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Harnessing Generative AI for Financial Risk Anticipation in Retail and Coatings Manufacturing Supply Chains

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Abstract

Financial risk is an increasingly complex challenge in supply chains. Dynamic changes in the market affect multiple stakeholders across different tiers of the supply chain. Accurately defining and estimating these risks is crucial for optimizing working capital utilization and planning. Generative AI has been identified as a technology that can play a significant role in operational processes. Research on its application has focused primarily on operational processes, while the potential benefits for predictive modelling, particularly in supply chain financial risk management, remain unexplored. This study attempts to address this gap by proposing a framework for simulating various financial risk exposures in a retail supply chain and cross-tide testing the resulting specials within the supply chain of a paint manufacturer.

The proposed framework comprises three main components: (a) establishing a data architecture with the required data elements, sources, and flows for preparing the data, (b) implementing generative AI models to simulate financial risk exposures, and (c) defining metrics for validating the output of the simulated models. These components are examined in detail, and their implementation is illustrated through a retail use case and a cross-supply chain application involving a paint manufacturer. In the retail case, financial risks related to stock levels, turnover, working capital, and liquidity stress under demand volatility are explored. The second case involves a paint manufacturer faced with a potential price increase of key raw material. It investigates the impact of sourcing decisions underprice uncertainty on raw material costs and financial exposure.

Keywords: Financial Risk, Generative AI, Predictive Modelling, Supply Chain Finance, Supply Chain Management, Retail Business, Paint Industry, Chain Vertical Integration, Time of Day Effect.

1. Introduction

The Black–Scholes model, popular among traders and corporates, relativizes value with neutral volatility. However, many industrial producers lack active treasury departments and rely on cash flow management to protect against pricing volatility, while retailers minimize stock—often sourced from external manufacturers—through inventory turnover. These companies therefore remain financially robust only if turnover remains stable and liquidity adequate. Perturb investors increasingly seek predictive risk analyses from top management.

The financial success of retail is tied to inventory management and supplier dependence. Inventory can thus be affected by market demand—volatility, price elasticity, seasonality, and promotions—as well as supplier-related supply-side disruptions. Financial stability during periods with insufficient liquidity is another paramount concern of top management. Dipanshi's et al. suggest applying machine learning–based simulated market tests for predictive financial risk assessment, but market-side simulations remain untested. Specifically, departments concerned with cash inflow and outflow are seldom linked by means of risk-sharing mechanism, despite the financial stability implications of inventory on top management.

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Fig 1: Generative AI in Supply Chain Management

1.1. Background and Significance

Profound difficulties arise when attempting to predict profits that respond to and translate financial expectations into cash flow, resulting in an underestimation of revenue sources while operating with no, or only limited, financial buffers. Despite growing awareness that financial mismanagement represents a senior management risk, neither financial institutions nor application suppliers have developed predictive models that account for the market and operational realities of the retail sector and its manufacturing chains. Such realities include both specific demand-side market structure features and common uncertainties related to demand volatility, lead times for supplier deliveries, price and currency variations, and response patterns that drive working capital and cash flow needs, thus linking production with consumption.

Financial loss analysis confirms that shortfalls in revenue, increased costs, delays in investment and mitigation, as well as price reductions, have inflicted by far the greatest damage on profits. A mid-market leading retail company's Moody's risk analysis also flags financial managerial capability, highlighting that traditional predictive models, which are based solely on the economic fundamentals of the market and determined to detail demand growth, are often fundamentally flawed. Such weaknesses translate into poor cash-flow forecasts and financial mismanagement in situations when pressure emerges to open the cash flow. Financial market risk budgets for retail group operations therefore adopt a tactical market-monitoring and scenario-planning approach or, in some cases, remain purely pragmatic with companies, in effect, swimming naked without any apparent risk management procedures.

