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An Explainable Robust Optimization Framework for Corporate Cash and Working Capital Allocation

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Abstract

Corporate financial management requires a recurring allocation of scarce internal funds among liquidity reserves, working capital, debt reduction, and strategic investment. These uses are usually evaluated in separate analytical routines, even though their value is jointly determined by financing frictions, cash-flow uncertainty, and downside exposure. This study develops an integrated Financial Resilience Index (FRI) and a scenario-based allocation model that combines expected financial benefit with Conditional Value-at-Risk (CVaR) of target shortfall. The framework also accommodates Explainable Artificial Intelligence (XAI) when machine-learning forecasts are used to estimate scenario payoffs: driver-level explanations can be generated with SHapley Additive exPlanations (SHAP) before the optimization stage, while the allocation model itself remains transparent. Because no observational dataset is assumed, the paper presents a fully disclosed synthetic decision experiment rather than empirical claims. In the illustration, a growth-first policy yields the highest expected benefit but produces severe downside losses, whereas a balanced policy reduces CVaR materially and a resilience-first policy lowers downside shortfall CVaR by approximately 97% relative to the growth-first solution while sacrificing about 20% of expected benefit. The framework therefore identifies an interpretable resilience frontier instead of a single mechanically "optimal" cash policy. The principal contribution is to connect working-capital efficiency, corporate liquidity, debt capacity, and strategic investment within one auditable financial-management architecture, allowing chief financial officers to choose an allocation consistent with explicit risk appetite and liquidity floors. The framework is intended as a decision-support model that can subsequently be calibrated and tested with firm-level accounting, treasury, and cash-flow data.

Keywords: Financial resilience, Working capital management, Corporate liquidity, Robust optimization, Conditional value-at-risk, Explainable artificial intelligence.

1 | Introduction

Financial management is fundamentally an allocation problem: Managers must decide how much capital to retain, deploy, borrow, repay, or distribute when the economic value of each action depends on risk, timing,

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and access to external finance. Classical corporate-finance theory establishes that financing and investment choices are linked once the frictionless assumptions underlying capital-structure irrelevance are relaxed [1]. Under asymmetric information, firms may prefer internal funds and debt over new equity, and valuable investments can be forgone when external capital is costly [2]. Agency considerations add a second tension: abundant free cash flow can protect operating flexibility but can also weaken capital discipline when managers control resources in excess of value-creating opportunities [3].

The practical significance of this allocation problem increases under financing constraints. Investment can become sensitive to internal funds when external finance is imperfect [4], while debt and liquidity constraints can directly alter the timing of real investment [5]. Firms facing financing frictions may save a larger portion of cash flow as cash [6], and survey evidence from the global financial crisis shows that constrained firms cut investment more aggressively, draw on credit lines, burn cash, and postpone attractive projects when financing capacity deteriorates [7]. These findings imply that liquidity is not simply an idle asset: its value is state-contingent and closely connected to future investment capacity.

A large corporate-liquidity literature reaches a related conclusion. Cash holdings vary systematically with growth opportunities, cash-flow risk, and access to capital markets [8]. The secular rise in corporate cash has been linked especially to higher idiosyncratic risk and changes in firm characteristics [9]. Dynamic models further show that financial flexibility has option-like value when external financing is costly and investment opportunities are uncertain [10]. Refinancing risk also induces firms to hold additional cash, particularly when short debt maturity makes future capital access more fragile [11]. Consistently, cash is more valuable for financially constrained firms when it enables investment that would otherwise be bypassed [12].

Working capital creates a parallel allocation problem inside the operating cycle. Empirical evidence links receivables, inventories, payables, and the cash conversion cycle to profitability [13], [14]. Small and medium-sized enterprises appear to manage toward target working-capital positions [15], and the relation between working capital and profitability is frequently non-linear, implying an interior optimum rather than a universal rule of "lower is always better" [16], [17]. Large-sample evidence similarly indicates that moving toward an optimal working-capital position can improve operating and stock performance [18], while the market value of marginal working-capital investment depends on financing conditions and bankruptcy risk [19]. The importance of working-capital efficiency can be stronger during economic downturns [20], and cross-country evidence shows that the value of net operating working capital varies with financial development and investor protection [21]. Operational reductions in the cash conversion cycle can therefore release financing capacity and improve value when they do not damage sales or supply continuity [22].

