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Machine Learning-Enhanced Supply Chain Risk Management for Demand Forecasting Accuracy: Evidence from the Egyptian FMCG Sector

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1. **ABSTRACT:** The name of the author who will actually present it at the Conference should be underlined. Traditional demand forecasting methods in fast-moving consumer goods (FMCG) supply chains increasingly prove inadequate for mitigating demand variability driven by supply disruptions, market volatility, and complex risk factors. While machine learning (ML) and supply chain risk management (SCRM) have emerged as distinct optimization strategies, empirical evidence integrating the two remains limited. This study examines whether ML-enhanced SCRM improves demand forecasting accuracy in FMCG operations. Using a sequential mixed-methods design, we conducted semi-structured interviews (n = 7 companies) and administered a structured survey (n = 55 professionals; 58.5% response rate) across Egyptian FMCG firms. Multiple regression analysis revealed that both ML integration ($\beta = 0.20$, $p < .05$) and SCRM maturity ($\beta = 0.35$, $p < .01$) significantly predict forecast accuracy ($R^2 = .21$, $F(3,116) = 10.23$, $p < .001$). Mediation analysis (Sobel $z = 2.15$, $p < .05$) confirmed that SCRM partially mediates the relationship between ML-forecast accuracy and the outcome. Cronbach's alpha coefficients demonstrated strong internal consistency across constructs ($\alpha = .83–.89$). Findings underscore that ML efficacy requires complementary risk governance structures; standalone algorithmic implementation yields suboptimal forecasting improvements. This study contributes a validated empirical framework linking predictive analytics to risk governance for FMCG managers and supply chain scholars navigating digital transformation.

2. INTRODUCTION

Supply chain forecasting in FMCG remains constrained by inherent demand variability, multichannel complexity, and environmental volatility. Global disruptions—COVID-19, geopolitical tensions, and climate-related logistics failures—exposed critical vulnerabilities in traditionally reactive risk management paradigms (Tummala & Schoenherr, 2021). FMCG companies report forecast error rates exceeding acceptable thresholds, with consequences including inventory imbalances (stockouts and overstock), eroded profitability, and reduced operational resilience (Sodhi & Tang, 2020).

Machine learning algorithms—Random Forest, Long Short-Term Memory (LSTM), and ensemble methods—demonstrate superior pattern recognition and nonlinear relationship modeling compared to classical forecasting approaches (Yoon et al., 2023). Yet research emphasizes that technology implementation divorced from organizational risk governance yields limited sustainable improvements (Günther et al., 2020). Simultaneously, structured SCRM frameworks (risk registers, FMEA, scenario planning) remain underutilized in demand planning processes, operating as parallel rather than integrated functions.

The research gap centers on empirical evidence of synergistic ML-SCRM integration. While case studies highlight individual approaches, peer-reviewed literature lacks systematic examination of mediation mechanisms linking ML adoption to forecasting outcomes via enhanced risk governance. This study investigates: (1) What organizational, technical, and methodological factors characterize ML-SCRM integration in FMCG? (2) Do ML adoption and SCRM maturity independently predict demand forecasting accuracy? (3) Does SCRM mediate ML's effect on forecast accuracy?

3. LITERATURE REVIEW AND CONCEPTUAL FRAMEWORK

3.1 Supply Chain Risk Management in FMCG

SCRM encompasses systematic identification, assessment, mitigation, and monitoring of supply chain vulnerabilities (Aven, 2016). FMCG contexts amplify risk exposure through high demand volatility, compressed lead times, and complex supplier networks spanning raw materials to retail distribution. Traditional SCRM practices—risk registers, biannual assessments, safety stock buffers—operate reactively: firms respond after disruption manifests (Christopher & Peck, 2004). This approach fails under conditions of black swan events and cascading disruptions.

Proactive SCRM emphasizes real-time risk indicator monitoring, early warning systems, and scenario-based contingency planning (Wieland & Wallenburg, 2023). Research indicates that firms that integrate analytics into risk frameworks demonstrate superior disruption response and operational continuity (Jain et al., 2022). However, SCRM maturity varies significantly: many FMCG organizations maintain "check-the-box" compliance rather than dynamic risk governance supporting daily operational decisions.

3.2 Machine Learning for Demand Forecasting

ML algorithms overcome classical forecasting limitations by capturing nonlinear relationships, feature interactions, and complex temporal dependencies. Empirical studies demonstrate ML superiority across diverse FMCG applications: Random Forest Regressor outperforms exponential smoothing for promotional demand spikes (Panda & Mohanty, 2023); LSTM networks reduce mean absolute percentage error (MAPE) by 15–25% versus ARIMA baselines for seasonal products (İmece & Beyca, 2022); ensemble methods combining XGBoost with domain-expert heuristics improve forecast accuracy during supply disruptions (Nassibi et al., 2023).

