



Original Article

# Predictive Analytics for Liquidity Risk Monitoring in Real-Time

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**Abstract** - Liquidity risk remains one of the most critical challenges for financial institutions, directly impacting their ability to meet short-term obligations and maintain regulatory compliance. Traditional liquidity risk monitoring methods rely heavily on static models and delayed reporting, which fail to provide timely insights into volatile markets. This paper introduces a predictive analytics framework for real-time liquidity risk monitoring, leveraging machine learning algorithms and streaming data architectures to forecast liquidity gaps and identify potential stress scenarios before they materialize. The proposed approach integrates time-series forecasting, advanced machine learning models such as Gradient Boosting and LSTM networks, and real-time data ingestion platforms to deliver actionable insights for treasury and risk management teams. A simulated case study demonstrates the effectiveness of predictive models compared to conventional approaches, highlighting improvements in accuracy, responsiveness, and operational resilience. The findings underscore the transformative potential of predictive analytics in enhancing liquidity risk management, reducing regulatory breaches, and strengthening financial stability.

**Keywords** - Liquidity Risk, Predictive Analytics, Real-Time Monitoring, Machine Learning, Deep Learning, LSTM, Gradient Boosting, ARIMA, Time-Series Forecasting, Basel III, Liquidity Coverage Ratio (LCR), Net Stable Funding Ratio (NSFR), Stress Testing, Streaming Data Architecture, Apache Kafka, Big Data Analytics, Financial Risk Management, Intraday Liquidity, Anomaly Detection, Ensemble Models, Cloud-Native Solutions, Explainable AI (XAI), Generative AI, Blockchain Integration.

## 1. Introduction

Liquidity risk is one of the most critical challenges faced by financial institutions, as it directly impacts their ability to meet short-term obligations without incurring significant losses. Inadequate liquidity management can lead to severe consequences, including regulatory breaches, reputational damage, and even systemic failures. Regulatory frameworks such as Basel III have introduced stringent requirements like the Liquidity Coverage Ratio (LCR) and Net Stable Funding Ratio (NSFR) to ensure institutions maintain adequate liquidity buffers. However, these measures primarily rely on static models and periodic reporting, which are insufficient in today's dynamic and volatile financial markets.

Traditional liquidity risk monitoring approaches often suffer from delayed data processing, limited predictive capabilities, and lack of real-time visibility. This creates a gap between risk identification and mitigation, exposing institutions to sudden liquidity shocks.

The increasing complexity of financial products, coupled with high-frequency transactions and global interconnectedness, demands a more agile and proactive approach.

Predictive analytics offers a transformative solution by leveraging historical and real-time data to forecast liquidity positions and identify potential stress scenarios before they materialize. By integrating advanced machine learning algorithms, time-series forecasting techniques, and real-time data streaming architectures, predictive analytics enables financial institutions to move from reactive risk management to proactive decision-making.

This paper explores the application of predictive analytics for real-time liquidity risk monitoring. It outlines the architectural components, modeling techniques, and implementation strategies required to build a robust predictive framework. Additionally, a simulated case study demonstrates the effectiveness of predictive models compared to traditional approaches, highlighting improvements in accuracy, responsiveness, and operational resilience.

## 2. Literature Review

Liquidity risk management has traditionally relied on static models and periodic reporting frameworks, such as those mandated by Basel III. These approaches primarily use historical data and predefined ratios like Liquidity Coverage Ratio (LCR) and Net Stable Funding Ratio (NSFR) to assess liquidity positions. While effective for regulatory compliance, they lack the agility to respond to sudden market shocks or intraday liquidity fluctuations.

Several studies have highlighted the limitations of conventional liquidity risk monitoring. Allen and Gale (2004) emphasized that static models fail to capture dynamic market conditions, leading to delayed risk identification. Similarly, Brunnermeier and Pedersen (2009) demonstrated how liquidity spirals during stress periods amplify systemic risk, underscoring the need for real-time monitoring.

Recent research has shifted toward predictive and real-time analytics. Tobias Adrian et al. (2018) explored the use of high-frequency data for liquidity forecasting, showing improved accuracy compared to traditional methods. Machine learning techniques such as Random Forest and Gradient Boosting have been applied to predict liquidity gaps using transactional and market data, as noted in studies by Khandani et al. (2010).

Furthermore, deep learning models like Long Short-Term Memory (LSTM) networks have demonstrated superior performance in capturing sequential patterns intraday liquidity flows.