Despite these advances, the corporate-cash and working-capital literatures are still frequently operationalized as separate managerial routines. Treasury teams set liquidity buffers; operations teams manage receivables and inventory; finance teams determine debt paydown; and investment committees evaluate growth projects. Yet these decisions compete for the same internal cash. A dollar committed to inventory cannot simultaneously serve as a liquidity reserve or debt repayment; a dollar used to retire debt changes refinancing exposure but also removes a liquid hedge against future cash-flow shocks. Trade credit further connects operating and financing decisions because constrained firms use supplier credit when financial-intermediary funding is limited [23], industry growth can depend on trade credit where financial development is weak [24], and financially distressed firms alter their use of trade credit [25].

The motivation of this study is therefore to replace siloed liquidity ratios with an integrated financial-resilience decision architecture. This is important because the marginal value of cash is not constant across firms or financial policies [26], corporate saving reflects both uncertainty and financing conditions [27], and cash cannot generally be treated as mechanically equivalent to negative debt when firms have hedging needs [28]. Liquidity can also preserve high-adjustment-cost investments such as research and development during financing shocks [29]. A useful financial-management model must consequently recognize expected return, liquidity insurance, debt capacity, operating continuity, and downside risk at the same time.

The paper makes four contributions. First, it defines a Financial Resilience Index (FRI) that organizes the balance-sheet and cash-flow dimensions most directly connected to a firm's ability to absorb shocks without destroying value. Second, it introduces a transparent scenario-based allocation model for four competing uses of internal funds: liquidity reserve, operating working capital, debt reduction, and strategic investment. The model extends the risk-return logic originating in portfolio selection [30] by penalizing Conditional Value-at-Risk (CVaR) of financial target shortfall [31] and by permitting robust scenario design in the spirit of robust optimization [32]. Third, it provides an explainability layer for data-driven forecasting. Machine learning can capture high-dimensional non-linearities in finance [33–35], but financial managers require traceable explanations; Local Interpretable Model-agnostic Explanations (LIME) [36] and SHapley Additive exPlanations (SHAP) [37] provide model-agnostic tools for identifying the drivers of individual forecasts. Fourth, the study demonstrates the framework with a fully transparent synthetic experiment. The numerical exercise is illustrative, not empirical, and is included to show how risk appetite changes the preferred allocation.

The remainder of the paper is organized as follows. Section 2 synthesizes the literature and defines the research gap. Section 3 develops the financial-resilience architecture and measurement logic. Section 4 formulates the robust allocation model and its explainability layer. Section 5 presents the synthetic decision experiment and managerial interpretation. Section 6 concludes with implications, limitations, and future research directions.

2 | Literature Review

2.1 | Corporate Liquidity, Financing Frictions, and Financial Flexibility

Corporate liquidity is valuable because internal funds and external finance are imperfect substitutes. The pecking-order mechanism in Myers and Majluf [2] provides a canonical explanation: information asymmetry can make external equity unattractive and can lead firms to preserve financing capacity. Financing-constraint research subsequently documented that investment behavior changes when internal liquidity is scarce [4], [5]. Almeida et al. [6] shifted attention from investment-cash-flow sensitivity toward the propensity of constrained firms to save cash from cash flow, providing a direct mechanism through which liquidity can be accumulated as a hedge against future financing shortfalls.

The cash-holdings literature identifies transaction, precautionary, tax, and agency motives, but the precautionary motive is particularly relevant for resilience. Opler et al. [8] show that firms with stronger growth opportunities and riskier cash flows tend to hold more cash, whereas firms with easier capital-market access hold less. Bates et al. [9] document a major increase in U.S. corporate cash over time and connect much of that increase to risk and changing firm characteristics. Theoretical work by Gamba and Triantis [10] formalizes the value of financial flexibility in a dynamic setting, while Harford et al. [11] connect cash holdings to refinancing risk. Denis and Sibilkov [12] show why the marginal value of cash can be especially high for constrained firms: Cash supports investment when outside finance is expensive.

Cash policy is also interdependent with debt policy. Faulkender and Wang [26] show that the marginal market value of cash varies with leverage, existing cash, and capital-market access. Riddick and Whited [27] demonstrate that corporate saving reflects both uncertainty and the response of investment to cash-flow shocks, cautioning against overly simple interpretations of cash accumulation. Acharya et al. [28] establish that cash and debt reduction have different hedging properties under financing frictions. These results motivate a joint allocation model in which liquidity reserve and debt paydown are separate decision variables rather than opposite signs of the same balance-sheet item.