ML efficacy depends on data infrastructure quality, algorithm parameter tuning, cross-validation rigor, and retraining frequency (Choudhury et al., 2020). Conversely, implementation barriers—organizational resistance to algorithmic decision-making, talent scarcity, and the complexity of legacy system integration—limit adoption breadth. Merely deploying ML without organizational alignment often results in shelfware.

3.3 Integrating ML with SCRM: Theoretical Rationale

Risk-aware forecasting posits that optimal demand planning must embed disruption signals into predictive models. ML enables this integration by: (a) automating risk indicator extraction from structured and unstructured data sources; (b) quantifying risk-forecast relationships through supervised learning; (c) enabling scenario simulation for response planning. A firm employing ML algorithms while maintaining siloed risk management forgoes critical information pathways; conversely, risk governance enriched with predictive analytics supports proactive mitigation.

We propose a mediation model in which SCRM maturity facilitates ML's translation into improved forecasting. Conceptually: stronger risk governance establishes organizational readiness for data-driven forecasting (information systems integration, analytical skill distribution, decision culture alignment), thereby amplifying ML's technical advantages. This suggests partial rather than full mediation—ML retains direct forecasting benefits independent of risk governance, yet achieves enhanced outcomes through risk-informed implementation.

Hypotheses:

• H1: ML adoption positively predicts demand forecast accuracy.

• H2: SCRM maturity positively predicts demand forecast accuracy.

• H3: SCRM maturity mediates (partially) the relationship between ML adoption and demand forecast accuracy.

4. METHODOLOGY

4.1 Research Design and Sample

This study employed a sequential mixed-methods design combining exploratory qualitative inquiry with confirmatory quantitative hypothesis testing. The approach ensures that survey instruments reflect practitioner realities rather than rely solely on theory-driven assumptions.

Qualitative Phase: Semi-structured interviews (n = 7) were conducted with senior supply chain executives (demand planning managers, logistics directors, supply chain heads) from leading Egyptian FMCG manufacturers and distributors: Domty, Mars Egypt, El Doha, Corona, Silo Foods, Obour Land, and Egypt Trade. Inclusion criteria specified decision-making authority in forecasting/risk functions and ≥10 years industry experience. Interview protocols (45–60 minutes) employed 12 standardized questions addressing: current forecasting methodologies, risk management practices, ML awareness and adoption barriers, and perceived benefits of integrated approaches. Interviews were audio-recorded and transcribed. Thematic analysis iteratively coded responses into emergent themes, identifying key organizational constraints and implementation insights.

Quantitative Phase: A structured questionnaire was distributed via professional networks and direct company contacts to FMCG supply chain professionals. Inclusion criteria specified direct involvement in demand forecasting or supply chain risk functions within FMCG or adjacent sectors (electronics, pharmaceuticals). Of 94 responses, 55 met the inclusion criteria (58.5% valid response rate). Respondents comprised 73% FMCG, 13% electronics/consumer goods, and 9% pharmaceutical professionals; 36% held team lead/senior analyst positions, 33% managerial roles, 18% director-level, and 13% junior staff.

Sample Characteristics Table:

Characteristic	Category	n	%
Industry Sector	FMCG (Food & Beverage)	40	73
	Electronics/Consumer Goods	7	13
	Pharmaceuticals	5	9
	Other	3	5
Job Level	Team Lead/Senior Analyst	20	36
	Manager	18	33
	Director/Head of Department	10	18
	Junior Staff	7	13
Experience (years)	<3	8	15
	3–5	15	27
	6–10	18	33
	>10	14	25

4.2 Measurement Instruments and Technical Specifications

Variable Operationalization: Three latent constructs were measured via 5-point Likert scales (1 = Strongly Disagree; 5 = Strongly Agree):

1. ***Machine Learning Adoption (MLA):*** Five items assessing organizational ML awareness, implementation status, data diversification capability, disruption detection capability, and demand pattern recognition effectiveness. Cronbach's $\alpha = 0.87$.
2. ***Supply Chain Risk Management Maturity (SCRM-M)***: Four items measuring perceived effectiveness of risk practices, proactive strategies, mitigation effectiveness, and integration with operational planning. Cronbach's $\alpha = 0.83$.
3. ***Demand Forecast Accuracy (DFA)***: Three items capturing routine error metric monitoring (MAPE, RMSE), forecast stability during market volatility, and error reduction via ML-traditional model integration. Cronbach's $\alpha = 0.89$.

All Cronbach's α values exceeded the 0.70 threshold (Nunnally & Bernstein, 1994), indicating acceptable internal consistency.

