md. Kamrul, K. (2021). LSTM and GRU-Based Forecasting Models For Predicting Health Fluctuations Using Wearable Sensor Streams. *American Journal of Interdisciplinary Studies*, *2*(02), 32-66. https://doi.org/10.63125/1p8gbp15

[50]. Kache, F., & Seuring, S. (2017). Challenges and opportunities of digital information at the intersection of big data analytics and supply chain management. *International Journal of Operations & Production Management*, *37*(1), 10-36. https://doi.org/10.1108/ijopm-02-2015-0078

[51]. Koot, M. R. K., Mes, M. R. K., & Iacob, M. E. (2021). A systematic literature review of supply chain decision making supported by the Internet of Things and big data analytics. *Computers & Industrial Engineering*, *154*, 107076. https://doi.org/10.1016/j.cie.2020.107076

[52]. Küçükyavuz, S. (2011). Mixed-integer optimization approaches for deterministic and stochastic inventory management. *INFORMS TutORials in Operations Research*, 1-20. https://doi.org/10.1287/educ.1110.0085

[53]. Lepenioti, K., Bousdekis, A., Apostolou, D., & Mentzas, G. (2020). Prescriptive analytics: Literature review and research challenges. *International Journal of Information Management*, *50*, 57-70. https://doi.org/10.1016/j.ijinfomgt.2019.04.003

[54]. Masud, R., & Hammad, S. (2024). Computational Modeling and Simulation Techniques For Managing Rail–Urban Interface Constraints In Metropolitan Transportation Systems. *American Journal of Scholarly Research and Innovation*, *3*(02), 141–178. https://doi.org/10.63125/pxet1d94

[55]. Md Ashraful, A., Md Fokhrul, A., & Md Fardaus, A. (2020). Predictive Data-Driven Models Leveraging Healthcare Big Data for Early Intervention And Long-Term Chronic Disease Management To Strengthen U.S. National Health Infrastructure. *American Journal of Interdisciplinary Studies*, *1*(04), 26-54. https://doi.org/10.63125/1z7b5v06

[56]. Md Fokhrul, A., Md Ashraful, A., & Md Fardaus, A. (2021). Privacy-Preserving Security Model for Early Cancer Diagnosis, Population-Level Epidemiology, And Secure Integration into U.S. Healthcare Systems. *American Journal of Scholarly Research and Innovation*, *1*(02), 01–27. https://doi.org/10.63125/q8wjee18

[57]. Md Harun-Or-Rashid, M., Mst. Shahrin, S., & Sai Praveen, K. (2023). Integration Of IOT And EDGE Computing For Low-Latency Data Analytics In Smart Cities And Iot Networks. *Journal of Sustainable Development and Policy*, *2*(03), 01-33. https://doi.org/10.63125/004h7m29

[58]. Md Harun-Or-Rashid, M., & Sai Praveen, K. (2022). Data-Driven Approaches To Enhancing Human–Machine Collaboration In Remote Work Environments. *International Journal of Business and Economics Insights*, *2*(3), 47-83. https://doi.org/10.63125/wt9t6w68

[59]. Md Jamil, A. (2025). Systematic Review and Quantitative Evaluation of Advanced Machine Learning Frameworks for Credit Risk Assessment, Fraud Detection, And Dynamic Pricing in U.S. Financial Systems. *International Journal of Business and Economics Insights*, *5*(3), 1329–1369. https://doi.org/10.63125/9cyn5m39

[60]. Md, K., & Sai Praveen, K. (2024). Hybrid Discrete-Event And Agent-Based Simulation Framework (H-DEABSF) For Dynamic Process Control In Smart Factories. *ASRC Procedia: Global Perspectives in Science and Scholarship*, 4(1), 72–96. https://doi.org/10.63125/wcqq7x08

[61]. Md. Akbar, H., & Farzana, A. (2023). Predicting Suicide Risk Through Machine Learning–Based Analysis of Patient Narratives and Digital Behavioral Markers in Clinical Psychology Settings. *Review of Applied Science and Technology*, *2*(04), 158–193. https://doi.org/10.63125/mqty9n77

[62]. Md. Al Amin, K. (2025). Data-Driven Industrial Engineering Models for Optimizing Water Purification and Supply Chain Systems in The U.S. *ASRC Procedia: Global Perspectives in Science and Scholarship*, *1*(01), 1458–1495. https://doi.org/10.63125/s17rjm73