2.2 | Working Capital as an Investment and Financing Decision

Working Capital Management (WCM) converts operating decisions into financial consequences. Deloof [13] reports that receivable and inventory days are associated with profitability, while García-Teruel and Martínez-

Solano [14] find similar value implications for smaller firms. Baños-Caballero et al. [15] show that small firms appear to adjust toward a target cash conversion cycle, indicating that working-capital positions are managed rather than purely accidental. Later studies sharpen the non-linearity argument: the working-capital-profitability relation can be concave, so too little working capital may restrict sales and continuity while too much ties up costly funds [16], [17].

This target perspective is reinforced by value-based evidence. Aktas et al. [18] find that firms moving toward an optimal working-capital position improve performance and can redeploy released resources to higher-value investments. Kieschnick et al. [19] demonstrate that the marginal value of net operating working capital depends on factors such as leverage, expected sales, financial constraints, and bankruptcy risk. Enqvist et al. [20] further show that active working-capital management becomes especially important in downturns. At the institutional level, Baños-Caballero et al. [21] find that net operating working capital is valued differently across countries depending on investor protection and financial development. Zeidan and Shapir [22] illustrate how cash-conversion-cycle improvements can release substantial cash without necessarily requiring lower operating margins.

Trade credit shows why WCM cannot be separated from financing policy. Petersen and Rajan [23] document that firms use supplier credit more when institutional finance is less available and that suppliers can possess information and liquidation advantages. Fisman and Love [24] show that trade-credit-intensive industries can grow faster where financial intermediaries are less developed. Molina and Preve [25] analyze trade credit in financial distress, confirming that supplier financing is part of the firm's crisis-finance architecture. Accordingly, receivables, inventory, and payables should be interpreted not only as operating ratios but also as uses and sources of short-term financing.

2.3 | Risk-Sensitive Optimization and Interpretable Analytics

Traditional financial allocation models are rooted in the risk-return trade-off. Markowitz [30] formalized portfolio choice as a balance between expected return and variance. For corporate resilience, however, symmetric variance is often less informative than downside shortfall because a positive upside surprise does not offset the operational consequences of a liquidity breach. Rockafellar and Uryasev [31] provide a tractable formulation of CVaR that directly measures expected loss in the tail beyond a chosen confidence level. Robust optimization extends this logic by seeking decisions that perform acceptably across uncertain parameter sets rather than only at a point estimate [32]. These tools are well suited to treasury and corporate-finance decisions because scenario stress tests are already embedded in practice.

At the same time, financial forecasting is increasingly data-driven. Gu et al. [33] show that machine-learning methods can capture high-dimensional and non-linear interactions in asset-pricing applications. Heaton et al. [34] discuss deep-learning architectures for financial prediction and risk management, while Fischer and Krauss [35] demonstrate the predictive potential of long short-term memory networks in market data. These studies establish technical capability but also expose a governance issue: high predictive accuracy is insufficient if a chief financial officer cannot understand why a model recommends preserving cash, reducing debt, or changing working capital. LIME [36] and SHAP [37] respond to this problem by attributing predictions to input features, with SHAP providing a unified additive feature-attribution framework.

2.4 | Research Gap and Positioning

The literature therefore provides mature evidence on individual components of financial resilience but a weaker integration across them. Cash studies focus on the level and value of liquidity; WCM studies focus on operating-cycle investment; capital-structure studies examine debt and financing constraints; risk research provides optimization tools; and machine-learning research improves forecasts. What remains underdeveloped is an auditable managerial model that converts these insights into one allocation decision over the same finite pool of internal funds. *Table 1* summarizes this gap and positions the proposed framework.

Table 1. Literature synthesis and unresolved financial-management gap.

Stream	Established Insight	Integration Gap and Role in this Study
Corporate liquidity	Cash provides precautionary value under financing frictions [6], [8–12], [26–29].	Cash level is often the outcome; here, liquidity reserve competes explicitly for the internal-funds budget.
Working capital	There is a target/optimal operating working-capital position [15–22].	Working capital is often optimized separately; here, it competes jointly with debt reduction and investment.
Debt and refinancing	Debt capacity and refinancing risk affect cash value and investment [5], [11], [28].	Debt reduction is rarely optimized jointly with WCM; here, debt paydown is an explicit allocation variable.
Risk optimization	CVaR and robust optimization capture tail loss and parameter uncertainty [31], [32].	These tools are usually portfolio-focused; here, tail shortfall is embedded in corporate cash allocation.
Machine learning/XAI	Machine learning improves non-linear forecasting and XAI explains predictions [33–37].	Forecasting and optimization are often disconnected; here, XAI explains payoff forecasts before transparent optimization.