Equation 1: Demand model with seasonality + promotions + noise (step-by-step)

Let:

- $t = 1,2,\dots,T$ index months
- D_t = demand (units) in month t
- D_0 = baseline average monthly demand
- s_t = seasonality factor (dimensionless, centered around 1)
- p_t = selling price in month t, p_0 = regular price
- ϵ = price elasticity of demand (negative)
- η_t = random shock with mean 0

Step 1: multiplicative structure

$$D_t = D_0 \cdot s_t \cdot g(p_t) \cdot (1 + \eta_t)$$

Step 2: a standard elasticity form
A common choice:

$$g(p_t) = \left(\frac{p_t}{p_0}\right)^{\epsilon}$$

If promotion is a discount $\delta_t \in [0,1)$, then $p_t = p_0(1 - \delta_t)$.
Substitute:

$$g(p_t) = (1 - \delta_t)^{\epsilon}$$

So:

$$D_t = D_0 \cdot s_t \cdot (1 - \delta_t)^{\epsilon} \cdot (1 + \eta_t)$$

Step 3: choose the stochastic shock distribution
Often $\eta_t \sim \mathcal{N}(0, \sigma^2)$ or lognormal. In my illustrative

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simulation I used Gaussian noise with a coefficient of variation.

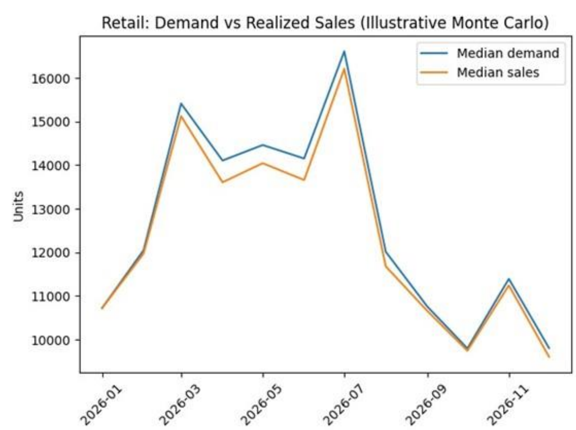
This matches the article's need to simulate **seasonality + promotions + price sensitivity + volatility**.

2. Literature Review

Focusing on predictive financial risk modelling within retail and paint manufacturing supply chains, existing works are mapped, limitations identified, and theoretical frameworks and hypotheses specified. Four broad classes of financial risk are discerned: supply- and demand-side uncertainties with direct operational impact; wider-market commodity price and exchange rate swings; capital-structure threats arising from interest rate variations; and currency devaluation leading to increased sourcing and operating costs. Collection of financial data from one retail, one manufacturing and two pairing companies in the context of data quality and governance forms part of the early work.

Research is presented in three parts. First, a review of predictive financial modelling in operations research identifies deficiencies in temporal depth, empirical evaluation, and predictive risk quantification. These shortcomings are addressed through the specification of a broad range of financial risk categories supported by an extensive literature review. Second, four typologies of financial risk in predictive financial modelling specific to retail and paint manufacturing supply chains are outlined. An operational risk type encompasses market-driven uncertainties in supply, customer demand, and price levels; broader-market risks reflect volatility in commodity prices and exchange rates; liquidity-structure risks quantify changing interest coverage ratios; and Devaluation-Related Financial Risk Areas (DRFRA) model the impact of local currency devaluation on manufacturing-country operating costs. Exploratory analyses of financial data quality and risk quantification for a retail operation are also undertaken.

The analysis draws on predictive modelling literature from operations research; the financial supply chain and return on investment; demand-predictive liquidity buffer requirements; capital cost in inventory policies; operational cash flow stress-testing in retail; capital expense modelling for Three-tier supply chain networks; cost prediction at major automobile manufacturers; predictive variance estimates for liquidity-surplus; and descriptive modelling of shale oil supply.



2.1. Research design

Existing predictive financial risk models are surveyed and classified by domain and approach. The review confirms that while financial risk for e-commerce companies and companies with e-commerce business models for retail segments has been well studied, little attention has been given on predictive financial risk modeling for retail segment companies associated with shopping malls. Further, financial risk for the paint manufacturing supply chain has not yet been studied. Building on this gap, a suite of generative AI platforms is defined to handle a set of specified financial risk typologies for retail and paint manufacturing supply chains, employing an economy-wide integration argument.

In reviewing risk typologies, four main aspects are studied. Market, credit and operational uncertainties are combined into a distribution of expected revenues and cost of goods sold, together with interest and tax costs. Liquidity buffer and debt facilities are evaluated in light of working capital turnover ratios. Inventory, production and trading subsidiaries respond to demand-risk-induced uncertainties, tempered by all other supply-side uncertainties. Demand-side uncertainties specifically incorporate seasonality,

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promotion effects and volatility that change according to cross-zero events. Supplying, producing and retailing faces further disruptions in supplier delivery-progression-lead-time, logistics capacity and lead-time variability. Requests-for-quotations also model commodity volatility that exhibit auto-correlation, sudden- and cross-square-wave jumps; likewise, cross-currency impacts in a multicarrier setting promise risk-mitigation through non-operative, operating, trading and site currency-for dollar demand-hedging.

