Machine-Driven Quantitative Modeling Approaches for Measuring Liquidity Risk Propagation Across Interconnected Financial Systems

Adegboyega Daniel During

Statistical Modeler,

Enterprise Risk Management,

United States

Abstract: Liquidity risk has emerged as one of the most critical threats to financial system stability, particularly in increasingly interconnected markets where shocks can propagate rapidly across institutions, asset classes, and geographies. Traditional liquidity measurement techniques often rely on static balance-sheet indicators or linear sensitivity models, which fail to capture nonlinear spillovers, dynamic feedback loops, and cross-market contagion. With growing market complexity and the rise of high-frequency trading, funding dependencies, and tightly coupled financial infrastructures, more advanced analytical tools are required to measure how liquidity stress travels through the system. Machine-driven quantitative modeling offers a powerful framework for detecting, quantifying, and forecasting liquidity risk propagation with far greater precision. This study examines machine-driven quantitative modeling approaches designed to measure liquidity transmission across interconnected financial systems. Broadly, the discussion begins by outlining the limitations of traditional liquidity metrics such as bid-ask spreads, coverage ratios, and static liquidity buffers in environments prone to rapid regime shifts and correlated withdrawals. It then shifts to advanced techniques capable of modeling systemic liquidity behaviour, including nonlinear network models, agent-based simulations, and machine learning algorithms that identify hidden propagation channels and emergent liquidity clusters. These methods allow for the identification of transmission pathways that may not be directly observable through conventional financial indicators. Narrowing the focus, the study explores how machine-driven models such as graph neural networks, stochastic process learning, and reinforcement-learning-based stress simulators capture dynamic liquidity interactions under stressed conditions. These tools enable more accurate forecasting of liquidity drains, intraday funding pressures, and cascading margin calls. By incorporating real-time market data, adaptive learning processes, and systemic interaction structures, these models provide early-warning insights that strengthen liquidity management frameworks. The paper concludes with practical considerations for implementation, data governance, and integrating machine-driven liquidity analytics into regulatory oversight.

Keywords: Liquidity Risk Propagation, Machine-Driven Modeling, Financial Networks, Systemic Contagion, Quantitative Risk Analysis, Market Liquidity Dynamics

1. INTRODUCTION

1.1 Rising Liquidity Fragility in Interconnected Financial Systems

Liquidity fragility has intensified across global financial systems as markets have become increasingly interconnected through dense funding linkages, cross-asset exposures, and synchronized trading architectures [1]. Modern financial networks rely heavily on real-time settlement, collateralized funding, and short-term refinancing channels, which amplify sensitivity to shifts in market liquidity. When one segment of the system experiences strain whether through declining market depth, widening spreads, or collateral shortages liquidity stress often propagates rapidly across multiple markets rather than remaining confined to its point of origin [2].

This interconnectedness contributes to liquidity spirals, where declining asset prices trigger higher margin requirements, which then force further liquidation and accelerate market dislocation. Such spirals are particularly pronounced during episodes of intraday volatility, where even small shocks can escalate into systemic disruptions through feedback loops within algorithmic trading, repo markets, and derivatives clearing systems [3].

Post-crisis structural reforms have not eliminated these vulnerabilities. Although higher capital standards and improved transparency have strengthened certain buffers, they have also increased reliance on collateralized funding channels and reduced market-making capacity in key fixed-income markets, inadvertently heightening fragility during stress episodes [4]. The combination of tighter balance-sheet constraints and interconnected liquidity dependencies underscores the need for more adaptive approaches to modelling liquidity dynamics across financial networks [5].

1.2 Limitations of traditional liquidity measurement techniques

Traditional liquidity assessment tools such as static liquidity-coverage ratios, bid-ask spread indicators, and average daily trading volumes provide useful baseline information but are insufficient for capturing the nonlinear transmission of liquidity shocks in modern markets [6]. These metrics assume stable relationships between funding conditions and market depth, an assumption that collapses during rapid stress events when liquidity evaporates unevenly across assets and trading venues.

Static buffer ratios capture inventory sufficiency under normal conditions but fail to identify dynamic vulnerabilities created by intraday margin cycles or collateral shortages [7].

Similarly, bid-ask metrics reflect local market tightness but overlook network-level transmission, where stress in one liquidity node alters behaviour in another. The inability of conventional measures to capture nonlinear spillovers, contagion effects, and microstructure disruptions limits their usefulness for systemic-risk forecasting, particularly in environments characterized by high-frequency market interactions and leveraged funding dependencies [8].

1.3 Purpose, research objectives, and article overview

This article proposes a machine-driven modelling framework for identifying liquidity fragility and tracing how shocks propagate across interconnected financial networks [9]. The objective is to integrate market-microstructure signals, funding-stress indicators, and cross-asset dependencies into a unified analytical system capable of capturing nonlinear liquidity dynamics. The broader contribution lies in advancing systemic-risk analysis by moving beyond static liquidity assessments toward models that adapt to evolving market conditions [5]. The article proceeds by outlining liquidity-shock transmission mechanisms, reviewing nonlinear modelling foundations, and presenting an integrated machine-learning–supported framework. Figure 1 illustrates the primary liquidity-shock transmission pathways across financial networks.

Figure 1 Primary liquidity-shock transmission pathways across financial networks.

2. FOUNDATIONS OF LIQUIDITY RISK, MARKET MICROSTRUCTURE, AND SYSTEMIC PROPAGATION

2.1 Liquidity formation mechanisms and intraday market behaviours

Liquidity in modern financial markets is shaped by a combination of market-microstructure features, order-flow interactions, and balance-sheet constraints that influence how quickly assets can be traded without inducing significant price impact [7]. Market microstructure determines how trading venues aggregate buy and sell interests, match orders, and adjust prices in response to incoming information. These mechanisms shape the sensitivity of liquidity to shocks because market depth and order-book resilience vary significantly across assets and trading environments.

Order-flow dynamics play a particularly central role. Liquidity tends to thin quickly when aggressive order flow concentrates on one side of the market, causing spreads to widen and depth to evaporate. This behaviour intensifies during periods of uncertainty, where even small information shocks can produce outsized liquidity withdrawals as traders adjust positions abruptly [8]. High-frequency interactions amplify these effects: as algorithmic traders detect shifts in order-book imbalance, they modify strategies in milliseconds, accelerating the rate of liquidity depletion.