3 | Financial Resilience Analytics Framework

3.1 | Decision Architecture

Financial resilience is defined here as the firm's capacity to meet near-term obligations, preserve strategically important investment, and continue core operations under adverse cash-flow or financing shocks without resorting to value-destructive emergency actions. This definition is deliberately narrower than broad organizational resilience: it focuses on financial-management levers that a chief financial officer can monitor and allocate. The proposed architecture contains five layers: Data preparation, resilience diagnostics, scenario forecasting, robust allocation, and explanation/governance. *Fig. 1* depicts the sequence.

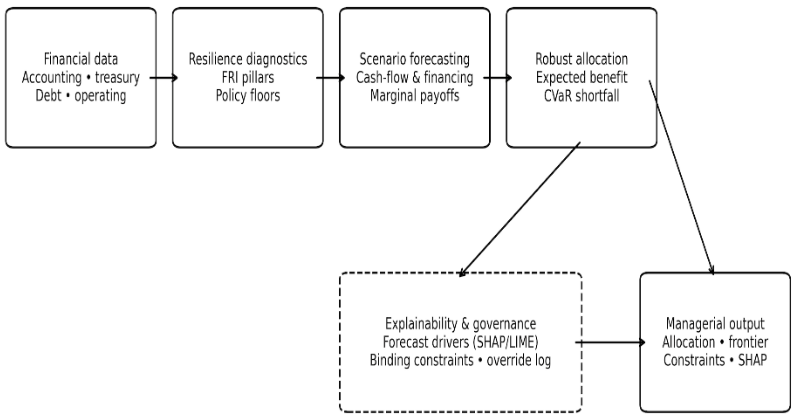

Fig. 1. Proposed financial-resilience analytics architecture linking diagnostics, scenario forecasting, robust allocation, and managerial explanation.

The architecture begins with accounting and treasury data such as cash balances, receivable and payable aging, inventory, debt maturity schedules, interest expense, covenant headroom, operating cash flow, and committed credit lines. These are converted into normalized diagnostics. A scenario engine then maps macroeconomic, operating, and financing shocks into expected marginal benefits for alternative uses of cash. The optimization layer chooses an allocation conditional on management's downside-risk aversion and policy constraints. Finally, the explanation layer reports both the drivers of forecasted scenario payoffs and the binding constraints that determine the recommended allocation.

3.2 | Financial Resilience Index

The FRI is not intended to replace detailed financial statements. Its purpose is to summarize whether the current configuration leaves enough capacity to absorb shocks. Five pillars are proposed: liquidity adequacy, operating cash-conversion efficiency, debt-service capacity, cash-flow stability, and external financing flexibility. Each raw indicator is transformed to a common 0–1 orientation in which higher values indicate stronger resilience. For indicators where lower values are preferable, such as cash-conversion days or short-term debt concentration, the normalization is reversed. The index is then defined as:

$$\mathrm{FRI}_t = \sum_{k=1}^{K} w_k\, z_{k,t}, \quad w_k \geq 0, \quad \sum_{k=1}^{K} w_k = 1, \tag{1}$$

where $z_{k,t}$ is the normalized score for resilience dimension k and w_k is its governance weight. The framework does not impose universal weights because the economic importance of liquidity, leverage, and working-capital continuity varies across industries. Weights may be set by board-approved risk policy, estimated from historical distress outcomes, or subjected to sensitivity analysis. The index should therefore be interpreted as a decision dashboard, not as a claimed universal bankruptcy score.

Table 2. Proposed financial-resilience diagnostics.

Pillar	Financial Interpretation	Representative Indicators and Preferred Direction
Liquidity adequacy	Ability to meet obligations without emergency financing	Cash/short-term obligations; undrawn committed credit; minimum cash runway. Preferred direction: higher.
Cash-conversion efficiency	Amount and duration of cash tied in operations	Receivable, inventory, and payable days; cash conversion cycle. Preferred direction: context-dependent and shorter only without harming service.
Debt-service capacity	Capacity to service and refinance debt under stress	Interest and debt-service coverage; covenant headroom; short-maturity share. Preferred direction: higher coverage and lower near-term concentration.
Cash-flow stability	Predictability of internally generated liquidity	Operating cash-flow volatility; downside forecast error; customer concentration. Preferred direction: greater stability.
Financing flexibility	Ability to raise funds when internal cash is insufficient	Unused credit lines; secured borrowing capacity; debt-maturity dispersion. Preferred direction: higher.

