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Original Research Article

Intelligent Financial Decision Models for Cash Flow Optimization and Liquidity Risk Reduction in Large Saudi Corporations

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Abstract: Large Saudi corporations operate with substantial capital commitments, complex supplier and customer networks, exposure to commodity and interest-rate shocks, and increasingly digital finance functions. These conditions make cash flow optimization and liquidity risk reduction a dynamic decision problem rather than a static ratio-management exercise. This review synthesizes recent research on corporate cash holdings, working capital, trade credit, financial forecasting, machine learning, explainable artificial intelligence, and Gulf-region liquidity behavior to develop an integrated view of intelligent financial decision models. Evidence indicates that advanced forecasting can improve the timing and granularity of liquidity estimates, but prediction alone does not determine an economically optimal action. Effective models must connect forecasts to working-capital levers, liquidity buffers, financing choices, scenario constraints, and governance controls. Saudi and Gulf evidence further shows that cash policies respond to financial constraints, macroeconomic weakness, policy uncertainty, geopolitical risk, oil-price volatility, Shariah-related financing structures, and sector characteristics. The review therefore proposes a layered decision architecture that combines transaction-level data, probabilistic cash forecasting, optimization, stress testing, explainability, and managerial override. The synthesis argues that the most useful corporate treasury systems should optimize expected liquidity while preserving resilience under adverse scenarios and should measure forecast value by decision outcomes rather than prediction accuracy alone. Research priorities include Saudi-specific benchmarking, causal evaluation of treasury interventions, multi-entity liquidity optimization, interpretable reinforcement or prescriptive learning, and governance standards for model risk. The resulting framework offers a practical research agenda for large Saudi corporations seeking to reduce idle cash, shorten the cash conversion cycle, improve funding decisions, and protect operational continuity without creating opaque automated financial control.

Keywords: Cash Flow Optimization, Liquidity Risk, Machine Learning, Treasury Analytics, Working Capital, Saudi Arabia, Decision Support.

INTRODUCTION

Cash is simultaneously a low-yield asset, a strategic buffer, and an operating necessity. For large corporations, treasury decisions therefore involve a persistent trade-off between the opportunity cost of excess liquidity and the disruption cost of liquidity

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shortfalls. Saudi corporations face an especially demanding version of this problem because many operate across capital-intensive energy, industrial, construction, logistics, telecom, retail, and diversified business structures. Their cash positions can be affected by large project disbursements, customer concentration, long procurement chains, commodity-price movements, bank-funding conditions, and the timing of government or enterprise payments. Earlier Saudi evidence shows that leverage, firm size, capital expenditure, net working capital, and cash-flow volatility materially influence corporate cash holdings, suggesting that liquidity is endogenous to both operating structure and financing conditions (Guizani, 2017). More recent Saudi evidence identifies a non-linear relation between cash holdings and firm performance, reinforcing the proposition that neither maximum cash nor minimum cash is an economically defensible objective (Alnori, 2020).

The central managerial challenge is consequently not to forecast cash in isolation, but to decide how much liquidity is required, where it should be located, when it should be mobilized, and which operating or financing action should be triggered when projected balances move outside acceptable ranges. Conventional treasury practices often combine spreadsheet forecasts, deterministic assumptions, static minimum-cash thresholds, aging reports, and managerial judgment. These tools remain valuable for accountability, yet they can struggle with nonlinear payment behavior, entity-level heterogeneity, changing seasonality, correlated shocks, and high-frequency transaction data. Machine learning has become increasingly relevant to financial planning because it can extract predictive patterns from large structured datasets and improve out-of-sample forecasting when the information set is sufficiently rich (Wasserbacher & Spindler, 2022). Corporate-level evidence also shows that algorithmic liquidity forecasting can outperform classical internal approaches across several forecasting tasks, especially when models use detailed covariates for customer receipts, supplier payments, and net liquidity (Singh *et al*., 2024).

However, predictive improvement is not equivalent to better financial decisions. A highly accurate model can still recommend poor actions if it ignores financing costs, covenant limits, cash pooling restrictions, supplier relationships, tax or Shariah considerations, or asymmetric penalties from shortfalls. Research on machine learning in corporate finance similarly cautions that predictive relationships should not automatically be treated as causal decision rules (Amini *et al*., 2021; Wasserbacher & Spindler, 2022). Explainability is also important because treasury, internal audit, boards, banks, and regulators may require decision rationales, not only output probabilities (Weber *et al*., 2024). The financial value of intelligence therefore depends on integration: forecasting must be linked to prescriptive optimization, stress testing, working-capital actions, funding alternatives, and human governance.