Dealer balance-sheet constraints further shape liquidity formation across intraday cycles. Because many dealers rely on repo financing and face regulatory capital requirements, their ability to intermediate markets during stress is limited [9]. Balance-sheet optimization forces them to reduce inventories as volatility rises, which diminishes their market-making capacity. This withdrawal reduces available depth across multiple asset classes simultaneously, reinforcing fragility at precisely the moment when liquidity is most needed.

The convergence of microstructure frictions, order-flow imbalances, and dealer constraints creates a landscape where liquidity is both dynamic and highly sensitive to short-lived stresses. As a result, traditional liquidity assessments those assuming stable market depth fail to capture the nonlinear intraday patterns that define modern trading systems [10]. These systemic features highlight the need for analytical frameworks capable of interpreting liquidity behaviour as a continuously evolving process influenced by structural and behavioural factors.

2.2 Nonlinear contagion mechanisms in funding and trading networks

Liquidity stress spreads through financial systems via nonlinear contagion pathways that link trading venues, dealer inventories, and funding networks [11]. One mechanism arises from feedback loops, which intensify stress through recursive interactions. When asset prices fall, margin requirements increase, forcing leveraged traders to liquidate positions. These liquidations depress prices further, triggering additional margin calls and exacerbating liquidity withdrawal. This recursive cycle represents a core mechanism through which relatively small shocks transform into system-wide dislocations [12].

Another pathway is fire-sale contagion, which occurs when distressed actors liquidate assets rapidly, transmitting price declines across otherwise unrelated markets. Because many institutions hold overlapping portfolios, fire sales can propagate quickly, especially when assets share common risk factors or collateral classifications. As institutions respond

simultaneously to falling prices, market depth collapses, creating discontinuities that amplify volatility [13].

Clearinghouses introduce additional nonlinear amplification channels. Although designed to reduce counterparty risk, clearinghouses impose intraday variation margin calls that adjust rapidly in response to price movements. During volatility spikes, these margin adjustments escalate sharply, draining liquidity from participants and forcing additional asset sales [14]. As participants struggle to meet rising margin requirements, funding stresses cascade across the network, pushing liquidity pressure into markets that were not initially affected.

These contagion mechanisms underscore that liquidity fragility is rarely linear. Instead, stress propagates through interconnected channels where behavioural synchrony such as simultaneous risk aversion merges with structural dependencies embedded in funding and collateral networks. Table 1, "Liquidity Risk Characteristics in Linear vs. Nonlinear Systemic Environments," summarizes these amplification channels and highlights why small disturbances can translate into abrupt system-level liquidity deterioration [15].

Understanding these nonlinear processes is critical for constructing models capable of forecasting liquidity withdrawal under dynamic and stressed conditions. Without such insights, risk assessments underestimate the speed and scale of liquidity contagion.

Table 1. Liquidity Risk Characteristics in Linear vs. Nonlinear Systemic Environments

Dimension	Linear Liquidity Environment	Nonlinear (Systemic) Liquidity Environment
Market Depth Response	Depth adjusts proportionally to order-flow changes; spreads widen gradually.	Depth evaporates suddenly once stress thresholds are crossed; spreads widen exponentially.
Correlation Behaviour	Asset correlations remain stable across regimes; diversification benefits persist.	Correlations spike abruptly across markets, eliminating diversification and synchronizing stress.
Price Impact	Price responds smoothly to trades; impact functions remain predictable.	Small trades trigger disproportionate price jumps due to order-book thinning and liquidity withdrawal.
Funding Market Sensitivity	Funding conditions move steadily with macro indicators; haircuts remain	Funding constraints tighten sharply; haircuts surge and unsecured funding evaporates

Dimension	Linear Liquidity Environment	Nonlinear (Systemic) Liquidity Environment
	stable.	rapidly.
Contagion Pathways	Stress transmits slowly and is often contained within individual markets.	Stress propagates through collateral chains, clearing cycles, and cross-market linkages at high speed.
Dealer Balance-Sheet Constraints	Dealers absorb order-flow fluctuations with stable inventories and market-making capacity.	Dealers retreat simultaneously due to leverage limits and regulatory constraints, deepening liquidity freezes.
Feedback Loops	Minimal feedback; liquidity conditions respond linearly to shocks.	Strong positive feedback loops (fire sales, margin spirals, volatility bursts) amplify initial shocks.
Volatility–Liquidity Interaction	Volatility has a mild, linear relationship with liquidity metrics.	Volatility accelerates liquidity depletion; liquidity withdrawal further accelerates volatility in a reinforcing loop.
Stress Propagation Speed	Gradual adjustments allow time for intervention and rebalancing.	Shock propagation is instantaneous or near-instantaneous, especially in algorithmic markets.
System-Level Fragility	System remains stable under moderate stress; buffers are sufficient.	Even small disturbances can trigger systemic breakdowns due to nonlinear amplification mechanisms.

2.3 Statistical foundations for modeling liquidity propagation

Statistical modelling of liquidity propagation requires tools capable of capturing heavy-tailed behaviours, high-frequency volatility, and network-driven transmission patterns that define stress episodes in modern financial markets [16]. High-frequency volatility models such as realized-variance estimators and intraday volatility signatures enable researchers to detect rapid market-depth fluctuations and microstructure noise that traditional daily volatility metrics obscure [10]. These models reveal how liquidity transforms in real time, highlighting patterns such as volatility clustering and asymmetric depth responses during stressed trading intervals.

Liquidity propagation is also influenced by tail-risk distributions, which capture the probability of extreme liquidity shortfalls. Heavy-tailed distributions better represent

the abrupt, discontinuous declines in market depth observed during stress periods, where price jumps and sudden spread widening dominate market behaviour [12]. Incorporating tail-risk features improves the accuracy of stress-scenario modelling and enhances understanding of how rare events cascade across assets.

Network-based statistical metrics provide another essential foundation. Measures such as node centrality, connectivity density, cross-asset correlation structures, and contagion path lengths offer insight into how liquidity shocks traverse interconnected markets [9]. By quantifying structural vulnerabilities, network metrics help identify nodes such as major dealers or collateral hubs where local liquidity stress is most likely to propagate into broader systemic disruptions.