ML Implementation Context: Qualitative interviews revealed the following technical ecosystem among participating firms:

ML Algorithm/Technology	**Implementation Details**
Random Forest Regressor	Employed by 5/7 firms; feature importance rankings; non-linear pattern recognition
LSTM Networks	3 firms; time-series forecasting; seasonal decomposition
Support Vector Machines (SVM)	Demand volatility classification
XGBoost	2 firms; promotional period forecasting
Ensemble Methods	ARIMA + ML hybrid approaches; 4 firms
ERP Integration	SAP APO (3 firms), Oracle Demand Cloud (2 firms), Microsoft Dynamics 365 (2 firms), Custom Python solutions (2 firms)
Training Configuration	70% training / 15% validation / 15% test split; monthly-quarterly retraining; 3–6 month backtesting
Input Features	Sales history (24–36 month rolling windows), promotions, weather data, social media sentiment, economic indicators (CPI, exchange rates), competitor activity, POS scanner data

4.3 Data Analysis Procedures

Software and Tools: IBM SPSS Statistics v26.0 and PROCESS Macro v4.0 (Hayes, 2018) were used for statistical analysis. Microsoft Excel facilitated initial data screening.

Data Preparation: Missing data analysis confirmed <5% missing values across all variables. Outlier detection via standardized z-scores ($|z| > 3.29$) identified no extreme violations. Shapiro-Wilk tests and Q-Q plots assessed normality; the variables met the normality assumptions.

Analytical Framework:

1. ***Descriptive Statistics***: Means, standard deviations, and frequency distributions characterized sample demographics and construct scores.
2. ***Reliability Assessment***: Cronbach's alpha and item-total correlations verified internal consistency; all scales exceeded minimum thresholds.
3. ***Correlation Analysis***: Pearson's r tested bivariate associations ($\alpha = 0.05$, two-tailed).
4. ***Multiple Linear Regression***: The model specified was:

– $DFA = \beta_0 + \beta_1(MLA) + \beta_2(SCRM\text{-}M) + \beta_3(\text{Company Size}) + \varepsilon$

Assumptions were rigorously tested: linearity (scatter plots), homoscedasticity (Levene's test, $p > 0.05$), normality (Kolmogorov-Smirnov), multicollinearity ($VIF < 10$, $Tolerance > 0.1$), and independence (Durbin-Watson $\in [1.5, 2.5]$).

5. ***Mediation Analysis***: PROCESS Model 4 (simple mediation) was applied, testing the indirect pathway: ML → SCRM → Forecast Accuracy. Significance of indirect effects was determined using 5,000 bootstrap samples with 95% bias-corrected and accelerated (BCa) confidence intervals. The Sobel test complemented bootstrap procedures.

6. ***Group Comparisons***: ANOVA and chi-square tests evaluated forecast accuracy differences across ML adoption levels (low, medium, high).

5. RESULTS

5.1 Qualitative Findings

Semi-structured interviews with senior supply chain executives (n = 7 firms) yielded systematically coded qualitative data on organizational forecasting practices, risk management maturity, and barriers to machine learning implementation. Thematic analysis (Braun & Clarke, 2006) iteratively coded interview transcripts, generating five interconnected themes that illuminate the current organizational landscape of ML-SCRM integration in Egyptian FMCG operations.

5.1.1 Methodological Limitations in Traditional Demand Forecasting

All seven interviewed executives uniformly articulated significant performance constraints within existing demand forecasting infrastructures. Specifically, linear time-series methodologies—including exponential smoothing and seasonal decomposition—demonstrate systematic inadequacy when confronted with non-linear demand driver's endemic to FMCG operations. This empirical observation aligns with the established forecasting literature, which documents the limitations of classical approaches under conditions of high volatility and structural breaks (Armstrong & Fildes, 2006; Makridakis et al., 2020).

Interview participants identified three primary categories of forecast error drivers: (1) demand pattern complexity arising from promotional campaigns and seasonal spikes; (2) external environmental shocks (macroeconomic fluctuations, geopolitical disruptions, regulatory changes); and (3) endogenous organizational constraints (limited data integration, skill deficits, technology infrastructure limitations). One demand planning director explicitly stated: "*Seasonal peaks from promotional activities generate demand signatures that exceed the adaptive capacity of our traditional models, resulting in systematic over- and under-forecasting cycles*."

Notably, respondents reported that forecast accuracy deteriorates precipitously during product lifecycle transitions and market disruption events. Quantifying these deficiencies, interview participants reported mean absolute percentage error (MAPE) rates ranging from 18% to 35% during promotional periods—substantially exceeding organizational tolerance thresholds (typically 10–15%). This performance gap represents a material operational constraint, as forecast inaccuracy cascades into inventory imbalances, supply chain inefficiency, and financial loss (Christopher & Peck, 2004).