This review addresses that integration problem in the context of large Saudi corporations. It draws together streams that are often studied separately: AI-enabled finance, cash forecasting, cash holdings, working capital, trade credit, supply-chain finance, and Gulf-specific liquidity determinants. The review develops a critical synthesis, identifies where international evidence transfers plausibly to Saudi corporate treasury, and proposes a decision architecture oriented toward cash-flow optimization and liquidity-risk reduction.

Aim of the Study

The aim of this review is to critically synthesize recent evidence on intelligent financial decision models that can improve cash-flow planning, working-capital allocation, liquidity buffering, and short-term financing decisions in large Saudi corporations. It seeks to move beyond a narrow comparison of forecasting algorithms by examining how predictive models should interact with corporate liquidity objectives, risk constraints, institutional conditions, and managerial governance. The intended outcome is an integrated conceptual framework that is academically grounded, operationally interpretable, and suitable for future empirical validation in Saudi multi-entity corporate environments.

Research Objectives

The review pursues five distinct objectives. First, it evaluates how machine learning and AI-based forecasting can improve the timeliness, granularity, and scenario sensitivity of corporate cash-flow estimates. Second, it synthesizes evidence on cash holdings, working capital, cash conversion cycles, trade credit, and supply-chain finance to identify controllable liquidity levers. Third, it examines Saudi and GCC evidence to isolate contextual variables that should enter intelligent liquidity models, including policy uncertainty, oil-price volatility, financing constraints, macroeconomic conditions, and Shariah-related structures. Fourth, it develops a transparent decision architecture linking prediction, optimization, stress testing, and managerial intervention. Fifth, it defines research gaps and validation priorities for assessing whether intelligent treasury systems create measurable improvements in liquidity resilience, financing cost, and operating performance.

Research Questions

The review is guided by five questions. RQ1 asks which data and modeling approaches are most useful for forecasting corporate receipts, payments, and net liquidity under complex operating conditions. RQ2 asks how cash forecasts can be converted into prescriptive decisions concerning working capital, cash buffers, borrowing, investment, and internal liquidity transfers. RQ3 asks which Saudi and GCC-specific economic, institutional, and sector variables should condition model outputs. RQ4 asks how explainability, model-risk governance, and human override can be incorporated without eliminating the efficiency benefits of automation. RQ5 asks which outcome metrics and empirical designs are required to demonstrate that an intelligent decision model improves treasury performance rather than merely forecast accuracy.

REVIEW METHODOLOGY

A structured integrative review design was adopted because the research question spans corporate finance, accounting, operations, and computational intelligence. The substantive search emphasis was 2020–2025, while earlier studies were retained selectively when they provide Saudi-specific foundations or concepts that remain necessary for interpreting newer evidence. Searches were designed around Scopus, Web of Science, ScienceDirect, SpringerLink, Emerald Insight, Wiley Online Library, and publisher-hosted journal pages. Crossref-style DOI records and publisher pages were used to verify bibliographic identities and DOI links. The review did not report numerical screening counts because no registered database export with auditable duplicate-removal logs was created; inventing a PRISMA-style flow would therefore be methodologically inappropriate.

Search strings combined four concept families. The first covered liquidity outcomes: “cash flow forecasting,” “liquidity forecasting,” “cash holdings,” “working capital,” “cash conversion cycle,” “trade credit,” and “liquidity risk.” The second covered intelligent methods: “artificial intelligence,” “machine learning,” “deep learning,” “explainable AI,” “financial forecasting,” and “decision support.” The third introduced corporate decision terms such as “treasury,” “financial planning,” “financing,” “optimization,” and “corporate finance.” The fourth restricted or contextualized evidence using “Saudi Arabia,” “GCC,” “MENA,” “oil price volatility,” “policy uncertainty,” and “Shariah compliance.” Backward and forward relevance checks were used to connect forecasting studies with corporate-liquidity research and to avoid treating technology and finance as isolated literatures.

Studies were included when they were peer-reviewed journal articles with a clear relationship to corporate liquidity, working-capital decisions, financial forecasting, AI-enabled finance, or Gulf/Saudi cash-management conditions. Priority was given to empirical studies using firm-level or transaction-level data and to systematic reviews that clarified methods or research gaps. Articles centered exclusively on retail trading, cryptocurrency price speculation, or consumer credit were excluded unless they contributed a transferable modeling or explainability principle. Purely technical papers without an identifiable corporate financial decision were also excluded from the core synthesis. Because this is an integrative rather than a meta-analytic review, heterogeneous outcome measures were not converted into a common effect size.