These statistical methods converge to support a unified modelling framework where liquidity propagation is treated as a dynamic, nonlinear process rather than a static equilibrium outcome. Methods that combine high-frequency volatility analytics, tail-distribution modelling, and network metrics provide a more realistic lens for evaluating how shocks evolve. Table 1 reinforces the distinction between linear assumptions and nonlinear propagation behaviours by summarizing structural differences in liquidity response patterns. This integration forms the analytical base for developing machine-supported liquidity fragility models in subsequent sections.

3. EMPIRICAL EVIDENCE OF LIQUIDITY RISK PROPAGATION AND NETWORK SPILLOVERS

3.1 Historical liquidity crises and spillover signatures

Historical liquidity crises reveal consistent patterns of abrupt market dysfunction, rapid funding-route deterioration, and cascade effects that spread across multiple asset classes long before price indicators fully reflect the level of stress. Crisis-era liquidity collapses have often emerged from seemingly localized disruptions such as funding shortages in short-term credit markets or sharp reductions in dealer market-making capacity before rapidly escalating into system-wide dislocations [13]. During these episodes, liquidity evaporates simultaneously across instruments, highlighting deep structural linkages that traditional linear models fail to capture.

One defining feature of past crises is the breakdown of funding routes, particularly within repo markets and unsecured overnight lending channels. As lenders become increasingly risk-averse, haircuts rise, collateral eligibility tightens, and borrowers experience unexpected freezes in critical funding lines [14]. These disruptions spread outward, affecting institutions not directly connected to the initial stress point but exposed indirectly through collateral chains, derivative obligations, or asset holdings.

Spillover signatures become especially visible when liquidity declines in one market trigger sudden withdrawals in others.

For example, forced deleveraging in credit markets has historically spilled into equities, while disruptions in money markets have propagated to FX and derivatives markets through heightened margin requirements and cross-market hedging pressure [15].

These crisis signatures demonstrate that liquidity stress rarely behaves as an isolated phenomenon. Instead, it spreads through multiple transmission pathways including collateral cycles, margining dynamics, and synchronized investor behaviour that amplify the original shock. Recognizing these patterns is essential for constructing models that realistically reflect historical liquidity fragility and its nonlinear spillovers [16].

3.2 Empirical studies on cross-market liquidity co-movement

A robust body of empirical research demonstrates that liquidity co-movement across markets intensifies during periods of uncertainty, revealing interconnected stress behaviours that challenge assumptions of asset-class independence. Studies of debt-equity linkages show that liquidity shocks in corporate-bond markets often precede tightening conditions in equity order books, as investors rebalance portfolios or unwind positions to manage funding constraints [17]. These interactions reflect co-dependence in market microstructure features, trading strategies, and dealer balance-sheet management.

Similarly, cross-market studies highlight strong FX–interest rate spillovers, especially when global macro uncertainty rises. Liquidity declines in FX markets frequently align with abrupt rate-market repricing, driven by shared reliance on leveraged carry strategies, collateralized funding, and hedging flows that directly impact both asset classes [18]. Intraday liquidity patterns demonstrate strong co-movement as volatility accelerates and traders adjust exposures across currency, bond, and derivative instruments in near real time.

These empirical findings emphasize that liquidity is not merely a market-specific characteristic but a system-wide property shaped by cross-market interdependencies. Interconnected trading strategies, margin call dynamics, and risk-transfer channels cause liquidity conditions to tighten in a synchronized manner when stress emerges in any part of the network [19].

As cross-asset liquidity co-movement intensifies during stress, diversification benefits deteriorate. Portfolio managers relying on cross-class hedging discover that liquidity constraints emerge simultaneously across their hedges and underlying assets, undermining risk-management strategies [15]. The empirical literature consistently finds that co-movement increases disproportionately in stressed environments, revealing nonlinear dependencies that traditional liquidity metrics fail to capture [20]. Recognizing these patterns is crucial for modelling liquidity dynamics accurately in multi-asset systems.

3.3 Failure of traditional models during stressed liquidity regimes

Traditional liquidity models often based on stable buffer ratios, average spreads, and historical turnover measures break down sharply during stressed conditions due to their inability to represent nonlinear liquidity deterioration. As volatility surges, static liquidity buffers deplete far faster than expected because margin requirements rise, repo haircuts widen, and balance-sheet constraints limit the willingness of dealers to absorb order-flow imbalances [14]. These changes occur abruptly, causing liquidity to disappear across multiple markets within minutes rather than gradually.

Classical prediction tools assume that liquidity responds proportionally to changes in order flow or volatility; however, empirical evidence shows steep nonlinear drops in market depth once stress thresholds are crossed [18]. This misalignment results in significant underprediction of liquidity shortages, particularly during events that trigger funding-market disruptions or forced deleveraging.

Moreover, regression-based liquidity models calibrated on historical averages exhibit prediction breakdown, as structural changes during crises invalidate underlying assumptions about market-making capacity, trader behaviour, and funding-cost stability [16]. These failures are particularly evident in multi-asset portfolios where liquidity strain emerges simultaneously across asset classes due to synchronized risk aversion.
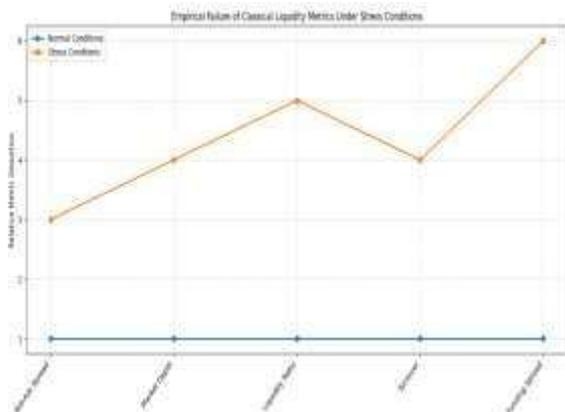

Figure 2, "Empirical Failure of Classical Liquidity Metrics Under Stress Conditions

The shortcomings of traditional approaches are illustrated in Figure 2, "Empirical Failure of Classical Liquidity Metrics Under Stress Conditions," which depicts how standard indicators collapse in explanatory power as liquidity regimes transition from normal to stressed. These observations underscore the need for dynamic, nonlinear modelling frameworks capable of adapting to evolving market conditions and capturing systemic liquidity fragility.