3.3 | Scenario Construction and Financial Payoffs

The scenario engine converts uncertain conditions into marginal financial benefits for each allocation category. Let $j \in \{L, W, D, I\}$ index liquidity reserve (L), working capital (W), debt reduction (D), and strategic investment (I). Let s index economic and financing scenarios. The coefficient $b_{j,s}$ represents the incremental financial benefit generated by one monetary unit allocated to category j under scenario s. Benefits can be estimated from treasury models, historical sensitivities, structural cash-flow forecasts, or machine-learning predictions. The interpretation is broader than accounting profit: a liquidity reserve can generate value by avoiding emergency borrowing or disruption; debt reduction generates interest and refinancing benefits; working capital supports contribution margin and continuity; and strategic investment generates project cash flow but may be especially vulnerable in adverse scenarios.

Scenario probabilities should be governance inputs rather than hidden model outputs. A firm may use a base case plus operating, demand, interest-rate, refinancing, and supply-cost shocks. When probabilities are unreliable, the robust-optimization variant can use probability ranges or worst-case neighborhoods. The central requirement is traceability: managers must be able to see the assumptions connecting each scenario to each allocation payoff.

3.4 | Governance Rules and Decision Constraints

A resilience model should not be permitted to trade away non-negotiable financial safeguards merely because a risky project has a high expected payoff. Accordingly, the optimization layer includes hard policy constraints: a minimum liquidity reserve, minimum debt reduction when refinancing risk exceeds a threshold, minimum working capital required for operating continuity, upper limits on discretionary investment, and optional covenant or leverage constraints. These rules convert board risk appetite into mathematical boundaries. They also make the recommendation auditable because the user can distinguish between an allocation chosen because of expected payoff and one forced by a policy floor.

4 | Robust Financial Allocation Model

4.1 | Decision Variables and Expected Financial Benefit

Let B denote the amount of internal funds available for allocation over the planning horizon and x_j the amount assigned to use j. The budget constraint is $\sum_j x_j = B$. Under scenario s, the incremental financial benefit is:

$$V_s(x) = \sum_j b_{j,s} x_j - C(x), \tag{2}$$

where $C(x)$ captures transaction, adjustment, or implementation costs. The expected financial benefit is $E[V(x)] = \sum_s p_s V_s(x)$, where p_s is the probability of scenario s. A purely expected-value policy can be attractive in stable conditions but can over-allocate to actions with severe stress losses. The model therefore introduces a financial target, such as the minimum incremental benefit required to preserve a target liquidity trajectory, and measures scenario shortfall as:τ

$$\ell_s(\mathbf{x}) = \max\{0, \tau - V_s(\mathbf{x})\}. \tag{3}$$

4.2 | Conditional Value-at-Risk of financial Shortfall

For confidence level α, the CVaR of shortfall is the expected loss in the worst tail of the shortfall distribution. Using the Rockafellar-Uryasev representation [31], it can be expressed as:

$$\mathrm{CVaR}_\alpha(\ell) = \min_\eta \left[\eta + \frac{1}{1-\alpha} \sum_s p_s \max\{0, \ell_s(\mathbf{x}) - \eta\}\right]. \tag{4}$$

This quantity has an intuitive treasury interpretation. It answers: If the firm enters the adverse tail of modeled conditions, how large is the expected miss relative to the chosen financial target? Unlike variance, it does not penalize upside surprises. This asymmetry is appropriate for resilience because the managerial concern is breach of liquidity or financial-performance floors.