Quality assessment focused on four criteria: relevance of the decision setting, transparency of data and model specification, adequacy of identification or validation, and interpretability of findings for corporate liquidity management. Forecasting studies were examined for out-of-sample design, benchmark comparisons, and leakage risk. Corporate-finance studies were evaluated for dynamic specifications, endogeneity treatment, and the fit between empirical measures and theoretical mechanisms. Gulf studies were assessed for sample period, institutional scope, and whether claims were Saudi-specific or region-wide. The synthesis then used thematic coding across six domains: forecasting intelligence, optimal cash buffers, working-capital optimization, trade-credit and supply-chain liquidity, external-risk conditioning, and governance/explainability. Table 1 summarizes these domains.

The review deliberately separates prediction from prescription. Evidence that an algorithm predicts liquidity accurately is treated as support for a forecasting layer, not proof that automated actions maximize firm value. Prescriptive recommendations are inferred only when linked to economic mechanisms such as financing costs, transaction needs, precautionary motives, working-capital trade-offs, or resilience constraints. This distinction is important because machine-learning models excel at pattern recognition while managerial interventions change the data-generating process. The methodological limitation is that published studies use different sectors, countries, time horizons, and liquidity definitions. Consequently, the proposed architecture is a theoretically informed synthesis requiring prospective validation in Saudi corporations rather than a claim that one universal algorithm is already established.

Table 1: Thematic evidence synthesis and decision relevance

Theme	Representative evidence	Decision implication for Saudi corporations
AI and liquidity forecasting	Singh *et al*., (2024); Wasserbacher & Spindler (2022); Kureljusic & Karger (2023)	Use hierarchical, out-of-sample forecasts for receipts, payments and net liquidity; separate prediction from intervention.
Cash buffers and target liquidity	Guizani (2017); Alnori (2020); Al-Hamshary *et al*., (2025)	Estimate dynamic buffers by entity, risk state and financing constraints rather than applying one fixed minimum cash ratio.
Working capital and cash conversion	Hussain *et al*., (2021); Jabbouri *et al*., (2022); Kouaib & Bu Haya (2024)	Treat receivables, inventory and payables as controllable but constrained decision levers.
Trade credit and supply-chain liquidity	Amberg *et al*., (2021); Shang (2020); Parida *et al*., (2022)	Optimize liquidity without transferring unsustainable stress to critical suppliers or customers.
Saudi/GCC external risk	Guizani & Talbi (2023); Guizani & Ajmi (2023); Bugshan (2022)	Adjust buffers and scenario weights for macroeconomic weakness, geopolitical risk and oil-price volatility.
Explainability and governance	Weber *et al*., (2024); Bahoo *et al.,* (2024)	Provide decision-level explanations, model monitoring, override logging and control ownership.

Thematic Literature Review and Critical Analysis

Recent AI research in finance shows a clear movement from rule-based analytics toward supervised learning, deep learning, text analytics, and hybrid decision-support systems. Reviews by Bahoo *et al*., (2024), Pattnaik *et al*., (2024), and Li *et al*., (2023) find that forecasting and risk assessment are among the most established application areas, but they also reveal a gap between technical model development and organizational implementation. In accounting, Kureljusic and Karger (2023) similarly report that AI forecasting often remains at pilot stage despite structured data availability. This matters for treasury because implementation depends on data lineage, process ownership, forecast horizons, and decision rights. Sezer *et al*., (2020) show that recurrent and deep architectures are powerful for nonlinear financial time-series patterns, yet complex architectures are not automatically preferable when corporate cash series are sparse, structurally changing, or dominated by scheduled events. For treasury, model selection should therefore be horizon-specific and benchmarked against simpler alternatives.

The most directly relevant evidence comes from Singh *et al*., (2024), who demonstrate that machine-learning models using extensive covariates can improve liquidity forecasts at both corporate and subsidiary levels. Their setting illustrates an important design principle for large Saudi groups: consolidated liquidity is not simply a scaled version of entity liquidity. Customer receipts, supplier payments, tax schedules, payroll, intercompany transfers, project milestones, and local banking constraints can behave differently across subsidiaries. An intelligent model should therefore use hierarchical forecasting, generating entity predictions that reconcile with group-level totals. Forecast uncertainty should also be represented explicitly. A point estimate such as "SAR 500 million closing cash" is less useful than a distribution showing the probability of breaching minimum liquidity under alternative receipt delays or payment accelerations.