4. MACHINE-DRIVEN QUANTITATIVE MODELING TECHNIQUES FOR LIQUIDITY PROPAGATION

4.1 Network-based machine learning for liquidity transmission

Machine-driven modelling has opened new pathways for understanding how liquidity shocks propagate across modern financial networks, particularly through the use of graph-based learning architectures that capture structural dependencies between markets, institutions, and funding channels [11]. Network-based machine learning approaches, especially graph neural networks (GNNs), have emerged as powerful tools for representing liquidity as an evolving process influenced by node connectivity, edge weights, and dynamic market features [19]. Unlike traditional regression models, GNNs encode market structure directly, allowing them to model how stress originating in one node (such as a dealer, clearing member, or collateral pool) diffuses across the network through nonlinear contagion pathways [20].

Within these frameworks, centrality-weighted contagion models play a central role, as they incorporate concepts such as eigenvector centrality, betweenness, and funding-flow intensity to identify "systemically influential" nodes whose liquidity deterioration is likely to trigger broader market stress [21]. For example, a central dealer with high connectivity to multiple funding markets may amplify liquidity shocks disproportionately compared to peripheral participants. Machine learning models trained on historical stress events can learn these patterns and forecast which nodes are likely to transmit liquidity strain during emerging disruptions.

Because GNNs incorporate both topological and statistical features, they excel at modelling interconnected market behaviours, including cross-asset liquidity co-movement, funding-route fragility, and intraday correlation spikes. Their ability to learn nonlinear transformation functions allows them to capture state-dependent liquidity deterioration far more effectively than linear risk tools, especially during periods characterized by abrupt margin adjustments or synchronized risk aversion [22].

Collectively, network-based machine learning tools provide a structural foundation for modelling liquidity transmission as a dynamic, relational phenomenon, enabling earlier detection of fragility in systems where shocks rarely remain isolated but instead cascade rapidly through interconnected trading and funding channels [23].

4.2 Agent-based and simulation-driven liquidity stress models

Agent-based models (ABMs) complement machine learning approaches by simulating the behaviour of heterogeneous market participants whose decisions collectively shape liquidity conditions. In these models, agents such as dealers, hedge funds, clearing members, asset managers, and high-frequency traders act according to predefined behavioural

rules that reflect budget constraints, regulatory requirements, leverage restrictions, and trading strategies [24]. Because agents interact with one another and respond adaptively to evolving market signals, ABMs can recreate the nonlinear feedback loops observed in real markets.

One advantage of agent-based simulation is its ability to incorporate adaptive agents whose behaviour changes under stress. For example, when volatility rises, agents may reduce inventories, widen bid–ask spreads, or retreat from market-making activities, thereby reducing market depth. These endogenous reactions generate liquidity spirals similar to those documented in historical crises, revealing how small shocks can escalate into major dislocations through behavioural synchrony [19].

Fire-sale simulations extend these insights by modelling how forced asset liquidations propagate across portfolios and asset classes. When one institution liquidates assets to meet margin calls or funding shortages, price declines force other institutions with similar holdings to respond in kind, generating system-wide contagion [25]. ABMs can incorporate price-impact functions, portfolio overlap metrics, and collateral eligibility rules to simulate how quickly fire sales spread and which participants are most vulnerable to cascading losses.

Another critical component is clearinghouse bottleneck modelling, which examines how margin cycles, variation-margin calls, and collateral demands contribute to liquidity strain. Clearinghouses play a stabilizing role under normal conditions but can amplify stress when margin schedules tighten abruptly. ABMs that incorporate clearinghouse rules and counterparty exposures can simulate how liquidity demands escalate across intraday cycles and identify thresholds where funding constraints trigger systemic liquidity withdrawal [26].

Through adaptive, rule-driven simulations, agent-based models offer a granular view of liquidity stress evolution, capturing the behavioural and structural nonlinearities that are often invisible in classical liquidity analyses. Their strength lies in reproducing the dynamic interactions that shape contagion pathways, making them an essential tool for forward-looking liquidity stress testing.

4.3 Hybrid statistical–ML frameworks for liquidity forecasting

Hybrid modelling frameworks integrate statistical time-series methods with machine learning algorithms to capture the dual nature of liquidity dynamics its predictable patterns under normal conditions and its nonlinear behaviour under stress. These frameworks often combine ML-augmented vector autoregression (VAR) models with flexible nonlinear regressors to improve the accuracy of liquidity forecasts [27]. Under this approach, traditional VARs handle stable linear relationships, while ML components capture regime shifts, intraday volatility bursts, and structural breaks that arise during stress.

Nonlinear regressors such as gradient boosting machines, random forests, or recurrent neural networks enhance predictive performance by learning complex interactions between microstructure signals, funding spreads, and cross-market liquidity indicators that linear models overlook [23]. These algorithms excel at identifying early-warning signals of liquidity deterioration, such as synchronized order-book thinning or widening cross-asset spreads.

Ensemble-based spillover prediction frameworks provide additional resilience by aggregating multiple modelling approaches, reducing sensitivity to individual model weaknesses. Ensembles can combine statistical features (e.g., autocorrelation, volatility signatures) with machine learning outputs to produce more stable forecasts across diverse market conditions [22].

Hybrid frameworks often outperform standalone models because they capture both structural liquidity behaviours and dynamic contagion effects. By integrating statistical interpretability with machine learning flexibility, these models form a strong foundation for monitoring and forecasting liquidity risk in high-frequency, highly interconnected trading environments. Table 2 summarizes the strengths of these hybrid systems relative to traditional and purely machine-driven approaches.

4.4 Real-time liquidity signal extraction using advanced analytics

Real-time liquidity signal extraction has become essential in markets where liquidity can evaporate within minutes. Advanced analytics leverage streaming data ingestion pipelines that process order-book updates, quotes, and trade flows at sub-second frequencies to detect early signs of fragility [20]. These pipelines incorporate anomaly-detection algorithms capable of identifying unusual spikes in volatility, abrupt depth withdrawals, or sudden changes in trade intensity that precede liquidity stress.

Microstructure-informed alert systems enhance monitoring by combining transactional indicators with network-based features, such as dealer withdrawal rates or cross-venue liquidity imbalances [24]. These systems generate alerts when market conditions deviate from historical norms, allowing risk managers to respond before disruptions escalate.