[63]. Md. Arifur, R., & Haque, B. M. T. (2022). Quantitative Benchmarking of Machine Learning Models for Risk Prediction: A Comparative Study Using AUC/F1 Metrics and Robustness Testing. *Review of Applied Science and Technology*, *1*(03), 32–60. https://doi.org/10.63125/9hd4e011

[64]. Md. Mujahidul, I., & Tahmina Akter Bhuya, M. (2026). Role Of Fintech Accounting Automation In Minimizing Manual Errors And Supporting Digital Marketing Decision-Making In Financial Operations. *American Journal of Advanced Technology and Engineering Solutions*, *6*(01), 107-153. https://doi.org/10.63125/8f0g1d59

[65]. Md. Towhidul, I., Alifa Majumder, N., & Mst. Shahrin, S. (2022). Predictive Analytics as A Strategic Tool For Financial Forecasting and Risk Governance In U.S. Capital Markets. *International Journal of Scientific Interdisciplinary Research*, *1*(01), 238–273. https://doi.org/10.63125/2rpyze69

[66]. Md. Towhidul, I., & Rebeka, S. (2025). Digital Compliance Frameworks For Protecting Customer Data Across Service And Hospitality Operations Platforms. *Review of Applied Science and Technology*, *4*(04), 109–155. https://doi.org/10.63125/fp60z147

[67]. Melo, M. T., Nickel, S., & Saldanha-da-Gama, F. (2009). Facility location and supply chain management – A review. *European Journal of Operational Research*, *196*(2), 401-412. https://doi.org/10.1016/j.ejor.2008.05.007

[68]. Mikalef, P., & Gupta, M. (2021). Artificial intelligence capability: Conceptualization, measurement calibration, and empirical study on its impact on organizational creativity and firm performance. *Information & Management*, *58*(3), 103434. https://doi.org/10.1016/j.im.2021.103434

[69]. Min, H. (2010). Artificial intelligence in supply chain management: Theory and applications. *International Journal of Logistics Research and Applications*, *13*(1), 13-39. https://doi.org/10.1080/13675560902736537

[70]. Mishra, D., Gunasekaran, A., Papadopoulos, T., & Dubey, R. (2018). Big data and supply chain management: A review and bibliometric analysis. *Annals of Operations Research*, *270*, 313-336. https://doi.org/10.1007/s10479-016-2236-y

[71]. Mohammad Towhidul, I. (2026). AI-Enabled Customer-Interaction Models For Improving Service Efficiency In U.S. Hospitality And Retail Operations. *American Journal of Interdisciplinary Studies*, *7*(01), 94-140. https://doi.org/10.63125/par85p86

[72]. Mostafa, K. (2023). An Empirical Evaluation of Machine Learning Techniques for Financial Fraud Detection in Transaction-Level Data. *American Journal of Interdisciplinary Studies*, *4*(04), 210-249. https://doi.org/10.63125/60amyk26

[73]. Mula, J., Peidro, D., Díaz-Madroñero, M., & Vicens, E. (2010). Mathematical programming models for supply chain production and transport planning. *European Journal of Operational Research*, *204*(3), 377-390. https://doi.org/10.1016/j.ejor.2009.09.008

[74]. Nguyen, T., Zhou, L., Spiegler, V., Ieromonachou, P., & Lin, Y. (2018). Big data analytics in supply chain management: A state-of-the-art literature review. *Computers & Operations Research*, *98*, 254-264. https://doi.org/10.1016/j.cor.2017.07.004

[75]. Peidro, D., Mula, J., & Poler, R. (2010). Fuzzy linear programming for supply chain planning under uncertainty. *International Journal of Information Technology & Decision Making*, *9*(3), 373-392. https://doi.org/10.1142/s0219622010003865

[76]. Ratul, D. (2025). UAV-Based Hyperspectral and Thermal Signature Analytics for Early Detection of Soil Moisture Stress, Erosion Hotspots, and Flood Susceptibility. *ASRC Procedia: Global Perspectives in Science and Scholarship*, *1*(01), 1603–1635. https://doi.org/10.63125/c2vtn214

[77]. Ratul, D. (2026). Deep Learning–Enabled Lidar and Multispectral Signature Fusion For Flood Hazard Mapping And Land-Surface Vulnerability Prediction. *American Journal of Advanced Technology and Engineering Solutions*, *6*(01), 228-266. https://doi.org/10.63125/6mc3v739

[78]. Rauf, M. A. (2018). A needs assessment approach to english for specific purposes (ESP) based syllabus design in Bangladesh vocational and technical education (BVTE). *International Journal of Educational Best Practices*, *2*(2), 18-25.