Cash-holding research provides the economic objective that forecasting alone lacks. Saudi evidence indicates that firms move toward endogenous target cash ratios and that target levels vary with leverage, capital expenditure, net working capital, size, and cash-flow volatility (Guizani, 2017). Alnori (2020) finds a non-linear relation between cash holdings and performance, implying that excess cash can destroy value after precautionary benefits have been satisfied. More recent Saudi evidence shows that risk-taking and financial constraints interact with cash accumulation (Al-Hamshary *et al*., 2025). At GCC level, Alnori *et al*., (2022) show that determinants differ between Shariah-compliant and non-compliant firms, while Guizani and Ajmi (2023) demonstrate that weak macroeconomic conditions affect both cash levels and adjustment dynamics. These findings argue against a single fixed minimum-cash threshold across a diversified Saudi group.

External uncertainty should be modeled as a state variable rather than treated as a narrative overlay. Guizani and Talbi (2023) report that Saudi corporate cash holdings respond positively to economic-policy uncertainty and geopolitical risk, consistent with precautionary buffering. Bugshan (2022) finds that oil-price volatility affects GCC cash holdings and adjustment speed, with important implications for oil-exposed sectors. Together, these studies support regime-sensitive liquidity policies: the acceptable buffer during stable credit and commodity conditions should differ from the buffer during stressed regimes. An intelligent decision model can operationalize this by adjusting liquidity constraints, scenario weights, or confidence intervals when external risk indicators deteriorate. Such adaptation is preferable to discretionary overreaction because the trigger logic can be documented and tested.

Working-capital evidence identifies the most actionable path from forecast to intervention. Hussain *et al*., (2021) show that macroeconomic conditions and working-capital flows jointly influence firm performance, while Jabbouri *et al*., (2022) find that financial constraints shape whether aggressive working-capital policies improve performance in emerging markets. Ahmad *et al*., (2022) demonstrate that working-capital effects differ across crisis periods and performance measures, indicating that optimization should not mechanically minimize the cash conversion cycle. Regional evidence from El-Ansary and Al-Gazzar (2021) and emerging-market evidence from Kayani *et al*., (2023) further show that working-capital effectiveness depends on operating and financing conditions. In Saudi manufacturing, Kouaib and Bu Haya (2024) link management of cash-conversion-cycle components to performance, while Shaik *et al.,* (2023) identify a material relationship between working capital and performance in the Saudi energy sector. The implication is that receivables, inventory, and payables should be modeled as decision variables with commercial constraints, not merely accounting outcomes.

A prescriptive treasury system can therefore convert a projected liquidity deficit into ranked interventions. For example, it may compare collection acceleration, dynamic discounting, inventory reduction, payment-term renegotiation, intercompany pooling, revolving-credit drawdown, sukuk or bank facilities, and temporary suspension of discretionary outflows. Each action has a different cost, execution delay, relationship effect, and risk profile. The optimal choice depends on the size and duration of the projected deficit. A two-day timing gap may justify internal cash mobility; a persistent structural deficit may require working-capital redesign or funding. Conversely, forecast surpluses should be allocated among debt reduction, short-term investment, supplier-finance support, capital expenditure, or strategic reserves according to risk-adjusted value.

Trade credit and supply-chain finance widen the liquidity decision boundary beyond the legal entity. Amberg *et al*., (2021) show that firms respond to liquidity shocks by adjusting trade-credit positions, confirming that supplier and customer terms can function as reserve liquidity. Shang (2020) and Islam *et al*., (2022) further connect market or asset liquidity with trade-credit behavior, while Hasan and Cheung (2021) show that trade-credit use varies across firm life-cycle stages. Parida et al. (2022) document the evolution of supply-chain finance and emphasize its multi-party financial perspective. For large Saudi corporations with extensive contractor and supplier ecosystems, aggressive payable extension may improve immediate cash while transferring stress downstream. Intelligent optimization should therefore include supplier criticality, concentration, default risk, and strategic value so that liquidity improvement does not increase operational fragility.

Network effects make this especially important. Trade-credit and supply-chain-finance research indicates that liquidity shocks are transmitted through commercial relationships rather than remaining confined to one balance sheet (Amberg *et al.*, 2021; Parida *et al*., 2022). The treasury implication is that receivables and payables are not independent rows in a ledger; they connect counterparties whose payment behavior can become correlated during stress. A major customer delay can weaken suppliers if the focal firm passes the shock through. Scenario models should therefore stress clusters of counterparties, not only single invoices. Supplier-finance programs can also be modeled as resilience instruments when they lower supplier funding costs without forcing the focal corporation to sacrifice payment discipline.