Together, streaming analytics and microstructure-aware models enable real-time surveillance of liquidity risks, bridging the gap between traditional end-of-day metrics and the rapid dynamics of modern market stress. Table 2 provides a comparative overview of how these machine-driven approaches differ in analytical capability and predictive strength.

Table 2. Comparison of Machine-Driven Liquidity Propagation Models and Their Analytical Strengths

Model Category	Core Analytical Approach	Strengths in Liquidity Propagation Analysis	Limitations / Challenges
Graph Neural Networks (GNNs)	Learns market-network structure using node connectivity, edge features, and dynamic graph embeddings.	• Excellent at modelling liquidity contagion across interconnected markets. • Captures nonlinear stress-transmission pathways. • Identifies systemically influential nodes and funding hubs.	• Requires large, high-quality relational datasets. • Interpretability can be limited without explainability layers.
Centrality-Weighted Contagion Models	Uses network centrality (degree, eigenvector, betweenness) to infer stress-propagation intensity.	• Strong for systemic-risk mapping and vulnerability scoring. • Useful for early warning based on structural fragility.	• Static centrality assumptions may understate dynamic behaviour.
Agent-Based Liquidity Stress Simulations (ABMs)	Simulates adaptive behaviour of heterogeneous market participants under varying conditions.	• Captures behavioural feedback loops, fire-sale spirals, and clearing bottlenecks. • Highly flexible for scenario exploration.	• Computationally intensive. • Output sensitive to agent-rule calibration.
Fire-Sale and Margin-Spiral Models	Models recursive price impact, forced deleveraging, and collateral-driven dynamics.	• Excellent for reproducing stress amplification and intraday liquidity collapses. • Captures nonlinear propagation via collateral and leverage	• Less suited for cross-asset interactions without hybrid integration.

Model Category	Core Analytical Approach	Strengths in Liquidity Propagation Analysis	Limitations / Challenges
		channels.	
Hybrid Statistical–ML Systems	Combines VAR, time-series statistics, and ML regressors (GBM, RF, RNNs) for joint forecasting.	• Balances interpretability with predictive power. • Adapts to structural breaks and nonlinear liquidity shifts.	• Requires robust feature engineering. • May underperform without frequent retraining.
Ensemble-Based Spillover Predictors	Aggregates forecasts from multiple models across assets, markets, and temporal resolutions.	• Provides the most stable and robust predictions. • Reduces overfitting and model-specific bias.	• High computational cost. • Complex coordination of ensemble weights.
Real-Time Streaming Analytics Engines	Uses streaming pipelines and microstructure-aware anomaly detection for intraday monitoring.	• Detects emerging liquidity stress within seconds. • Ideal for market surveillance and real-time risk dashboards.	• Requires dedicated infrastructure and low-latency data access.

5. INTEGRATED LIQUIDITY PROPAGATION MODELING FRAMEWORK

5.1 Architecture for a unified machine-driven liquidity risk engine

A unified machine-driven liquidity risk engine requires a robust and extensible computational architecture that integrates heterogeneous data sources, high-frequency market signals, and network-level structural indicators into a coherent analytical system [25]. At its foundation lies a multi-layer data architecture, incorporating transactional data from order books, quote feeds, and trade repositories, along with balance-sheet metrics, collateral flows, and cross-venue liquidity indicators. This architecture must support both streaming and batch-processing modes to accommodate intraday volatility monitoring as well as broader structural liquidity assessments.

The next layer consists of a multi-stage modelling pipeline designed to capture the evolving dynamics of liquidity formation and stress propagation. The pipeline typically begins with microstructure preprocessing modules that clean, normalize, and align high-frequency data. These modules extract key attributes such as order-book depth, trade aggressiveness, quote revisions, and cross-asset price impacts [26]. Above this preprocessing layer sits a network-analytics module that transforms market interactions into graph structures, enabling the engine to evaluate centrality, connectivity, and stress-transmission intensity across institutions and trading venues.

The modelling tier fuses statistical components with machine learning algorithms to generate both explanatory variables and predictive outputs. Statistical models capture baseline behaviours during normal regimes, while nonlinear architectures such as graph neural networks and ensemble-based predictors identify structural shifts indicative of emerging liquidity fragility [27]. A supervisory control layer evaluates model consistency, calibrates hyperparameters, and integrates scenario-testing modules for forward-looking stress simulations. Collectively, this architecture forms a holistic engine capable of synthesizing real-time signals and structural features into actionable liquidity-risk intelligence [28].

5.2 Feature engineering for liquidity stress detection

Effective liquidity stress detection hinges on a rich, well-structured feature set that captures the behavioural and structural dimensions of liquidity variation. Trade-based features provide a fundamental signal layer, encompassing order aggressiveness, trade-size imbalances, quote depletion rates, and clustering of marketable orders. These metrics highlight early indications of liquidity withdrawal as traders shift toward defensive positioning [29].

Complementing trade-based attributes are funding-pressure indicators, which capture liquidity stress emerging from the funding ecosystem rather than from trading behaviour alone. These include repo-rate dislocations, collateral-haircut adjustments, dealer inventory compression, and changes in unsecured funding spreads. During stress periods, these indicators often react before observable liquidity declines, making them valuable early-warning features [30].

A third class of engineered features focuses on margin-call predictors, capturing variables related to volatility acceleration, cross-asset hedging pressure, and intraday variation-margin sensitivity. These features allow machine-driven systems to detect when price moves are likely to trigger forced deleveraging or collateral exhaustion. Feature-engineering frameworks integrate these dimensions into a unified dataset, enabling models to detect both microstructure-driven and funding-driven liquidity stress with greater precision [31].

5.3 Scenario construction and liquidity-shock simulation

Scenario-building frameworks are essential for evaluating how liquidity shocks propagate across markets under different structural and behavioural conditions. Multi-market stress scenarios integrate simultaneous shocks to equities, fixed income, FX, and derivatives markets, focusing on how pricing shifts translate into collateral demands, dealer balance-sheet pressure, and cross-market liquidity withdrawal [28]. These scenarios incorporate volatility escalation, rate dislocations, and cross-venue liquidity gaps to simulate interactions between risk factors that traditional models typically treat in isolation.