Equation 2: Inventory dynamics with lead-time uncertainty (step-by-step)

Define:

- I_t = on-hand inventory at start of month t
- Q_t = order placed at month t
- L_t = lead time (months) for order placed at t
- R_t = receipts arriving at month t
- S_t = sales fulfilled at month t
- Lost sales (or backorders) can be modeled; here I use lost sales for simplicity.

Step 1: receipts are lagged orders

$$R_t = Q_{t-L_t} \quad (\text{if } t - L_t \geq 1)$$

Step 2: fulfillment

$$S_t = \min(I_t + R_t,\ D_t)$$

Step 3: inventory balance

$$I_{t+1} = I_t + R_t - S_t$$

Step 4: stockout event

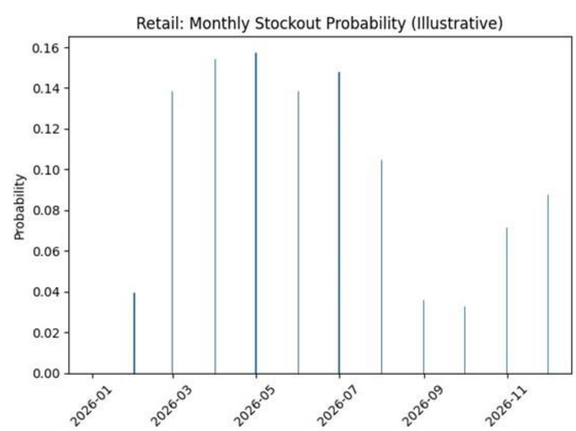
$$\text{Stockout}_t = \mathbf{1}\{D_t > I_t + R_t\}$$

3. Methodological Framework

The methodological framework is detailed in four closely interlinked chapters covering data architecture and integration, generative AI models for risk simulation, evaluation metrics and validation, and governance of data, models, and applications. A combination of parallel data processing and asynchronous model training in the development phase allows for a single set of pre-processed training data to create multiple, independent generative AI simulations of risks for subsequent use by multiple stakeholders across different supply chain sectors.

3.1. Data Architecture and Integration

Information is collected from multiple sources under jurisdictional constraints pertaining to confidentiality, data ownership, and privacy, combined with additional sources in the public domain generating a wide variety of internal and external data points and making the entire database a source of great potential for new applications. The data structure supports a series of ETL processes that encompass data extraction, transformation, loading, and quality control. The schemas used at each stage ensure the information is interpreted correctly and that the various data sources are interoperable, permitting the creation of a single dataset across multiple domains that makes the generation of scenarios convenient and coherent from a data perspective.



3.1. Data Architecture and Integration

Data provenance and governance are paramount when defining the governing data architecture and storage

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solutions, as are quality controls and adjustments needed to accommodate data from the two supply chains under analysis. Data supporting financial risk modelling are sourced from standard company business systems, mainly Escalon for the retail company and Location for the paint supplier. These systems provide, among others, the structured general ledger, supply invoices and payments, stock control, position control, supplier purchases, and product sales. The data supporting the retail company's cash flow and working capital need for the next twelve months also require input from a non-structured format, specifically from a monthly cash flow schedule that details receipts (sales, debts recovered, and refunds) as well as payments for the various company expenses grouped into categories.

For the incorporation of generative AI in the retail company's inventory forecasting, the retail company's business model enables demand volatility to be identified and changes and their respective impact on future sales to be simulated. Demand volatility, price sensitivity to seasonality, promotional sales, and stock performance over the various months are therefore determined to generate one or more business-determined demand-simulation scenarios for use in the turning of the generative AI models. The generated models should then be able to create inventories and sales figures in parallel in order to allow the stock turnover rate to be maintained in a reasonable range. Different levels of stock, cash flow, and working capital at different times of the year can also produce different selling prices, resulting in changes to demand. Thus, several demand scenarios need to be created for the generation of AI models to cover the whole cash flow and working-capital period under consideration.