Capital-market liquidity provides another reminder that cash motives are multidimensional. Nyborg and Wang (2021) find that more liquid stocks can be associated with higher cash holdings through a repurchase motive, while Im *et al*., (2022) identify a real-investment channel linking stock liquidity and cash. These mechanisms may be less central to daily treasury than operating liquidity, but they demonstrate why a corporate cash model cannot assume that all cash is precautionary. Cash may support acquisitions, buybacks, strategic investment, covenant compliance, or rating objectives. The intelligent system should therefore distinguish operational minimum cash, contingency reserves, committed strategic cash, and truly deployable excess cash. Otherwise, optimization may incorrectly sweep or invest funds that are economically earmarked.

Explainability and governance determine whether an intelligent system can be trusted. Weber *et al*., (2024) show that explainable AI is especially important in regulated financial contexts where users need traceable rationales. In corporate treasury, explanations should be decision-centered: which drivers caused the forecast revision, which scenario generated the risk breach, which constraint made a funding option infeasible, and how sensitive the recommended action is to assumptions. This is more useful than generic feature-importance charts. Model governance should include data-quality controls, benchmark models, override logging, back-testing, drift monitoring, and escalation thresholds. Human override is not a weakness when it is structured; it becomes a source of learning if reasons for overrides and realized outcomes are captured.

The evidence also supports hybrid rather than purely autonomous decision making. Amini *et al*., (2021) show that machine learning can improve prediction of corporate financing dynamics, but managerial actions involve causal and strategic considerations beyond pattern recognition. Accordingly, the proposed model separates a prediction engine from a constrained optimization engine and a governance layer. The forecast estimates distributions for receipts, payments, and balances. The optimization engine selects actions subject to liquidity floors, funding limits, counterparty constraints, and business priorities. Stress testing challenges the recommendation under adverse regimes. Explainability translates model logic for finance users, while authorized managers approve or override material actions. Figure 1 represents this synthesis as a closed loop rather than a one-way forecast.

Table 1 indicates that the literature is strongest on individual components but thinner on end-to-end treasury integration. AI reviews explain forecasting methods; working-capital studies explain performance trade-offs; Saudi and GCC studies explain contextual cash determinants; trade-credit studies explain inter-firm liquidity channels. What is missing is a validated architecture that unifies these insights at transaction, entity, and group levels. This integration gap is particularly relevant to large Saudi corporations because national economic transformation is increasing the scale and complexity of investment while finance functions are simultaneously adopting enterprise data platforms and automation. The decision problem is therefore well suited to intelligent support, but only if optimization remains economically interpretable and organizationally governable.