4.3 | Risk-Adjusted Allocation Objective

The core model maximizes expected benefit while penalizing downside shortfall and excessive reallocation from the current policy. A convenient formulation is:

$$\max_{\mathbf{x}} \sum_s p_s V_s(\mathbf{x}) - \lambda \mathrm{CVaR}_\alpha\big(\ell(\mathbf{x})\big) - \rho \parallel \mathbf{x} - \mathbf{x}^0 \parallel_1, \tag{5}$$

where $\lambda \geq 0$ is management's downside-risk aversion, $\rho \geq 0$ penalizes unnecessary turnover, and x^0 is the current allocation. Increasing λ moves the solution from growth-oriented to resilience-oriented. The model is subject to the budget constraint, category-specific lower and upper bounds, the liquidity floor $x_L \geq L_{min}$, operating-continuity bounds for x_W, and any debt/covenant constraints. With linear scenario benefits and an L_1 turnover term, the formulation can be solved as a linear program after introducing standard auxiliary variables. More complex non-linear project payoffs can be incorporated when necessary, but the linear version has the advantage of being highly interpretable.

A robust extension can replace fixed scenario coefficients with uncertainty sets. For example, $b_{j,s}$ can be allowed to vary within stress ranges estimated from forecast errors. The optimization then protects against unfavorable coefficients within that set. This follows the broader robust-optimization principle described by Bertsimas et al. [32] and is especially relevant when historical data contain few true crisis observations.

4.4 | Explainability and Managerial Audit Trail

The proposed framework separates forecast explainability from optimization transparency. If $b_{j,s}$ is generated by a machine-learning model, SHAP values can identify how cash-flow volatility, receivable aging, debt maturity, covenant headroom, revenue concentration, or macro variables contribute to the predicted payoff [37]. LIME can provide a local surrogate explanation as an alternative [36]. The optimization itself then reports a second explanation: marginal payoff, downside contribution, binding constraints, and the effect of changing λ.

For each recommendation, the financial manager should therefore receive four outputs: 1) the recommended amounts x_j, 2) scenario-level financial benefits V_s, 3) expected benefit and CVaR shortfall, and 4) an explanation report showing forecast drivers and active policy constraints. This structure also supports challenger models and human override because every component of the recommendation can be inspected separately.

5 | Illustrative Application and Managerial Insights

5.1 | Synthetic Decision Experiment

To demonstrate the mechanics without fabricating empirical evidence, this section uses a synthetic mid-sized manufacturing case. All numbers are constructed for illustration and are not observations from a real company. The firm has an allocatable cash budget of USD 10 million and four uses: liquidity reserve, operating working capital, debt reduction, and strategic investment.

Five scenarios are assigned explicit probabilities. The coefficients in *Table 3* represent the incremental financial benefit generated by one dollar allocated to each use under each scenario. Positive values indicate financial benefit; negative values indicate scenario-specific value destruction. Strategic investment has the highest upside but the largest stress losses; liquidity and debt reduction become more valuable under credit stress.

Table 3. Synthetic scenario assumptions for the illustrative allocation experiment.

Scenario and Probability	Marginal Financial-Benefit Coefficients
Expansion	$L = 0.015;\ W = 0.110$
$p = 0.15$	$D = 0.035;\ I = 0.280$
Baseline	$L = 0.020;\ W = 0.080$
$p = 0.40$	$D = 0.040;\ I = 0.160$
Input-cost shock	$L = 0.050;\ W = 0.020$
$p = 0.15$	$D = 0.055;\ I = -0.060$
Demand shock	$L = 0.060;\ W = 0.010$
$p = 0.15$	$D = 0.050;\ I = -0.100$
Credit squeeze	$L = 0.090;\ W = 0.005$
$p = 0.15$	$D = 0.080;\ I = -0.120$

In *Table 3*, p denotes scenario probability and L, W, D, and I denote the marginal benefit coefficients for liquidity reserve, working capital, debt reduction, and strategic investment, respectively. The allocation bounds are also transparent: liquidity USD 1–5 million, working capital USD 0.5–4 million, debt reduction USD 0.5–4 million, and strategic investment USD 0.5–6 million. The financial target τ is USD 0.45 million of incremental benefit and $\alpha = 0.80$. Three policies are compared: growth-first (low downside penalty), balanced, and resilience-first (high downside penalty). These are not claimed to be universally optimal risk preferences; they illustrate how the same business assumptions produce different decisions when managerial risk appetite changes.

5.2 | Allocation Results and Resilience Frontier

The synthetic results are reported in *Table 4*. The growth-first policy allocates USD 6.0 million to strategic investment and only USD 1.0 million to the liquidity reserve. It achieves the highest expected incremental benefit, USD 0.583 million, but produces negative scenario benefits in all three stress states and a shortfall CVaR of approximately USD 1.006 million. This is a classic expected-value solution with poor resilience.