A second set of scenarios involves intraday propagation modelling, which emphasizes short-horizon contagion pathways. These simulations replicate stress mechanisms such as order-book evaporation, intraday variation-margin cycles, and correlated asset liquidations. By modelling microstructure reactions at sub-minute intervals, these simulations reveal nonlinear dynamics that emerge well before end-of-day liquidity metrics reflect stress events [32].

Advanced scenario engines integrate empirical market microstructure parameters, network-topological metrics, and behavioural assumptions derived from historical crisis data. Through these simulations, institutions can evaluate how liquidity shocks spread, identify systemically influential nodes, and determine which markets are most vulnerable to accelerated contagion. This multi-layer stress architecture supports early-risk detection and informed decision-making under rapidly evolving market conditions.

5.4 Combining statistical inference with adaptive ML algorithms

Combining statistical inference with adaptive machine-learning techniques enables a more resilient liquidity-risk modelling framework. Statistical models contribute interpretability, stable baseline relationships, and economic coherence, while adaptive ML algorithms provide flexibility for capturing nonlinear interactions, structural breaks, and emergent contagion patterns [27]. Hybrid integration frameworks blend autoregressive structures with nonlinear predictors, ensuring that both stable-regime dynamics and stress-specific anomalies are represented.

This joint approach enhances robustness by mitigating overfitting, improving scenario reliability, and enabling models to adjust dynamically to evolving market conditions. Figure 3 illustrates the full architecture of the proposed machine-driven liquidity-propagation framework.
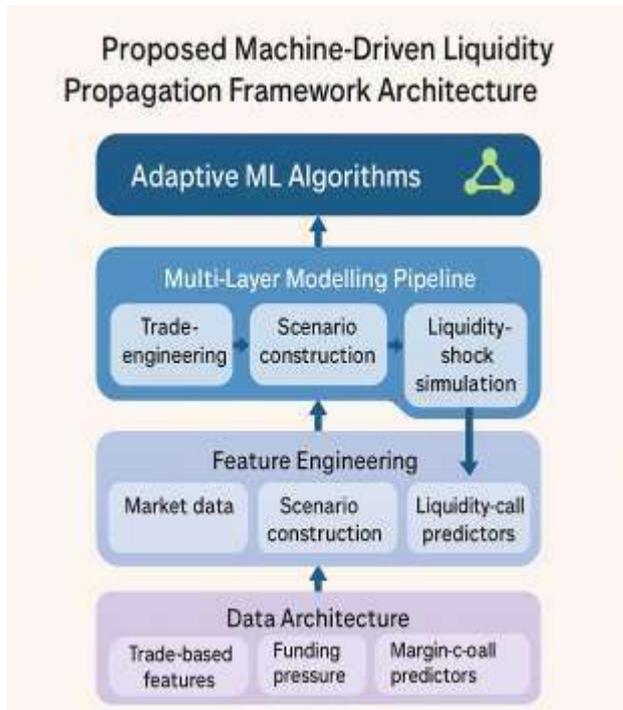
Figure 3 Full architecture of the proposed machine-driven liquidity-propagation framework.

6. APPLICATION CASE STUDIES

6.1 Liquidity stress modelling in equity and derivative markets

Liquidity stress in equity and derivative markets is characterized by rapid shifts in intraday order-book dynamics, sudden reductions in market depth, and cross-asset spillovers that reflect tightly coupled trading behaviours. During volatility spikes, order books thin dramatically as liquidity providers widen spreads or retract quotes, causing price impact to rise sharply even for moderate trade sizes [30]. This behaviour is amplified in algorithmically dominated markets where order-flow imbalance triggers automated withdrawal of quotes, accelerating liquidity evaporation.

Derivatives amplify these stresses through margining cycles and cross-hedging pressures. When volatility rises, variation-margin calls increase substantially, prompting leveraged traders to liquidate positions or reduce exposures across related assets [33]. As positions unwind simultaneously, equity liquidity deteriorates further, and options market makers widen implied-volatility surfaces to compensate for increased risk.

These dynamics frequently create cross-asset liquidity withdrawal, where liquidity vanishes not only in equities but also in options, futures, and volatility products linked through hedging flows. During stress episodes, a change in liquidity conditions in one asset often produces synchronized dislocations elsewhere, revealing non-linear dependencies that traditional liquidity models fail to anticipate [31]. The interaction between order-book fragility and derivative-driven funding pressure underscores the need for dynamic simulation frameworks capable of capturing intraday liquidity spirals [34].

6.2 Interbank funding liquidity contagion analysis

Interbank funding markets present a distinct set of liquidity contagion mechanisms rooted in counterparty exposures, funding corridors, and collateralized lending structures. When liquidity dries up in the unsecured funding market, banks increasingly rely on secured lending facilities, which can trigger rapid escalation in haircuts and funding spreads [32]. As these funding corridors become stressed, counterparties tighten lending terms or withdraw altogether, setting off a chain reaction that affects institutions far beyond the initial liquidity shortfall.

Counterparty network failures represent a critical propagation channel. Banks are connected through overlapping funding positions, repos, and derivatives obligations, meaning a disruption in one node can transmit liquidity stress throughout the network [36]. The withdrawal of a major funding provider forces dependent institutions to seek alternative liquidity sources at elevated costs, which in turn exacerbates balance-sheet constraints and heightens the risk of a broader funding freeze.

Empirical evidence shows that when a bank experiences a liquidity shock, its counterparties simultaneously reduce exposures, generating synchronized funding stress that can cascade into full-scale interbank dysfunction [30]. These network-driven propagation patterns demonstrate why stress in interbank markets often escalates faster than in trading markets. Because funding liquidity is a prerequisite for market liquidity, disruptions in the interbank system tend to magnify stress across all associated markets, reinforcing the need for network-aware modelling techniques [37].

6.3 Liquidity propagation across global multi-asset systems

Global financial markets exhibit strong cross-asset and cross-region liquidity dependencies, which become particularly visible during systemic stress episodes. One prominent catalyst is sovereign-spread shocks, where widening credit spreads in sovereign debt markets transmit liquidity stress into equities, corporate bonds, and FX markets due to shared risk-premia channels and collateral requirements [35]. When sovereign yields spike, risk-sensitive funding channels tighten, causing liquidity to contract simultaneously across multiple asset classes.