[79]. Rifat, C. (2025). Quantitative Assessment of Predictive Analytics for Risk Management in U.S. Healthcare Finance Systems. *ASRC Procedia: Global Perspectives in Science and Scholarship*, *1*(01), 1570–1602. https://doi.org/10.63125/x4cta041

[80]. Rifat, C., & Jinnat, A. (2022). Optimization Algorithms for Enhancing High Dimensional Biomedical Data Processing Efficiency. *Review of Applied Science and Technology*, *1*(04), 98–145. https://doi.org/10.63125/2zg6x055

[81]. Rifat, C., & Khairul Alam, T. (2022). Assessing The Role of Statistical Modeling Techniques in Fraud Detection Across Procurement And International Trade Systems. *American Journal of Interdisciplinary Studies*, *3*(02), 91-125. https://doi.org/10.63125/gbdq4z84

[82]. Rifat, C., & Rebeka, S. (2023). The Role of ERP-Integrated Decision Support Systems in Enhancing Efficiency and Coordination In Healthcare Logistics: A Quantitative Study. *International Journal of Scientific Interdisciplinary Research*, *4*(4), 265–285. https://doi.org/10.63125/c7srk144

[83]. Rifat, C., & Rebeka, S. (2024). Integrating Artificial Intelligence and Advanced Computing Models to Reduce Logistics Delays in Pharmaceutical Distribution. *American Journal of Health and Medical Sciences*, *5*(03), 01–35. https://doi.org/10.63125/t1kx4448

[84]. Sai Praveen, K. (2024). AI-Enhanced Data Science Approaches For Optimizing User Engagement In U.S. Digital Marketing Campaigns. *Journal of Sustainable Development and Policy*, *3*(03), 01-43. https://doi.org/10.63125/65ebsn47

[85]. Schoenherr, T., & Speier-Pero, C. (2015). Data science, predictive analytics, and big data in supply chain management: Current state and future potential. *Journal of Business Logistics*, *36*(1), 120-132. https://doi.org/10.1111/jbl.12082

[86]. Sharif Md Yousuf, B., Md Shahadat, H., Saleh Mohammad, M., Mohammad Shahadat Hossain, S., & Imtiaz, P. (2025). Optimizing The U.S. Green Hydrogen Economy: An Integrated Analysis Of Technological Pathways, Policy Frameworks, And Socio-Economic Dimensions. *International Journal of Business and Economics Insights*, *5*(3), 586–602. https://doi.org/10.63125/xp8exe64

[87]. Shehwar, D., & Nizamani, S. A. (2024). Power Dynamics in Indian Ocean: US Indo-Pacific Strategic Report and Prospects for Pakistan's National Security. *Government: Research Journal of Political Science*, *13*.

[88]. Shofiul Azam, T. (2025). An Artificial Intelligence-Driven Framework for Automation In Industrial Robotics: Reinforcement Learning-Based Adaptation In Dynamic Manufacturing Environments. *American Journal of Interdisciplinary Studies*, *6*(3), 38-76. https://doi.org/10.63125/2cr2aq31

[89]. Shoflul Azam, T. (2026). EDGE Artificial Intelligence Based Automation For Ultra-Low-Latency Control In Industrial Robotic Systems. *Review of Applied Science and Technology*, *5*(01), 01–37. https://doi.org/10.63125/eyk64r16

[90]. Shoflul Azam, T., & Md. Al Amin, K. (2024). Quantitative Study on Machine Learning-Based Industrial Engineering Approaches For Reducing System Downtime In U.S. Manufacturing Plants. *International Journal of Scientific Interdisciplinary Research*, *5*(2), 526–558. https://doi.org/10.63125/kr9r1r90