The balanced policy substantially changes the composition: strategic investment falls to its lower bound, working capital rises to USD 4.0 million, debt reduction rises to USD 4.0 million, and liquidity increases to USD 1.5 million. Expected benefit decreases to USD 0.503 million, but CVaR shortfall falls to USD 0.154 million.

The resilience-first policy further raises the liquidity reserve to about USD 4.318 million and reduces working capital to about USD 1.182 million while maintaining USD 4.0 million of debt reduction. Expected benefit becomes USD 0.465 million and shortfall CVaR falls to approximately USD 0.029 million. Relative to the growth-first policy, this corresponds to about a 97% reduction in downside shortfall CVaR for an expected-benefit reduction of roughly 20%.

Table 4. Synthetic allocations and risk-adjusted outcomes.

Policy	Allocation (USD Million)	Risk-Adjusted Outcome (USD Million)
Growth-first	$L = 1.000;\ W = 2.500$	$E[V] = 0.583$
	$D = 0.500;\ I = 6.000$	$CVaR = 1.006$
Balanced	$L = 1.500;\ W = 4.000$	$E[V] = 0.503$
	$D = 4.000;\ I = 0.500$	$CVaR = 0.154$
Resilience-first	$L = 4.318;\ W = 1.182$	$E[V] = 0.465$
	$D = 4.000;\ I = 0.500$	$CVaR = 0.029$

In *Table 4*, L, W, D, and I are allocation amounts in USD millions; $E[V]$ is expected incremental financial benefit in USD millions; and $CVaR$ is shortfall CVaR in USD millions. *Fig. 2* traces the resilience frontier across a range of λ values. The figure should be read as a managerial choice set rather than a statistical confidence region: Moving toward the lower-left reduces expected benefit but sharply reduces tail shortfall until the frontier flattens. The existence of a flat region is economically important because it identifies allocations where further conservatism produces little additional downside protection.

In practice, the board or treasury committee can use this frontier to choose an explicit risk appetite rather than delegating that choice implicitly to a model.

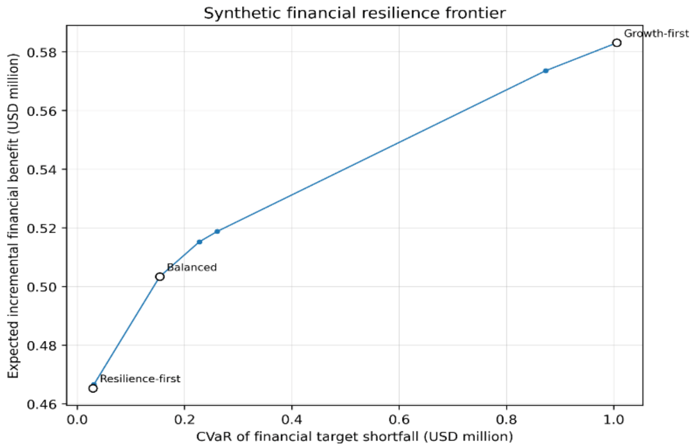

Fig. 2. Synthetic resilience frontier: expected financial benefit versus CVaR of financial target shortfall as downside-risk aversion changes.

Fig. 3 makes the composition effect visible. The main shift from growth-first to resilience-first is not a uniform reduction in risk-taking. It is a substitution away from strategic investment toward liquidity and debt reduction, with working capital initially increasing under the balanced policy because adequate working capital still supports operating value in the baseline and expansion states. Only at high risk aversion does the model shift additional funds from working capital into the liquidity buffer. This illustrates why a simple instruction to "minimize working capital" or "maximize cash" can be financially inferior to joint optimization.

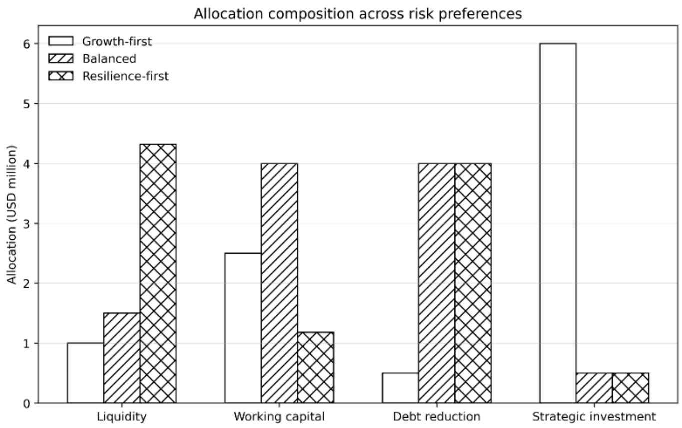

Fig. 3. Allocation composition under growth-first, balanced, and resilience-first financial policies.