Another propagation mechanism is FX–equity–bond liquidity co-crashes, where liquidity collapses concurrently across several markets as investors unwind positions across currencies, equities, and rates to cover losses or meet margin calls [38]. These co-crashes tend to occur when global volatility indices rise sharply, triggering uniform deleveraging across risk-parity, carry-trade, and cross-asset arbitrage strategies.

Because global portfolios increasingly rely on integrated hedging and collateral chains, stress in one region rapidly affects liquidity conditions elsewhere. For example, funding stress in European repo markets can swiftly migrate to U.S. dollar funding markets due to extensive cross-currency swap activity, ultimately constraining liquidity in equity and fixed-income markets abroad [33].

Traditional liquidity models, which often evaluate markets in isolation, fail to capture these global feedback loops. Understanding multi-asset liquidity propagation therefore requires models capable of integrating sovereign-spread dynamics, FX-bond linkages, and cross-market hedging flows into a unified analytical system [36].

7. CONCLUSION

7.1 Key insights from machine-driven liquidity propagation research

Recent advances in machine-driven liquidity modelling have significantly improved understanding of how stress evolves and propagates across modern financial markets. Unlike classical liquidity models that rely on static assumptions, machine-driven approaches incorporate dynamic, nonlinear interactions across trading venues, funding channels, and collateral networks. This shift has enabled more accurate detection of early fragility signals, improved representation of stress amplification mechanisms, and deeper insight into how microstructure disruptions escalate into system-wide liquidity events.

By integrating network analytics, high-frequency signals, and behavioural simulations, these methods reveal structural vulnerabilities that traditional models consistently overlook. Machine-driven research also contributes to broader market stability analysis by demonstrating how liquidity shocks spread across interconnected asset classes, how intra-day volatility accelerates funding pressure, and how feedback loops significantly amplify risk. Collectively, these insights provide a stronger analytical foundation for regulators, financial institutions, and market participants seeking to anticipate and mitigate liquidity-driven instability.

7.2 Future opportunities for integrated systemic liquidity modelling

Looking forward, multiple opportunities exist for building more comprehensive liquidity-risk frameworks capable of supporting both market participants and policy institutions. One promising direction is the development of real-time systemic-risk dashboards that synthesize high-frequency microstructure signals, network contagion metrics, and machine-learning forecasts into a single monitoring interface. Such dashboards would allow institutions to identify liquidity deterioration minutes or even seconds before it becomes systemically relevant, substantially improving early-warning capabilities.

Another frontier lies in the use of multi-agent reinforcement learning, where heterogeneous agents learn optimal behaviour under varying market conditions. These systems can model dynamic feedback loops and competitive interactions in ways that more closely resemble real-world stress responses. By training agents under diverse simulation scenarios, researchers can uncover emergent behaviours and structural tipping points that traditional stress-testing frameworks cannot reproduce.

At a broader level, machine-driven liquidity models hold significant promise for policy-level implementation. Regulators could apply these tools to evaluate the systemic implications of margin requirements, collateral standards, or dealer balance-sheet constraints under different stress environments. Embedding machine-learning-enhanced liquidity analytics into macroprudential policy design would enable more adaptive and responsive regulation, ultimately strengthening financial-system resilience.

8. REFERENCE

1. Martins Pereira C. Unregulated algorithmic trading: testing the boundaries of the european union algorithmic trading regime. Journal of Financial Regulation. 2020 Sep 20;6(2):270-305.

2. Mamela TL. Assessment of the impact of artificial intelligence on the performance of the workforce at a South African banking institution. University of Johannesburg (South Africa); 2021.

3. Houssein EH, Dirar M, Hussain K, Mohamed WM. Artificial neural networks for stock market prediction: a comprehensive review. Metaheuristics in machine learning: theory and applications. 2021 Jul 14:409-44.

4. Leinweber D, Sisk J. Relating news analytics to stock returns. The handbook of news analytics in finance. 2011 May 16:147-72.

5. Chukwunweike J. Design and optimization of energy-efficient electric machines for industrial automation and renewable power conversion applications. *Int J Comput Appl Technol Res*. 2019;8(12):548–560. doi: 10.7753/IJCATR0812.1011.

6. Hansen KB. The virtue of simplicity: On machine learning models in algorithmic trading. Big Data & Society. 2020 May;7(1):2053951720926558.

7. Arrighi G. The long twentieth century: Money, power, and the origins of our times. verso; 1994.

8. John BI. Integration of intelligent scheduling optimization systems improving production flow, minimizing delays, and maximizing throughput across large-scale industrial operations. *Global Journal of Engineering and Technology Advances*. 2020;5(3):156–169. Available from: https://doi.org/10.30574/gjeta.2020.5.3.0118

9. Ogunyemi FM. Carbon Accounting Automation Through Machine Learning and Natural Language Processing: Reducing Compliance Costs and Enhancing Data Quality in Enterprise ESG Reporting. International Journal of Science and Research Archive. 2021;4(1):490–501. doi:10.30574/ijsra.2021.4.1.0213.

10. Sedighi A, Jacobson D. Computational Challenges and Opportunities. InSmart Computing and Communication:

4th International Conference, SmartCom 2019, Birmingham, UK, October 11–13, 2019, Proceedings 2019 Nov 4 (Vol. 11910, p. 310). Springer Nature.

11. McGroarty F, Booth A, Gerding E, Chinthalapati VR. High frequency trading strategies, market fragility and price spikes: an agent based model perspective. Annals of Operations Research. 2019 Nov;282(1):217-44.

12. Derera R. Machine learning-driven credit risk models versus traditional ratio analysis in predicting covenant breaches across private loan portfolios. *International Journal of Computer Applications Technology and Research*. 2016;5(12):808-820. doi:10.7753/IJCATR0512.1010.

13. Ogunyemi FM. Designing accessible carbon accounting frameworks for small and medium enterprises: overcoming technical and financial barriers to ESG compliance. International Journal of Computer Applications Technology and Research. 2018;7(12):556–566.

14. Onyechi VN. Pipeline integrity and risk prevention: Real-time monitoring, structural health analytics, and failure mitigation in harsh operating environments. *Magna Scientia Advanced Research and Reviews.* 2021;3(2):139–151. doi:10.30574/msarr.2021.3.2.0093

15. Hofmeister J, Portner B. Risk Management in Retail and the Consumer Goods Industry. InPerformance Management in Retail and the Consumer Goods Industry: Best Practices and Case Studies 2019 Jun 22 (pp. 283-296). Cham: Springer International Publishing.