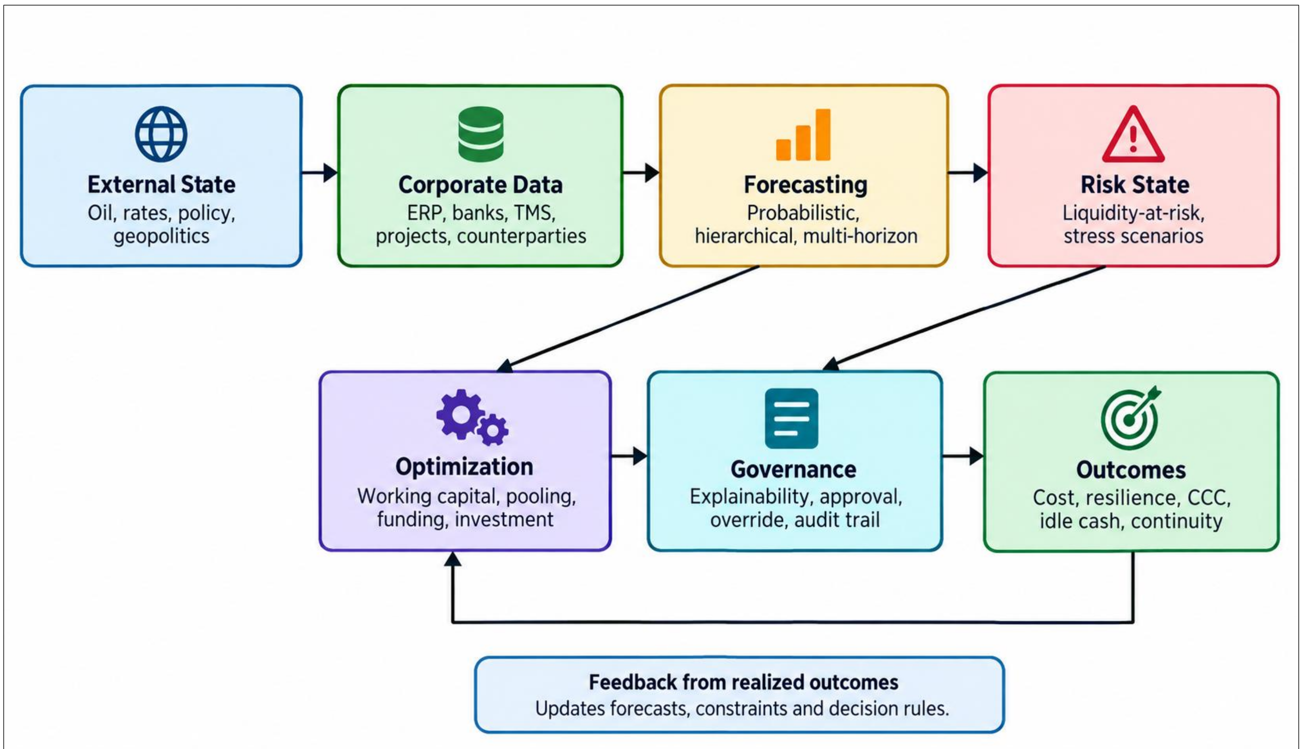

Figure 1: Review synthesis: contextual risk and corporate data feed forecasting, risk assessment, optimization, governance, and a learning feedback loop

DISCUSSION

The synthesis suggests that "intelligent" liquidity management should be defined by decision quality, not by algorithmic complexity. Three conclusions follow. First, forecast accuracy is necessary but insufficient. A model that reduces forecast error without changing collection priorities, funding timing, cash allocation, or resilience thresholds may deliver limited economic value. Evaluation should therefore connect forecast performance to realized overdraft avoidance, interest savings, working-capital release, reduced idle balances, fewer emergency funding events, and improved service continuity.

Second, liquidity optimization is inherently multi-objective. Large corporations simultaneously seek low funding cost, high cash utilization, supplier continuity, covenant headroom, investment flexibility, and protection against adverse shocks. These objectives can conflict. The proposed framework therefore treats liquidity as a constrained optimization problem in which expected financial value is maximized subject to resilience requirements. Table 2 translates this synthesis into an operational sequence in which data, forecasting, optimization, risk, and governance layers each have explicit controls rather than relying on one opaque forecasting engine. This aligns with evidence that excessive cash can impair performance while insufficient cash raises financing and disruption risk (Alnori, 2020). It also accommodates the finding that constrained firms may need different working-capital policies from unconstrained firms (Jabbouri *et al*., 2022).

Third, Saudi context should enter the model explicitly rather than through informal judgment after the forecast. Oil-price volatility, macroeconomic regimes, policy uncertainty, sector exposure, Shariah-related financing constraints, and counterparty structures can alter both the desired liquidity buffer and the feasible action set (Alnori *et al*., 2022; Bugshan, 2022; Guizani & Talbi, 2023). A Saudi corporate treasury platform should thus combine internal transaction data with external state indicators and should recalibrate decisions when the state changes. Figure 2 expresses this as a layered architecture in which data, prediction, optimization, risk controls, and governance are connected through feedback from realized cash outcomes.

A further implication is that treasury model design should reflect the economic asymmetry of forecast errors. Underpredicting a severe cash deficit can trigger emergency borrowing, covenant pressure, or delayed operational payments, whereas overpredicting a deficit can leave cash unnecessarily idle. Loss functions should therefore weight errors by their financial consequences rather than treating every forecasting deviation equally. The same principle applies across horizons: daily forecasting supports payment execution and cash concentration, weekly forecasting informs short-term facilities and receivable actions, and monthly forecasting supports capital allocation and funding strategy. A coherent architecture should reconcile these horizons so that short-term actions do not contradict longer-term liquidity objectives. This multi-horizon consistency is particularly important in project-intensive corporations where milestone receipts and capital expenditures can shift abruptly while contractual obligations remain fixed. Decision dashboards should show both expected cash and downside liquidity so that managers can distinguish ordinary variability from genuine risk. Forecast confidence should decline visibly when data quality weakens, preventing automated certainty from masking missing invoices or delayed bank feeds. Entity models should reconcile to group totals because unbalanced aggregation can create misleading surplus signals at the consolidated level. Optimization should price committed but undrawn facilities as insurance rather than treating them as costless cash substitutes. Counterparty concentration should be included because one delayed customer can dominate short-horizon liquidity even when aggregate receivables appear diversified. Back-testing should evaluate not only forecast error but also whether recommended actions would have remained feasible under realized payment timing. Finance teams should compare algorithmic recommendations with documented treasury rules to identify where automation adds value and where controls should remain deterministic. An intelligent system should preserve scenario histories so that management can examine how repeated shocks changed buffers, funding choices, and realized outcomes. Risk thresholds should be calibrated to business criticality because a temporary deficit in a nonessential entity is not equivalent to a deficit that threatens payroll or strategic suppliers. The system should also flag when apparent excess cash is legally restricted, operationally trapped, or committed to near-term capital expenditure.