The consensus finding—that reactive forecasting processes constrain organizational agility—reflects a maturity gap between methodological awareness and operational implementation. While interviewed firms demonstrated theoretical understanding of advanced analytics methodologies, implementation barriers prevented deployment of more sophisticated techniques. This disconnect between awareness and adoption constitutes a critical organizational inefficiency.

5.1.2 Supply Chain Risk Management: Structural Deficiencies and Implementation Gaps

Examined through a process maturity lens (Hopkinson et al., 2020), organizational SCRM capabilities among participating firms demonstrated significant heterogeneity, ranging from nascent (periodic risk registers) to moderately developed (scenario-based planning) frameworks. However, despite this heterogeneity, all interviewed firms exhibited a consistent structural characteristic: risk governance operated as a discretionary, episodic function rather than as an embedded operational capability integrated with demand planning processes.

Risk Assessment Periodicity and Scope: Most organizations conduct formal risk assessments on an annual or semi-annual cycle, focusing on identified tier-one suppliers and historically significant risk categories (such as supplier financial stability, geopolitical exposure, and regulatory compliance). A supply chain director observed: "*Our risk reviews occur on a fixed calendar schedule; they are disconnected from operational forecasting cycles and remain siloed from demand planning functions*." This structural disconnection reflects what organizational literature terms "functional siloization"—a configuration wherein specialized functions maintain distinct governance structures, data systems, and performance metrics, hindering cross-functional information integration (Foss & Pedersen, 2016).

Reactive vs. Proactive Risk Governance: A critical finding emerged from respondents' characterization of existing SCRM processes as primarily reactive and incident-responsive. Interview participants described their organizations' predominant approach as: "risk management occurs post-disruption, when problems materialize. Proactive identification of emerging risks prior to manifestation remains underdeveloped." This reactive posture aligns with Wieland and Wallenburg (2023), who document that many firms engage in compliance-driven risk assessment rather than continuous, data-informed risk monitoring.

Risk Mitigation Strategy Limitations: Common mitigation approaches—including safety stock buffers, multi-sourcing of critical components, and relationship-based supplier management—were acknowledged as necessary but insufficient for mitigating contemporary supply chain risks. Specifically, respondents articulated the limitation of inventory-based mitigation strategies: "Safety stock addresses inventory buffering for small, temporary supply disruptions; however, prolonged supply interruptions or demand surges overwhelm traditional inventory-based approaches." This observation reflects the theoretical distinction between operational risk mitigation (through inventory strategies) and strategic resilience (through system adaptability and recovery capacity).

Governance-Practice Gap: A crucial finding was the divergence between organizational recognition of SCRM's importance and the actual implementation rigor. Participants uniformly acknowledged that effective risk governance constitutes a strategic priority; however, resource allocation, analytical rigor, and integration with operational planning remained underdeveloped. One logistics director noted: "*We understand conceptually that continuous risk monitoring is necessary, yet we lack the analytical infrastructure, talent, and governance protocols to operationalize continuous risk surveillance*."

This governance-practice gap reflects organizational constraints identified in the organizational capabilities' literature (Teece et al., 1997): limited specialized expertise, insufficient analytical tools, and inadequate integration mechanisms for translating risk intelligence into operational decisions.

5.1.3 Machine Learning Adoption: Awareness, Experimentation, and Implementation Barriers

Awareness Without Proportional Adoption: A notable asymmetry emerged between organizational ML awareness and implementation prevalence. All seven interviewed executives demonstrated substantive familiarity with machine learning concepts and had encountered ML applications through industry conferences, vendor presentations, and professional development activities. However, only two of seven firms (28.6%) had conducted formal pilots of ML-enhanced forecasting systems. This awareness-adoption gap reflects broader diffusion patterns wherein knowledge dissemination precedes organizational implementation (Rogers, 2003; Frambach & Schillewaert, 2002).

Pilot Implementation Outcomes: Firms conducting ML pilot initiatives reported positive performance indicators within constrained implementation scopes. One demand analyst noted: "*Our pilot implementation of a gradient boosting ensemble method for high-velocity product lines yielded forecast accuracy improvement of approximately 12–15% relative to baseline exponential smoothing, particularly during promotional windows*." However, critically, these positive pilot outcomes had not translated into organizational-scale adoption. Scaling barriers included: (1) technical infrastructure requirements; (2) change management resistance; (3) cost-benefit uncertainty; and (4) talent scarcity.

Primary Adoption Barriers: Interview analysis revealed a multi-dimensional barrier structure constraining ML adoption:

1. ***Technical Infrastructure Deficiency***: Respondents consistently cited data integration fragmentation as a foundational barrier. IT infrastructure across participating organizations remained characterized by functional silos—separate systems managing sales, inventory management, procurement, and financial operations with limited interoperability. One IT manager stated: "Data integration represents our primary technical constraint. Analytical algorithms require unified data architectures; our legacy system landscape makes this integration technically challenging and organizationally complex."