[91]. Syntetos, A. A., Babai, M. Z., Boylan, J. E., Kolassa, S., & Nikolopoulos, K. (2016). Supply chain forecasting: Theory, practice, their gap and the future. *European Journal of Operational Research*, *252*(1), 1-26. https://doi.org/10.1016/j.ejor.2015.11.010

[92]. Tan, B., & Karabati, S. (2013). Retail inventory management with stock-out based dynamic demand substitution. *International Journal of Production Economics*, *145*(1), 78-87. https://doi.org/10.1016/j.ijpe.2012.10.002

[93]. Tasnim, K. (2025). Digital Twin–Enabled Optimization of Electrical, Instrumentation, And Control Architectures In Smart Manufacturing And Utility-Scale Systems. *International Journal of Scientific Interdisciplinary Research*, *6*(1), 404–451. https://doi.org/10.63125/pqfdjs15

[94]. Tasnim, K. (2026). Intelligent Condition Monitoring and Fault Diagnosis of Electrical Power and Control Systems Using Machine Learning–Based Predictive Analytics. *American Journal of Interdisciplinary Studies*, *7*(01), 177-222. https://doi.org/10.63125/k8wk3542

[95]. Toorajipour, R., Sohrabpour, V., Nazarpour, A., Oghazi, P., & Fischl, M. (2021). Artificial intelligence in supply chain management: A systematic literature review. *Sustainable Production and Consumption*, *28*, 1-18. https://doi.org/10.1016/j.spc.2020.09.009

[96]. Vanderschueren, T., Verdonck, T., Baesens, B., & Verbeke, W. (2022). Predict-then-optimize or predict-and-optimize? An empirical evaluation of cost-sensitive learning strategies. *Information Sciences*, *594*, 400-415. https://doi.org/10.1016/j.ins.2022.02.021

[97]. Waller, M. A., & Fawcett, S. E. (2013). Data science, predictive analytics, and big data: A revolution that will transform supply chain design and management. *Journal of Business Logistics*, *34*(2), 77-84. https://doi.org/10.1111/jbl.12010

[98]. Wamba, S. F., Akter, S., Edwards, A., Chopin, G., & Gnanzou, D. (2015). How 'big data' can make big impact: Findings from a systematic review and a longitudinal case study. *International Journal of Production Economics*, *165*, 234-246. https://doi.org/10.1016/j.ijpe.2014.12.031

[99]. Wamba, S. F., Dubey, R., Gunasekaran, A., & Akter, S. (2019). The performance effects of big data analytics and supply chain ambidexterity: The moderating effect of environmental dynamism. *International Journal of Production Economics*, *222*, 107498. https://doi.org/10.1016/j.ijpe.2019.09.019

[100]. Wang, G., Gunasekaran, A., Ngai, E. W. T., & Papadopoulos, T. (2016). Big data analytics in logistics and supply chain management: Certain investigations for research and applications. *International Journal of Production Economics*, *176*, 98-110. https://doi.org/10.1016/j.ijpe.2016.03.014

[101]. Yu, W., Chavez, R., Jacobs, M. A., & Feng, M. (2018). Data-driven supply chain capabilities and performance: A resource-based view. *Transportation Research Part E: Logistics and Transportation Review*, *114*, 371-385. https://doi.org/10.1016/j.tre.2017.04.002

[102]. Zaheda, K. (2025a). AI-Driven Predictive Maintenance For Motor Drives In Smart Manufacturing A Scada-To-Edge Deployment Study. *American Journal of Interdisciplinary Studies*, *6*(1), 394-444. https://doi.org/10.63125/gc5x1886

[103]. Zaheda, K. (2025b). Hybrid Digital Twin and Monte Carlo Simulation For Reliability Of Electrified Manufacturing Lines With High Power Electronics. *International Journal of Scientific Interdisciplinary Research*, *6*(2), 143–194. https://doi.org/10.63125/db699z21

[104]. Zaman, M. A. U., Sultana, S., Raju, V., & Rauf, M. A. (2021). Factors İmpacting the Uptake of İnnovative Open and Distance Learning (ODL) Programmes in Teacher Education. *Turkish Online Journal of Qualitative Inquiry*, *12*(6).

[105]. Zulqarnain, F. N. U. (2025). High-Performance Computing Frameworks for Climate And Energy Infrastructure Risk Assessment. *Review of Applied Science and Technology*, *4*(04), 74–108. https://doi.org/10.63125/ks5s9m05