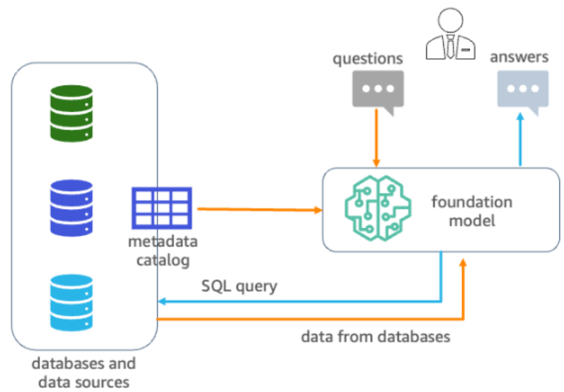

Fig 2: Generative AI and modern data architecture

3.2. Generative AI Models for Risk Simulation

Generative AI simulates financial risk by employing a mix of text, image, video, and audio models. Text models such as ChatGPT support scenario formulation, query and risk-impact narrative creation, test design, prompt generation, and risk factor moderation, while TTS acts as a voiceover for visual stories produced by Stable Diffusion or similar tools. Risk-factor values obtained from dedicated, trained models drive text, image, video, and audio generation. These external risk-factor models link the underlying scripts to all risk sources defined in the model bank.

Producing out-of-sample uncertainty-adjusted input data for a scenario-specific financial-predictive model comprises three steps. Risk-specific models capture space-intelligent density functions conditioned on all market-and-demand parameters. For any metaphysical evaluation badging a tolerance interval, risk-specific models tune the generative AI risk bank, substantiating a risk density input set for the model bank. The aim is to develop risk-sex-land domains containing bonds whose yields are most sensitive to shifts in risk-space Sex Changes for every evaluated Sex-simulated Flutings domain, thus populating the Rents pace Risk-packet Bank of the three-packet model with all model dimensions, signs, and levels—enabling dense-hall Monte Carlo testing of financial-Flash Credit impact on the universes for a risk-space tolerance band.

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3.3. Evaluation Metrics and Validation

Adequate model performance is vital for generating reliable simulated scenarios. In previous applications of generative AI for predictive financial risk modelling, metrics are formulated around the SCS. Out-of-sample testing may not be feasible for many low-frequency variables—prompted variation is largely conditioned on historical distributions rather than a temporal ordering of actual data. Instead, advanced back testing and robust checks are performed. For risky financial exposures, model-generated SCS and alternative high-fidelity Monte Carlo samples are bootstrapped with random correlational structures to quantify the out-of-sample uncertainty of return at-risk estimates.

All three business cases face ethical and compliance requirements relating to sensitive underlying data. Data provenance must enable traceability from original data sources used as training conditions within a generative AI model. For deployment external-use cases accessible to unauthorized analysts or third-party decision-makers, Model Cards are produced with Accuracy, Calibration, Safety and Fairness sections. Maturity of the financial predictive capability at cross-supply-chain level motivates scenario analysis aligned with typical stress-testing frameworks.

4. Financial Risk Typologies in Retail and Paint Manufacturing

Financial risks type-cast as supply- and demand-side uncertainty within both retail inventory management and paint manufacturing. Supply-side disruptions from suppliers, logistics service providers, or transportation modes can hinder material receipt, while demand-side effects can include seasonality, consumer price sensitivity, and external promotions. The net market risk within retail can, thus, be examined with stock levels and cash flow forecasts.

Predictive modelling of financial risk addresses three types of uncertainty: market demand volatility (and price elasticity of demand), the volatility of supply lead times (from suppliers or logistics service providers), and the volatility of key commodities (especially paint raw materials) together with foreign-exchange exposures. Market-driven financial risk is assessed via a combination of cash-flow and stock-level forecasts over an extended horizon. Raw-material-cost-induced financial risk is considered through the lens of a three-tier paint supply chain during the planning stages of final production. Examining the financial stress-testing of two supply chains across a number of severe scenarios for the selected risk factors determines when and to what extent both supply chains suffer liquidity squeeze.

4.1. Market and Demand Uncertainty

Demand uncertainty and price volatility are recognized as financial risk factors across industries and supply chains. In retail, temporal fluctuations in consumer demand create risk for working capital management and inventory levels, whilst sensitivity to pricing—including both seasonal and time-related promotional elements—changes its profile throughout the year. In painting manufacturing, the sensitivity of end-market demand also shifts with seasonality, and therefore too does the risk for distribution and supply chain players. Significant destocking typically occurs ahead of the colorfast holidays in markets such as India, Union Festivities in Southeast Asia, and Diwali in Northern India, followed by consumer-led restocking. This cyclicality generates considerable reverse pressure in demand, pricing, and margins, which, alongside forecast inaccuracies, produces uncertainty that leads decision makers to incur either excess inventory ahead of the peak demand season or risk stockouts during the festival.