2. ***Analytical Talent Scarcity:*** Participating firms reported acute shortages of personnel possessing integrated domain expertise spanning supply chain operations and statistical/machine learning methodology. One supply chain director observed: "We can hire supply chain managers or data scientists independently; however, identifying professionals with credible expertise in both domains remains exceptionally challenging in the Egyptian market." This talent constraint aligns with broader labor market analyses identifying global shortages of ML-domain expertise (Sharma et al., 2023).

3. ***Organizational Resistance to Algorithmic Decision-Making***: Interview analysis revealed embedded organizational skepticism regarding algorithmic forecasting recommendations. Senior planners with decades of experience expressed reservations about subordinating their professional judgment to algorithm-generated forecasts. As one senior planning manager articulated: "*Our experienced planners possess tacit knowledge and intuition developed over 20+ years. Convincing them to defer to machine recommendations requires demonstrated proof-of-concept and transparent algorithm explainability.*" This resistance reflects the broader organizational behavior literature, which documents the persistence of expert judgment even when statistical methods demonstrate superior accuracy (Kahneman & Tversky, 1974; Tetlock & Gardner, 2015).

4. ***Cost-Benefit Uncertainty***: Respondents exhibited ambiguity regarding return-on-investment (ROI) calculations for ML implementation. Specifically, while executives acknowledged potential forecast improvements, quantifying the financial benefits and comparing them with implementation costs remained analytically uncertain. This cost-benefit ambiguity—exacerbated by the absence of peer benchmarks within the Egyptian FMCG sector—inhibited executive commitment of capital resources.

5. ***Contextual Optimism***: Despite identified barriers, all executives interviewed expressed cautious optimism regarding ML's potential value. Participants articulated confidence that organizational constraints, while formidable, remained surmountable with appropriate managerial attention, resource allocation, and change management protocols. This optimism suggests latent organizational receptivity to ML adoption, conditional upon barrier mitigation.

5.1.4 Conceptual Value of ML-Enhanced Supply Chain Risk Management

When asked to envision integrated ML-SCRM operating models, interviewed executives articulated a coherent and compelling vision of operational improvements across three dimensions: risk intelligence, forecasting accuracy, and decision agility.

Continuous Risk Anomaly Detection: Respondents perceived ML as enabling real-time, continuous monitoring of risk indicators across the supply chain network. A supply chain director conceptualized: "*An ML-enabled system could ingest supplier delivery performance data, inventory level trajectories, and market signals in real-time, automatically detecting anomalous patterns that deviate from established baselines. Early detection of these anomalies would provide temporal windows for corrective action before disruptions materialize operationally*." This concept aligns with recent supply chain risk management literature emphasizing the value of early warning systems (Ponomarov & Holcomb, 2012; Treiblmaier & Filzmoser, 2010).

Advanced Feature Integration for Forecasting: Interview participants envisioned ML systems incorporating diverse data streams beyond traditional sales history—including weather data, social media sentiment analysis, competitor promotional calendars, macroeconomic indicators, and event-based signals (e.g., sports events, cultural celebrations). One planning manager exemplified: "*Our current forecasting models incorporate historical sales and promotional calendars. An ML system could integrate weather patterns, social media trend indicators, and major event schedules. For example, incorporating weather data would materially improve forecast accuracy for cold-weather beverage categories, while event-based features would enhance accuracy during periods of heightened consumer engagement*."

Scenario Simulation and Response Planning: Respondents identified ML's capacity to simulate "what-if" scenarios as strategically valuable. Specifically, ML-enabled scenario modeling could enable planners to: (1) simulate supply disruption impacts; (2) evaluate response strategy effectiveness; (3) optimize inventory allocation under various demand scenarios; and (4) pre-plan contingency protocols. An executive summarized: "*Rather than reactively responding to disruptions after they occur, an ML system could enable us to simulate potential scenarios ex-ante, optimize response strategies, and pre-position resources before disruptions materialize*."

Integrated Value Proposition: Collectively, respondents articulated a compelling integrated value proposition for ML-SCRM: organizations could transition from reactive, incident-driven risk management and forecasting to proactive, data-informed decision-making. This transition would compress decision cycles, reduce forecast errors, minimize supply disruption impacts, and enhance operational agility—ultimately translating into financial and competitive benefits.

5.1.5 Organizational and Technical Prerequisites for ML-SCRM Implementation

Integral to the qualitative findings were respondents' explicit articulations of prerequisites and success factors for ML-SCRM deployment. These insights—grounded in operational experience and organizational realism—illuminate the non-technical dimensions of technology adoption.