For diversified Saudi groups, the architecture should also distinguish liquidity visibility from liquidity mobility. A consolidated dashboard may show substantial group cash while legal, banking, tax, contractual, or minority ownership constraints prevent immediate transfer between entities. Optimization should therefore model each pool of cash as an asset with location, currency, availability date, transfer cost, and eligibility constraints. Intercompany loans, cash pooling, notional pooling, facility drawdowns, and short-term investments can then be evaluated jointly rather than sequentially. This approach would reduce a common treasury error in which gross cash is treated as freely deployable cash. It would also support reverse stress testing by asking which combination of delayed receipts, restricted balances, market shocks, and facility unavailability causes an operational liquidity breach. The resulting analysis gives management a clearer basis for contingency planning because it identifies not only the amount of liquidity required but also where liquidity must be accessible, how quickly it can be moved, and which fallback instrument remains feasible when the preferred intervention fails. These distinctions are essential when group solvency appears strong but entities remain operationally exposed.

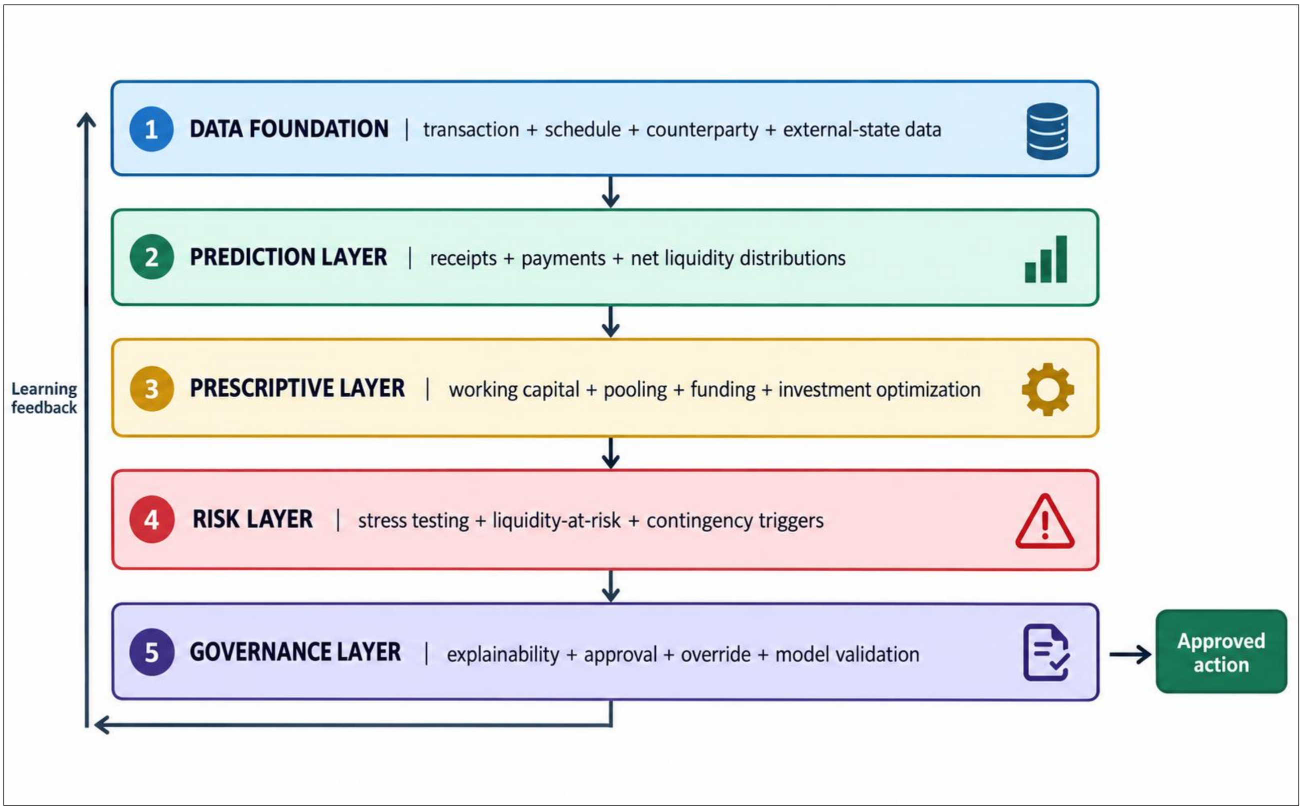

Figure 2: Proposed intelligent financial decision architecture for large Saudi corporations