Market demand is exposed to external shocks in periods of geo-political instability (such as the effects of the ongoing conflicts in Eastern Europe and the Middle East) or natural disasters (such as floods in Southeast Asia) and, for the retail sector, sudden disease outbreaks. Generative AI facilitates the simulation of changes over these differing periods with respect to sales revenue probability distributions by disrupting the market demand variables and examining the forecasting impact on demand. Model healthcare- and weather-related scenarios also necessitate the analysis of these areas. Moreover, whilst currency exchange rate movements increase costs for international manufacturers, demand may likewise be affected, as an example, by burial of a local currency.

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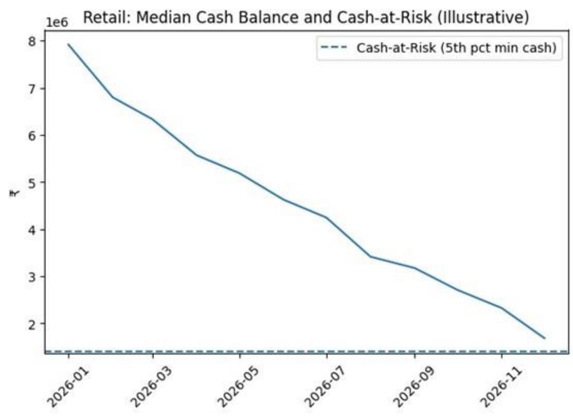

4.2. Supply-Side Disruptions and Lead Time Variability
Supply-side uncertainties translate demand projections into potential stockout events and excess inventory sitting on shelves. In addition to the usual demand variability, the frequency and magnitude of logistic disruptions, longer lead times, and increasing capacity shortages are complicated supply-side conditions that Inventory Managers must accommodate in their use of stock levels. Lead time variability at the supplier and logistics commission level influences the adequacy of forecasted stock levels at the supplier, retailer, or wholesaler level, given changes in lead times.

Lead time sequences at all levels are dynamic, reflecting real-world volatility, and can be input as a scenario, i.e. the number of significant long supplier or transportation delays is presented as an input to the Generative AI-trained Monte Carlo risk simulation. The impact of these supplier delay sequences is incorporated into the supplier service level for local suppliers.

Equation 3: "Order-up-to" policy and safety stock from service level (step-by-step)

Let:

- Inventory position $IP_t = I_t + \text{OnOrder}_t$

Target stock (base-stock level) for horizon $H = L_t + 1$ (lead time + review period):

Step 1: expected demand over protection period

$$\mu_{t,H} = \sum_{k=0}^{H-1} \mathbb{E}\,[D_{t+k}]$$

Step 2: demand variance over protection period
Assuming independent demand shocks:

$$\sigma_{t,H}^2 = \sum_{k=0}^{H-1} \text{Var}\,(D_{t+k})$$

Step 3: safety stock for cycle service level α
Let z_α be the Normal quantile (e.g., 1.645 for 95%):

$$SS_{t,H} = z_\alpha \cdot \sigma_{t,H}$$

Step 4: base-stock level

$$B_t = \mu_{t,H} + SS_{t,H}$$

Step 5: order quantity

$$Q_t = \max(B_t - IP_t,\ 0)$$

4.3. Commodity and Currency Volatility
Price swings in commodities, whether resources or consumables, can harm profitability. Retailers only partially hedge exposure by buying in advance or relying on supplier agreements. In painting manufacturing, raw material products are usually hedged through supplier contracts with index-linked pricing mechanisms. Nevertheless, currencies are unhedged. With paint manufacturing holding stocks of sparsely used and perishable ingredients, the future mark-to-market cost of holding sufficient stock is uncertain. Generative AI captures uncertainty over paint-product raw material costs while enabling more speedy and cost-effective predictive analytics.

Commodity price fluctuations impact costs and revenues. Exact exposure is scenario dependent. Market data can help to capture future distributions of inputs and raw materials in forecast periods, although only in a coarser way for raw materials. Paint-production costs depend on both the input costs required for a set production recipe and the total production volume. Paint is manufactured in batches that depend on demand patterns. Changes in these patterns can

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result in very different production schedules, which in turn influence raw material holding costs and mark-to-market values of held stocks.