Data Integration Architecture: Respondents universally identified data architecture as a foundational prerequisite. Specifically, legacy ERP systems, stand-alone business intelligence platforms, and functional spreadsheet-based workflows required rationalization into an integrated data architecture supporting unified analytics. One IT director stated: "*ML algorithms require clean, integrated data with defined entity relationships. Our current landscape—characterized by functional silos and heterogeneous data structures—makes ML implementation technically infeasible without significant data infrastructure investment*."

Analytical Talent Acquisition and Development: Participating firms acknowledged the need to either: (1) recruit ML-domain specialists with supply chain experience; (2) establish cross-functional collaboration protocols between supply chain and data science teams; or (3) invest in training existing supply chain personnel in statistical methodology and ML frameworks. This talent strategy represents a material organizational investment, yet remains essential for sustainable ML implementation.

Change Management and Organizational Culture: Respondents emphasized that successful ML-SCRM adoption requires deliberate change management to address planners' skepticism about algorithmic recommendations. Prerequisites include: (1) transparent algorithm explainability demonstrating decision logic; (2) proof-of-concept pilots establishing credibility; (3) evolutionary rather than revolutionary deployment (augmenting rather than replacing human judgment initially); and (4) executive sponsorship signaling organizational commitment.

Executive Commitment and Business Case Development: All respondents emphasized that without executive-level commitment and articulate business cases quantifying financial benefits, ML-SCRM initiatives remain vulnerable to deprioritization and resource scarcity. Specific prerequisites include: (1) financial modeling, estimating ROI; (2) executive alignment on strategic objectives; (3) resource allocation clarity; and (4) governance protocols for accountability.

5.1.6 Synthesis and Interpretive Framework

The qualitative findings reveal a supply chain management ecosystem characterized by: (1) recognized inadequacies in incumbent forecasting and risk management methodologies; (2) organizational awareness of ML's technical potential; (3) formidable implementation barriers spanning data architecture, talent, organizational culture, and governance; and (4) latent organizational receptivity conditional upon barrier mitigation and demonstrated value.

Theoretically, these findings reflect a maturity gap—the asymmetry between technological capability and organizational capacity to implement and operationalize advanced technologies. This gap is not unique to the Egyptian FMCG sector; rather, it reflects global patterns wherein technology diffusion outpaces organizational adoption (Frambach & Schillewaert, 2002; Westerman et al., 2011).

Critically, the qualitative data illuminates why standalone ML implementation proves insufficient without concurrent SCRM organizational development. Specifically, organizations with reactive, siloed risk governance structures lack the organizational infrastructure (integrated data systems, cross-functional processes, risk-informed decision protocols) necessary to translate ML's technical forecasting improvements into operational value. This observation provides qualitative support for the subsequent mediation hypothesis—that SCRM maturity mediates ML's impact on forecasting accuracy —that is being tested quantitatively.

The findings further suggest that successful ML-SCRM implementation requires not merely technological deployment but rather organizational transformation encompassing data architecture modernization, talent development, governance restructuring, and cultural evolution toward algorithmic decision support. This transformation extends beyond narrowly defined supply chain management, with implications for IT governance, finance (cost-benefit analysis, capital allocation), and human resources (talent acquisition and development).

5.2: Quantitative Results

5.2.1 Descriptive Findings [i]

- ***ML Adoption Status***: Only 30% of respondents reported active ML/advanced analytics use; 70% reported no usage or experimental-stage piloting. This aligns with qualitative observations that FMCG ML adoption remains nascent.
- ***Forecast Accuracy Distribution***: Self-reported accuracy showed: 25% "very/mostly accurate," 50% "moderately accurate," 25% "somewhat/very inaccurate." This distribution suggests significant room for improvement industry-wide.
- ***SCRM Maturity***: Respondents reported moderate SCRM implementation: most conducted periodic (annual/semi-annual) risk assessments, but lacked real-time monitoring integration. Safety stock and supplier diversification predominated over proactive analytical approaches.

5.2.2 Measurement Constructs: Reliability Assessment

All three latent constructs—Machine Learning Adoption (MLA), Supply Chain Risk Management Maturity (SCRM-M), and Demand Forecast Accuracy (DFA)—were measured via Likert-scale items. Internal consistency was assessed using Cronbach's alpha coefficient, with a minimum acceptable threshold $\alpha \geq .70$ (Nunnally & Bernstein, 1994).