16. Leinweber D. If You Had Everything Computationally... Journal of Portfolio Management. 2005 Oct 1;32(1):61.

17. Schwartz RA, Weber BW. Next-generation securities market systems: an experimental investigation of quote-driven and order-driven trading. Journal of Management Information Systems. 1997 Sep 1;14(2):57-79.

18. Rumbidzai Derera. HOW FORENSIC ACCOUNTING TECHNIQUES CAN DETECT EARNINGS MANIPULATION TO PREVENT MISPRICED CREDIT DEFAULT SWAPS AND BOND UNDERWRITING FAILURES. International Journal of Engineering Technology Research & Management (IJETRM). 2017Dec21;01(12):112–27.

19. John BI. Risk-aware project delivery strategies leveraging predictive analytics and scenario modelling to mitigate disruptions and ensure stable manufacturing performance. *International Journal of Science and Engineering Applications*. 2019;8(12):535–546.

20. Oloke K. Developing Secure, AI-Enabled Multi-Cloud Payment Gateways with Built-In Regulatory Compliance Automation. International Journal of Science and Research Archive. 2021;4(1):502–516. doi:10.30574/ijsra.2021.4.1.0214.

21. Ozenbas D, Pagano MS, Schwartz RA, Weber BW. Liquidity, Trading, and Price Determination in Equity Markets: A Finance Course Application. InLiquidity, Markets and Trading in Action: An Interdisciplinary Perspective 2021 Aug 26 (pp. 21-49). Cham: Springer International Publishing.

22. Schwartz RA, Weber BW. Simulation as a Research Tool for Market Architects. InHandbook of Financial Econometrics and Statistics 2015 (pp. 121-147). Springer, New York, NY.

23. Atanda ED. EXAMINING HOW ILLIQUIDITY PREMIUM IN PRIVATE CREDIT COMPENSATES ABSENCE OF MARK-TO-MARKET OPPORTUNITIES UNDER NEUTRAL INTEREST RATE ENVIRONMENTS. International Journal Of Engineering Technology Research & Management (IJETRM). 2018Dec21;2(12):151-64.

24. Nzekwe C. Scalable deep learning architectures incorporating automated interaction selection to improve robustness and prediction performance in massive high-dimensional datasets. *International Journal of Computer Applications Technology and Research*. 2020;9(12):475-486. doi:10.7753/IJCATR0912.1015.

25. Pungaliya RS, Wang Y. Machine invasion: Automation in information processing and the cross section of stock returns. Available at SSRN 3221816. 2018 Aug 1.

26. Martins Pereira C. Unregulated algorithmic trading: testing the boundaries of the european union algorithmic trading regime. Journal of Financial Regulation. 2020 Sep 20;6(2):270-305.

27. Gębarowski R, Oświęcimka P, Wątorek M, Drożdż S. Detecting correlations and triangular arbitrage opportunities in the Forex by means of multifractal detrended cross-correlations analysis. Nonlinear Dynamics. 2019 Nov;98(3):2349-64.

28. Lin TC. The new investor. UCLA L. Rev.. 2012;60:678.

29. Moosa I, Ramiah V. The regulation of high-frequency trading: an Asian perspective. Handbook of Asian Finance: REITs, Trading, and Fund Performance, Volume 2. 2014 May 15;2:153.

30. Di Tollo G, Lyra M. Elman nets for credit risk assessment. InDecision Theory and Choices: a Complexity Approach 2010 Dec 28 (pp. 147-167). Milano: Springer Milan.

31. Nair G. *Development of a Real-Time Business Intelligence (BI) Framework Based on Hex-Elementization of Data Points for Accurate Business Decision-Making* (Doctoral dissertation, Thesis, Westren Sydny University).

32. Houssein EH, Dirar M, Hussain K, Mohamed WM. Artificial neural networks for stock market prediction: a comprehensive review. Metaheuristics in machine learning: theory and applications. 2021 Jul 14:409-44.

33. MacKenzie D. A sociology of algorithms: High-frequency trading and the shaping of markets. Preprint. School of Social and Political Science, University of Edinburgh. 2014 Jun.

34. Crawley M, Wahlen J. Analytics in empirical/archival financial accounting research. Business Horizons. 2014 Sep 1;57(5):583-93.

35. Marszk A, Lechman E. Digitalization of financial markets. Milton Park: Routledge; 2021 Dec 1.

36. DeNisi A, Smith CE. Performance appraisal, performance management, and firm-level performance: A review, a proposed model, and new directions for future

research. Academy of Management Annals. 2014 Jan 1;8(1):127-79.

37. Pagnotta ES, Philippon T. Competing on speed. Econometrica. 2018 May;86(3):1067-115.

38. Gębarowskia R, Oświęcimkab P, Wątorekb M, Drożdża S. Multiscale cross–correlations and triangular arbitrage opportunities in the Forex. arXiv preprint arXiv:1906.07491. 2019 Jun.

39. Kolawole Oloke. CLOUD-ACCELERATED PREDICTIVE TREASURY MANAGEMENT USING DEEP REINFORCEMENT LEARNING AND FINANCIAL DIGITAL TWINS. International Journal Of Engineering Technology Research & Management (IJETRM). 2022Dec21;06(12):190–204.

40. Cook S. Understanding commodity cultures: Explorations in economic anthropology with case studies from Mexico. Rowman & Littlefield; 2004.

41. Riain SÓ. The rise and fall of Ireland's Celtic tiger: Liberalism, boom and bust. Cambridge University Press; 2014 Mar 20.

42. During D. Applied statistical methods for stress-testing credit portfolios and forecasting default probabilities in volatile markets. International Journal of Science and Research Archive. 2022;7(2):924-937. doi:10.30574/ijsra.2022.7.2.0360.

43. Mezzadra S, Neilson B. The politics of operations: Excavating contemporary capitalism. Duke University Press; 2019 Feb 14.

44. Vaknin S, von Mises L. Capitalistic Musings. Project Gutenberg.; 2005.

45. Nzekwe C. Next-generation AI methods optimizing variable interactions and prediction efficiency under ultra-high-dimensional conditions using multimodal large-scale data. *International Journal of Science and Engineering Applications*. 2021;10(12):210-220. doi:10.7753/IJSEA1012.1005.