Table 2: Operational architecture for an intelligent liquidity decision model

Layer	Inputs	Analytical function	Treasury output	Control requirement
Data foundation	ERP, bank, TMS, procurement, sales, project, counterparty and macro data	Validation, reconciliation, feature engineering	Trusted liquidity data mart	Data lineage and exception reporting
Forecasting	Historical and scheduled receipts/payments; seasonality; external states	Statistical/ML ensemble; hierarchical and probabilistic forecasting	Cash distributions by entity and horizon	Benchmarking, drift tests, back-testing
Optimization	Forecast distributions, costs, limits, maturities, working-capital levers	Constrained optimization and scenario ranking	Funding, pooling, collection, payment and investment actions	Feasibility rules and approval thresholds
Risk and stress	Policy uncertainty, oil volatility, rate shocks, delays, counterparty clusters	Stress testing and reverse stress testing	Liquidity-at-risk and contingency actions	Scenario governance and escalation
Governance and learning	Model explanations, overrides, realized outcomes	Explainability, audit trail, outcome attribution	Approved action and continuous improvement	Human accountability and periodic model validation

Research Gaps and Future Research

Five research gaps are prominent. First, there is limited Saudi transaction-level evidence comparing machine-learning liquidity forecasts with robust statistical and treasury benchmarks. Second, published corporate-finance studies often estimate associations rather than testing whether specific treasury interventions cause better outcomes. Future studies should use phased implementation, natural experiments, or randomized operational pilots where feasible. Third, multi-entity optimization under cash pooling, banking, tax, and Shariah constraints is underdeveloped relative to single-firm forecasting. Fourth, research should examine interpretable prescriptive methods, including scenario optimization and constrained reinforcement learning, while preventing unsafe exploration in live treasury environments. Fifth, model governance requires its own evidence base: future work should quantify the value of explanations, override protocols, drift alerts, and human-machine escalation rules. Saudi sector comparisons are especially valuable because energy, construction, industrial, telecom, retail, and service corporations exhibit different cash-cycle structures and exposure to external shocks.

Practical, Managerial, and Policy Implications

For CFOs and treasurers, implementation should begin with a measurable decision case rather than an enterprise-wide AI mandate. Suitable starting points include short-horizon receipt forecasting, entity-level liquidity buffers, overdue-receivable prioritization, or funding-draw timing. Data architecture should reconcile ERP, treasury-management, banking, procurement, sales, and project systems using consistent entity and counterparty identifiers. Managers should define risk appetite before optimization so that the model understands minimum liquidity, concentration limits, and actions requiring approval.

For boards and internal audit, model governance should be treated as part of financial control. Material automated recommendations need traceable inputs, versioned models, benchmark comparisons, override records, and post-decision review. For Saudi policymakers and market institutions, standardized digital invoicing, payment data, open banking interfaces, and stronger availability of corporate-risk indicators can improve the data environment for responsible treasury analytics. Policy should encourage innovation while preserving accountability for decisions that affect suppliers, creditors, employees, and systemic resilience.

Limitations

This review integrates heterogeneous literatures rather than estimating a pooled causal effect. The evidence includes different countries, sectors, horizons, liquidity definitions, and model classes, so transfer to Saudi corporations requires validation. Some AI studies address financial forecasting broadly rather than corporate treasury specifically. Saudi and GCC studies are mainly based on listed-firm panels and may not represent private conglomerates or project entities. Finally, the proposed framework is conceptual; its economic superiority must be demonstrated through prospective deployment and comparison with existing treasury processes.

CONCLUSION

Intelligent financial decision models can improve corporate liquidity management when they connect accurate forecasting to economically disciplined action. The literature supports the use of machine learning for richer liquidity prediction, but it also shows that cash decisions depend on working capital, financing constraints, trade credit, external uncertainty, strategic motives, and institutional context. For large Saudi corporations, a robust model should therefore combine entity-level cash forecasting, probabilistic scenarios, dynamic liquidity buffers, working-capital levers, funding alternatives, and explainable governance within a closed feedback loop. The principal research opportunity is not another isolated prediction algorithm; it is an empirically validated decision system that demonstrates lower liquidity risk and better capital efficiency under Saudi operating conditions. Such systems should augment treasury judgment, make assumptions visible, and learn from realized outcomes while preserving human accountability for material financial decisions.

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