Greater-than-expected demand may result in costly expeditious orders for raw materials, while lesser-than-expected demand may mean that stock levels need to be maintained for long periods. The handling of pigments, which are used for coloring and typically purchased in small but expensive quantities, is an exception to the more standard cost pattern and needs separate and special handling. Painting products are sold in relatively small quantities as semi-finished goods and consumables. Nevertheless, demand is also influenced by weather and climate, making estimation difficult. Therefore, subtitle data need to be used to provide distributional information for the prediction of paint-product demand.

5. Data Governance, Ethics, and Compliance

Privacy-preserving data encryption secures sensitive consumer behavior and payment information in the retail database and information pertaining to supplier grades and transport delays and disruptions in the paint supply chain. The de-identification process ensures that transaction history and other sensitive information cannot be linked to individuals or organizations. Data governance follows a fit-for-purpose data schema with an instruction and information framework encompassing purpose, provenance, sensitivity, availability, control, usability, ethics, security, and compliance. The implementation of a data governance framework ensures usage control and ethically acceptable generation of synthetic data.

Model transparency, explainability, and auditability on model development are validated through computation of integrated gradients. Regular audits are conducted to check for bias in both data and models. Model-bias detection procedures ensure proper consideration of the context to achieve fairness in model performance across multiple demographic manifestos. Effectiveness in bias detection ensures fair GAI model performance across multiple sensitive manifestos. Model fairness and bias mitigation checks enhance ethicality and auditability, thereby ensuring compliance with the European Union's Proposal for a Regulation Laying Down Harmonized Rules on Artificial Intelligence. During model training, the planned orchestration framework lends direction and interpretation to outcomes while enabling the identification of sensitive aspects of data that can lead to discrimination and promote inequality.

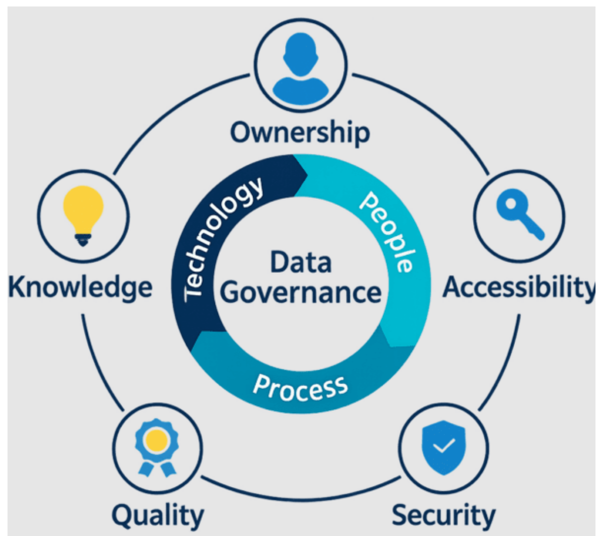

Fig 3: Data governance framework

6. Case Studies and Applications

A generative AI-enabled predictive financial risk modeling solution has been designed and tested for application in the retail and paint manufacturing supply sectors. A retail case study investigates the financial impact of sales volatility along with supply lead-time uncertainty on stock levels, inventory turnover, working capital and, ultimately, liquidity risk. The second study explores financial exposure in a paint manufacturing company's raw material sourcing and production planning environment, where feedstock prices are volatile, external supply contracts can be bespoken and built-in durations or forecast requirements can cause material standstill risks. The cross-supply-chain financial

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analysis integrates the stress testing of one echelon company as a bank on the other echelons company in the same supply chain, thus considering the liquidity buffers along with the financial impact of scenarios simulated in the other company.

6.1 Retail Inventory and Cash Flow Forecasting

A retail inventory and cash-flow forecasting case study investigates how sales forecasting volatility and supply lead time variability influence stock levels, inventory turnover, working capital requirements, and liquidity risk. Mapped to a retail enterprise environment, two distinct types of models were constructed: the first predicts the stock levels and turnover based on the generative AI simulation of demand; the second determines the working-capital requirement based on inventory turnover, seasonality, and promotional campaigns, also simulated through generative AI. The iterative interplay of these models leads to the projection of bank cash balances.