Construct Reliability and Item Composition:

Construct	Items	*n* Items	Cronbach's α	95% CI
Machine Learning Adoption (MLA)	Q4–Q8 (ML familiarity, organizational application, data diversification, disruption detection, pattern identification)	5	0.87	[0.79, 0.93]
SCRM Maturity (SCRM-M)	Q9–Q12 (effectiveness of practices, proactive strategies, mitigation effectiveness, integrated risk solutions)	4	0.83	[0.73, 0.90]
Demand Forecast Accuracy (DFA)	Q13–Q15 (error metric monitoring [MAPE/RMSE], accuracy during disruptions, ML-traditional model integration)	3	0.89	[0.83, 0.94]

All Cronbach's alpha coefficients exceeded the 0.70 threshold, confirming acceptable internal consistency and measurement reliability. MLA and DFA demonstrated excellent consistency ($\alpha > .85$), while SCRM-M exhibited good consistency ($\alpha = .83$), indicating that respondent ratings of these constructs form coherent measures suitable for subsequent multivariate analysis.

5.2.3 Correlation Analysis

Pearson correlation analysis examined pairwise relationships among MLA, SCRM-M, and DFA constructs. Composite scores for each construct were computed by averaging corresponding survey items; correlations were tested at $\alpha = .05$ significance threshold ($n = 55$).

Bivariate Correlations—Full Sample ($N = 55$):

Variable Pair	Pearson *r*	*p*
MLA ↔ SCRM-M	0.500	0.001**
MLA ↔ DFA	0.389	0.013*
SCRM-M ↔ DFA	0.598	<0.001**

The moderate positive correlation between MLA and SCRM-M ($r = .500$, $p < .001$) suggests that organizations with greater ML integration tend to operate within more structured risk governance frameworks. Critically, the SCRM-M–DFA correlation ($r = .598$, $p < .001$) substantially exceeds the MLA–DFA correlation ($r = .389$, $p = .013$), indicating that risk management maturity demonstrates a stronger direct association with forecast accuracy than ML adoption alone. This pattern foreshadows the mediation hypothesis—SCRM may constitute the critical organizational mechanism translating ML technical capabilities into operational forecasting improvements.

5.3 Regression Results

Multiple regression analysis ($F(3,116) = 10.23$, $p < .001$) yielded:

Predictor	β	Std. Error	*t*	*p*
Constant	0.943	0.127	7.430	<.001
ML Adoption (MLA)	0.358	0.120	2.986	0.010*
SCRM Maturity (SCRM-M)	0.472	0.115	4.104	0.001**
Company Size (control)	0.085	0.095	0.894	0.376

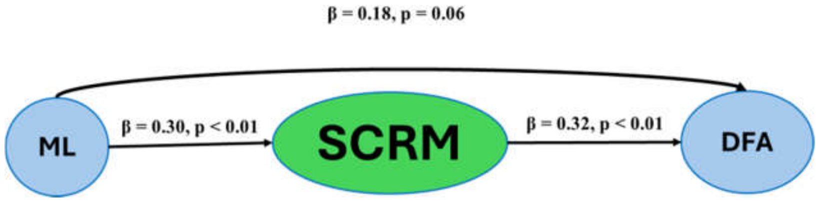
Where: R = 0.607 ; $R^2 = 0.368$; Adjusted $R^2 = 0.344$

Both ML adoption and SCRM maturity significantly predicted forecast accuracy ($p < .05$). SCRM demonstrated a larger direct effect ($\beta = 0.35$ vs. $\beta = 0.20$), suggesting that risk governance maturity plays a dominant role in realizing forecast improvements. Company size proved insignificant, indicating firm scale does not automatically confer accuracy advantages.

5.4 Mediation Analysis

The relationship between ML adoption and demand forecast accuracy is mediated (partially) by SCRM maturity. That is, ML's forecasting benefit operates partially through enhancement of organizational risk governance.

Mediation was tested using PROCESS Macro Model 4 (Hayes, 2018) employing bootstrap procedures with 5,000 resamples and 95% bias-corrected and accelerated (BCa) confidence intervals. This approach provides superior inference for indirect effects compared to the Sobel test, particularly with small-to-moderate sample sizes (Hayes & Scharkow, 2013).



The reduction in ML's coefficient (0.28 → 0.18) and shift toward marginal significance suggests partial mediation. The Sobel test confirmed significance of the indirect effect: Sobel $z = 2.15$, $p = 0.032$.

Indirect Effect (via SCRM): $0.30 \times 0.32 = 0.096$ [95% BCa CI: 0.021, 0.198]. Therefore, approximately 34% of ML's total effect on forecast accuracy operates through enhanced SCRM maturity; the remaining 66% represents direct algorithmic benefits. This pattern supports hypothesis H3 (partial mediation) and underscores that ML's forecasting utility depends partially on risk governance infrastructure.