5.3 | Managerial Interpretation

The illustration yields several managerial insights. First, the optimal liquidity reserve is endogenous to the opportunity set. Holding more cash is not inherently conservative or inefficient; its value depends on what the firm gives up and how much protection it creates against financing and operating shocks. Second, WCM should be evaluated as an investment with both revenue-support and financing costs. The model can therefore preserve working capital when cutting it would create service or sales losses, while still penalizing excessive operating cash lock-up. Third, debt reduction and cash are not treated as substitutes with identical state payoffs. Debt paydown is especially valuable when refinancing and interest costs dominate, whereas cash is especially valuable when future financing access is uncertain and immediate liquidity must be preserved.

Fourth, the resilience frontier makes risk appetite explicit. A chief financial officer can present to the board the expected-value sacrifice required to reduce tail shortfall by a specified amount. This is more informative than presenting separate liquidity, leverage, and working-capital ratios that may point in conflicting directions. Fifth, explainability is embedded at two levels. Forecast explanations show why a scenario coefficient changed;

optimization explanations show why the allocation changed. This separation is critical for model-risk governance because a weak forecast can be challenged without changing the optimization policy and vice versa.

The model can also support rolling financial planning. As actual receivable aging, cash balances, debt maturities, or cash-flow forecasts change, the scenario payoffs and resilience diagnostics can be updated. Re-optimization then produces a new allocation and identifies whether the change is driven by economics, risk appetite, or a binding policy constraint. The turnover penalty in Eq. (5) prevents unnecessary policy oscillation when forecast changes are economically small.

6 | Conclusion

This study develops an integrated financial-management framework for allocating internal cash among liquidity reserves, working capital, debt reduction, and strategic investment. The central argument is that these decisions should not be optimized in isolation because they compete for the same scarce resource and have different state-contingent values under financing frictions. Building on the corporate-liquidity, working-capital, financial-constraints, risk-optimization, and explainable-analytics literatures, the framework combines a FRI with scenario-based expected benefit and CVaR of financial target shortfall. It preserves managerial transparency through explicit policy constraints and a two-stage explanation architecture.

The synthetic experiment illustrates the economic logic without claiming empirical validation. A growth-first allocation can maximize expected benefit yet expose the firm to severe stress losses. Increasing downside-risk aversion shifts funds toward liquidity and debt reduction, generating a resilience frontier that quantifies the cost of downside protection. In the disclosed example, the resilience-first allocation reduces tail shortfall by about 97% relative to the growth-first policy while sacrificing about 20% of expected benefit. The managerial contribution is therefore not a universal “optimal cash ratio,” but an auditable method for choosing the desired point on an explicit risk-return-resilience frontier.

The framework has several limitations and these define the most important directions for future work. First, the numerical application is synthetic; future research should calibrate and validate the model with multi-year firm-level accounting, treasury, debt-maturity, credit-line, and cash-flow data across industries and business cycles. Second, scenario probabilities and payoff coefficients are model-dependent, so future studies should compare econometric, machine-learning, and structural forecasting methods and evaluate out-of-sample performance. Third, the present formulation is single-period; a multi-stage stochastic or distributionally robust extension could represent sequential borrowing, refinancing, working-capital adjustment, and investment deferral. Fourth, behavioral and governance constraints, such as managerial risk aversion, covenant renegotiation, bank relationships, and supplier dependence, could be modeled explicitly. Finally, empirical research should test whether firms that manage closer to the proposed resilience frontier experience lower crisis-period financing costs, fewer covenant breaches, and stronger post-shock investment recovery. These extensions are necessary before the framework can be interpreted as a validated predictive system rather than a rigorous decision-support architecture.

Author Contribution

M. Gholipour: Conceptualization, methodology, formal analysis, writing-original draft, writing-review and editing, and visualization: to be completed according to the final authorship list.

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Data Availability

No observational or proprietary dataset was used in this conceptual-methodological study. The numerical example is synthetic, and all assumptions required to reproduce it paper.

Conflicts of Interest

The author declares no conflict of interest.

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