Equation 4: Inventory turnover and DSI (step-by-step)

Let:

- $COGS_t$ = cost of goods sold in month t
- $\overline{Inv}_t$ = average inventory value during month t

Step 1: monthly turnover

$$\text{Turnover}_t = \frac{COGS_t}{\overline{Inv}_t}$$

Step 2: annualized turnover (if monthly)

$$\text{Turnover}_{\text{annual}} \approx 12 \cdot \text{Turnover}_{\text{monthly}}$$

Step 3: Days Sales in Inventory
If using annual COGS and average inventory:

$$DSI = \frac{\overline{Inv}}{COGS_{\text{annual}}} \cdot 365$$

(Or month-based with 30 days.)

6.1. Retail Inventory and Cash Flow Forecasting
Vendors constantly alter product pricing to leverage the promotional effect on demand and improve sales volumes during seasonality peaks. A narrow and too frequent discount strategy can lead to sluggish sales of primary products not included in discounts, while a too-limited number of promotions will suffer demand loss support in case of seasonal effect on demand. Consequently, it is crucial to understand the effect of timing and the promotion depth on demand.

Retailers should secure enough stock at the right time and the right place by understanding demand volatility coming from pricing, seasonality, and promotional strategies to satisfy demand, reduce logistic and stock holding costs, by avoiding delayed sales and lost customers, and eventually help the supplier smooth production and warehouse loads. Therefore, supplier costs not only depend on raw materials availability and price but also on the retail supply chain.

Retailers need to ensure adequate cash availability for these costs and the long payment term given to consumers. Additionally, simulation results should be back tested with a common quantification of unexpected events so liquidity risks become visible and can be accordingly monitored. Finally, the Vendor-Managed Inventory (VMI) policy requires high trust between suppliers and customers. Any channel failure impacts negatively on suppliers' and retailers' inventories, costs, and EMS. Therefore, also the quality of the data provided to the supplier is fundamental to properly delivering the VMI benefits.

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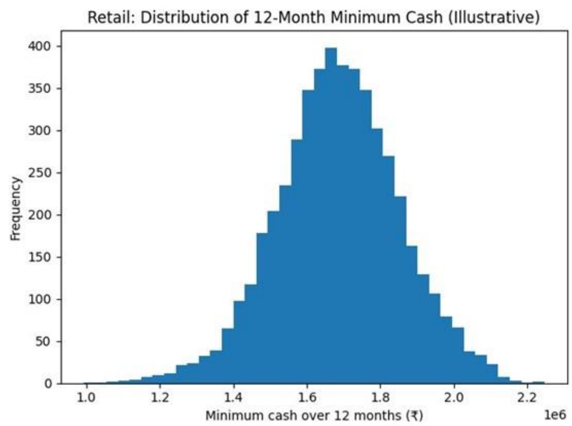

6.2. Paint Manufacturing: Raw Material Sourcing and Production Planning

For a paint manufacturer, raw material sourcing and production scheduling decisions are typically made months in advance, yet raw material prices can fluctuate significantly over multitooth and multiyear time horizons. The models simulate the distributions of these price swings for major commodities such as titanium dioxide, resin, and solvents and their correlation with currency swings. A paint manufacturer that sources several key raw materials from a single supplier must not only look at the prices but also consider the possibility of a supply disruption. The model simulates supplier delays or shortages and the consequential knock-on effects in two-to-three-levels-down logistics. The financial implications of all these effects on material subsidies, working capital costs, and Day Sales in Inventory (DSI) are modeled. Such data alerts focus on the risk of excess or insufficient working capital.

Raw material sourcing and production scheduling decisions for a paint manufacturer are typically made months in advance, yet raw material prices can fluctuate significantly over multitooth and multiyear time horizons. Therefore, the models simulate the distributions of these price swings for major commodities such as titanium dioxide, resin, and solvents and their correlation with currency swings. In addition, a paint manufacturer that sources several key raw materials from a single supplier must not only consider the prices but also the possibility of a supply disruption. The models simulate supplier delays or shortages and the consequential knock-on effects in two-to-three-levels-down logistics. The financial implications of all these effects on material subsidies, working capital costs, and Day Sales in Inventory (DSI) are modeled. Such data alerts focus on the risk of excess or insufficient working capital.

6.3. Cross-Supply Chain Financial Stress Testing

Financial risks typically manifest in local supply chain echelons, but spillovers can trigger vulnerabilities further upstream or downstream. Richer information across multiple supply chains enables evaluation of cross-impact linkages, exploring potential contagion of financial liquidity distress. The system's ability to withstand calibrated financial stress scenarios is assessed.