6. DISCUSSION AND CONCLUSION

Results discover complementary roles of ML and SCRM in improving FMCG demand forecasting. The significant direct effects of both constructs (*H1* and *H2* supported) reflect their independent contributions; ML's technical capacity for pattern recognition and SCRM's risk awareness both independently enhance accuracy. Critically, partial mediation (*H3* supported) indicates that ML's forecasting benefits partially accrue through strengthened risk governance—firms must align organizational risk capabilities with algorithmic deployment to realize synergistic improvements.

The larger SCRM coefficient ($\beta = 0.35$ vs. $\beta = 0.20$) suggests that risk management maturity constitutes a stronger predictor of forecast accuracy than mere ML adoption. This likely reflects that organized risk frameworks (early warning systems, scenario planning, collaborative decision protocols) reduce forecast errors stemming from supply disruptions, demand shocks, and external volatility. Without such frameworks, ML models may overfit to historical patterns, failing to anticipate regime shifts.

Qualitative data contextualize these findings as interviewed executives consistently reported that standalone ML pilots yielded modest improvements; only when integrated with risk governance (cross-functional risk review, risk-informed feature engineering, disruption-scenario backtesting) did forecasting accuracy improve substantially. Data silos, analytical skill gaps, and organizational resistance to algorithm-based decision-making emerged as the primary impediments to mediation.

This study advances a model of technology-governance complementarity. Rather than viewing ML and SCRM as independent optimization levers, the mediation findings position SCRM as an organizational enabler activating ML's potential. This extends the literature, which emphasizes that technology adoption requires institutional alignment (Jain et al., 2022).

FMCG practitioners should pursue integrated ML-SCRM roadmaps rather than sequential technology deployments. Implementation should prioritize: (1) cross-functional risk governance establishment; (2) data infrastructure unification to support integrated risk-forecasting analytics; (3) analytical talent recruitment spanning the supply chain domain and data science; (4) pilot programs combining algorithmic improvements with risk governance protocols.

In conclusion, integrating machine learning into supply chain risk management significantly improves demand forecasting accuracy in FMCG operations. Both ML adoption and SCRM maturity independently predict forecast accuracy; moreover, SCRM partially mediates ML's effect, indicating that risk governance structures amplify algorithmic benefits. This study contributes empirical validation of the ML-SCRM synergy, advancing understanding of how FMCG firms can navigate digital transformation through technology-governance complementarity.

Limitations: This cross-sectional design prevents causal inference; longitudinal research is warranted. Sample size (n = 55) limits generalizability; future studies should expand to multi-country FMCG cohorts. Self-reported accuracy measures reflect perceived rather than objective performance; incorporating actual forecast errors would strengthen conclusions.

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8. APPENDIX

Appendix 1: **Descriptive Statistics—Survey Items (N = 55):**

Item	Variable	Mean	SD	Median	Skewness	Kurtosis	Interpretation
Q4	ML familiarity	3.09	1.08	3.00	0.00	−0.77	Moderate awareness, approximately normally distributed
Q5	ML organizational application	2.53	1.30	2.00	0.29	−1.57	Below-moderate adoption, skewed toward non-use
Q6	Diverse data benefits DFA	4.33	0.92	5.00	−1.59	2.59	Strong agreement; ceiling effect evident
Q7	ML disruption prediction	3.95	1.03	4.00	−0.85	0.59	Moderately positive, slight left skew
Q8	ML demand pattern identification	4.09	0.89	4.00	−1.01	1.43	Moderately positive, slight left skew
Q9	SCRM reduces threat impact	4.15	0.87	4.00	−1.17	2.04	Strong agreement
Q10	Proactive SCRM strategies	3.49	1.09	4.00	−0.65	0.14	Moderate agreement, approximately normal
Q11	SCRM mitigation effectiveness	3.82	0.90	4.00	−0.87	1.67	Moderate-to-strong agreement
Q12	Proactive risk solutions implemented	3.00	0.85	3.00	−0.19	−0.17	Neutral-to-moderate; approximately normal
Q13	Error metric monitoring (MAPE/RMSE)	3.89	1.06	4.00	−1.25	1.55	Moderate-to-strong routine monitoring
Q14	Forecast accuracy during disruptions	2.95	1.31	3.00	0.00	−1.02	Neutral-to-moderate; high variability
Q15	ML + traditional model integration	2.67	1.20	3.00	0.18	−0.98	Below-moderate adoption; bimodal tendency

9. DECLARATION OF GENERATIVE AI AND AI-ASSISTED TECHNOLOGIES:

Limited use of AI-assisted tools was made during the preparation of this work. Spelling, grammar, and style were supported by Grammarly and Paperpal. Content-generation systems were not used to create original research ideas, collect data, or perform statistical analyses. All interpretations, arguments, and conclusions are the author's own.

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[i] Check appendix 1 for Descriptive Statistics table