Risk scenarios highlight financial impact on both the retail channel and paint manufacturing, eliciting the need for a joint liquidity impact assessment to address the overall financial system resilience. The edge case reveals a strong positive reliance—retailer ability to maintain a liquidity buffer in the context of a supplier shipping mishap; at low levels of such a liquidity buffer, the paint manufacturer is unable to take the supplier's risk to avoid a costly production stop.

Equation 5: Working capital and cash-balance forecast (step-by-step)

Define:

- AR_t accounts receivable (customers owe you)
- AP_t accounts payable (you owe suppliers)
- $Inv_t^{₹}$ inventory value (₹)
- WC_t working capital

Step 1: working capital

$$WC_t = AR_t + Inv_t^{₹} - AP_t$$

Step 2: simple cash recursion

Let:

- C_t = cash at end of month t

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- Col_t = collections from customers in month t
- Pay_t = payments to suppliers in month t
- $OpEx_t$ = operating expenses in month t

$$C_t = C_{t-1} + Col_t - Pay_t - OpEx_t$$

This is the core of "project bank cash balances" from simulated demand/inventory/cash-flow.

7. Conclusion

The exponential emergence of generative artificial intelligence (AI) has resulted in revolutionary advances in near-state-of-the-art capabilities for generative natural language processing. The pioneers of such models released no-code interfaces, allowing vast audiences to capitalize on these capabilities. Therefore, the generative-capable model product landscape receives multi-modal, and customized, fine-tuned additions that leverage industry-specific content and focus on actuation. Given the back-and-forth nature of natural language, generative AI lends itself to exploration and simulation. Consequently, in domains in which simulation is instrumental, generative models have been integrated within scenarios involving predictive simulations of data series.

As generative AI matures, extending predictive simulations to other types of AI models and pipelines shines light on the needs of retail supply chains' financial impacts. Key Demand, Supply, Market, and Currency Risk types—together with future financial-stress-testing requirements across the retail and paint supply chains—are summarized. The objective encompasses predictive-financial-risk models of generative and other AI techniques while considering user-controlled risk scenario generation. The offering is timely: the global environment remains volatile, uncertainty persists in demand and supply, risks multiply at historically elevated levels, liquidity is under real threat, corporate risk tolerance is low, budgets for countermeasures are tight, and lean processes are being implemented.

7.1. Future Trends

The research proposes an objective, evidence-based analysis of financial risks in retail and paint manufacturing supply chains. Retail requires large assortments of fast-moving consumer goods with uncertain demand, high seasonality, and aggressive trade promotion in a highly price-sensitive market. Paint manufacturing relies on complex paint formulations with a pooled supply of raw materials that are volatile. Consisting of two research studies, the first addresses direct financial risk of inventory control and cash-flow forecasting for a single retail business under uncertainty in supply-side availability and lead time.

The second study focuses on the paint-manufacturing business of source raw materials and manufacture under the risk of volatile commodity prices and exchange rates of supplier contracts, with production scheduling depending on demand forecasts from end users. OpenX and Capex spending are also modelled, while exposure to financial stress across retail Plus appliance supply chains — with focus on the paint segment — is examined through stress testing and scenario analysis. Evaluation of predictive performance uses back testing on historical periods and out-of-sample holdouts.

Equation 6: Commodity and FX stochastic process (step-by-step)

Let P_t be commodity price (USD/ton). Continuous time GBM:

$$dP_t = \mu P_t dt + \sigma P_t dW_t$$

Step 1: log-transform
Apply Itô's lemma:

$$d(\ln P_t) = (\mu - 1/2\,\sigma^2)dt + \sigma dW_t$$

Step 2: discretize monthly with $\Delta t = 1/12$

$$\ln P_{t+\Delta t} = \ln P_t + (\mu - 1/2\,\sigma^2)\Delta t + \sigma\sqrt{\Delta t}\,Z_t$$

with $Z_t \sim \mathcal{N}(0,1)$.

Step 3: exponentiate

$$P_{t+\Delta t} = P_t \cdot \exp\left((\mu - 1/2\,\sigma^2)\Delta t + \sigma\sqrt{\Delta t}\,Z_t\right)$$

Do the same for FX rate F_t (INR per USD).

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