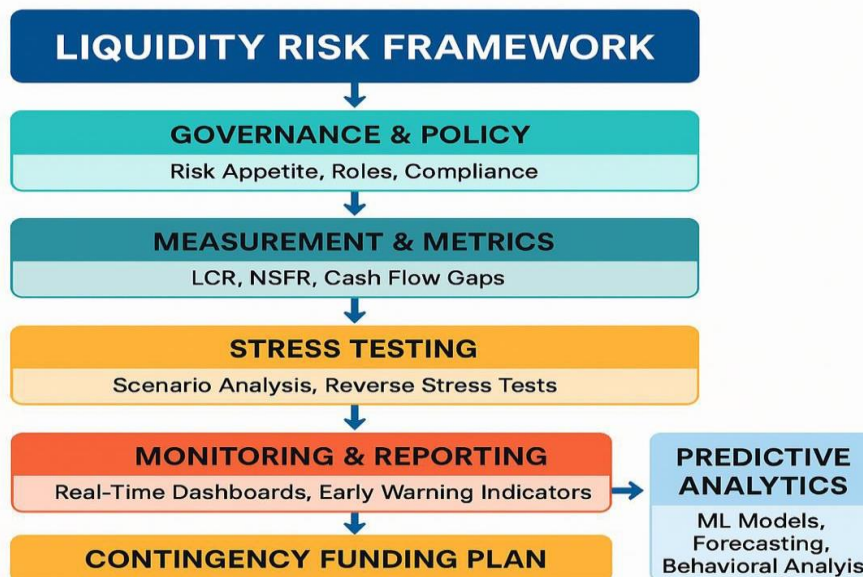
Industry reports from BCBS and European Banking Authority advocate for integrating advanced analytics into liquidity risk frameworks to meet evolving regulatory and operational demands. However, challenges remain in terms of data quality, model interpretability, and regulatory acceptance of AI-driven approaches.

This literature review establishes the gap between traditional liquidity risk management and the emerging need for predictive, real-time solutions. It provides the foundation for the proposed framework discussed in subsequent sections.

**Table 1: Traditional vs Predictive Liquidity Risk Monitoring**

Aspect	Traditional Approach	Predictive Analytics Approach
Data Source	Historical data, periodic reports	Real-time streaming data, transactional feeds
Frequency	Daily / Weekly reporting	Continuous, real-time monitoring
Model Type	Static ratios (LCR, NSFR), deterministic models	Dynamic models (ML, AI, time-series forecasting)
Risk Detection	Reactive – after liquidity shortfall occurs	Proactive – predicts potential liquidity gaps
Decision Support	Limited, based on past trends	Advanced, scenario-based forecasting
Regulatory Compliance	Manual stress testing	Automated stress testing with predictive scenarios
Technology	Legacy systems, batch processing	Streaming platforms (Kafka, Flink), cloud- based analytics
Response Time	Hours to days	Seconds to minutes
Accuracy	Moderate – depends on historical assumptions	High – adapts to changing patterns and market conditions

### 3. Liquidity Risk Framework



**Fig 1: Liquidity Risk Framework**

Liquidity risk refers to the risk that a financial institution will not be able to meet its short-term obligations due to insufficient liquid assets. A robust framework ensures proactive monitoring and mitigation of this risk.

Liquidity risk management is built on three core components:

### 3.1. Governance & Policy

- Define roles and responsibilities.
- Establish liquidity risk appetite and tolerance levels.
- Regulatory compliance (e.g., Basel III LCR, NSFR).

### 3.2. Measurement & Metrics

- Liquidity Coverage Ratio (LCR): High- quality liquid assets vs. net cash outflows.
- Net Stable Funding Ratio (NSFR): Available stable funding vs. required stable funding.
- Cash Flow Projections: Short-term and long- term liquidity gaps.

### 3.3. Stress Testing

- Simulate adverse scenarios (market stress, funding shocks).
- Assess resilience under extreme conditions.

### 3.4. Monitoring & Reporting

- Real-time dashboards for liquidity positions.
- Early warning indicators (EWI) for potential liquidity shortfalls.

### 3.5. Contingency Funding Plan

- Predefined strategies for emergency liquidity needs.
- Access to central bank facilities or repo markets.

### 3.6. Predictive Analytics Integration

- Use machine learning models to forecast liquidity needs.
- Incorporate behavioral patterns, market volatility, and macroeconomic indicators.

## 4. Predictive Analytics Overview



Fig 2: Predictive Analytics Overview

### 4.1. Data Collection

**Purpose:** Gather historical and real-time data from multiple sources.

**Sources:**

- Transactional data (payments, settlements).
- Market data (interest rates, FX rates, liquidity spreads).
- Behavioral data (customer withdrawal patterns).

**Key Considerations:**

- Data quality and completeness.
- Integration from disparate systems.
- Real-time streaming for immediate insights.

**4.2. Data Analysis**

**Purpose:** Transform raw data into meaningful insights.

**Steps:**

- Data Cleaning: Remove duplicates, handle missing values
- Normalization: Standardize formats for consistency.
- Pattern Identification: Detect trends, anomalies, and correlations.

**Tools:**

- SQL, Python (Pandas, NumPy).
- Visualization tools (Power BI, Tableau).

**4.3. Machine Learning Models**

**Purpose:** Predict future liquidity needs and risks.

**Common Models:**

- Regression Models: For continuous liquidity forecasts.
- Time-Series Models: ARIMA, LSTM for trend prediction.
- Classification Models: Identify high-risk scenarios.

**Features Used:**

- Historical liquidity ratios.
- Market volatility indicators.
- Behavioral patterns of counterparties.

**4.4. Forecasting**

**Purpose:** Generate actionable predictions for decision-making.

**Types of Forecasts:**

- Short-Term: Intraday liquidity positions. Medium-Term: Weekly or monthly liquidity gaps.
- Stress Scenarios: Impact of market shocks or funding disruptions.

**Outputs:**

- Predictive dashboards.
- Alerts for potential liquidity shortfalls.
- Recommendations for contingency actions.

**5. Real-Time Data Architecture**

This architecture enables continuous ingestion, processing, and analysis of data streams for immediate insights and actions. It is critical for liquidity risk monitoring because decisions often need to be made within seconds.

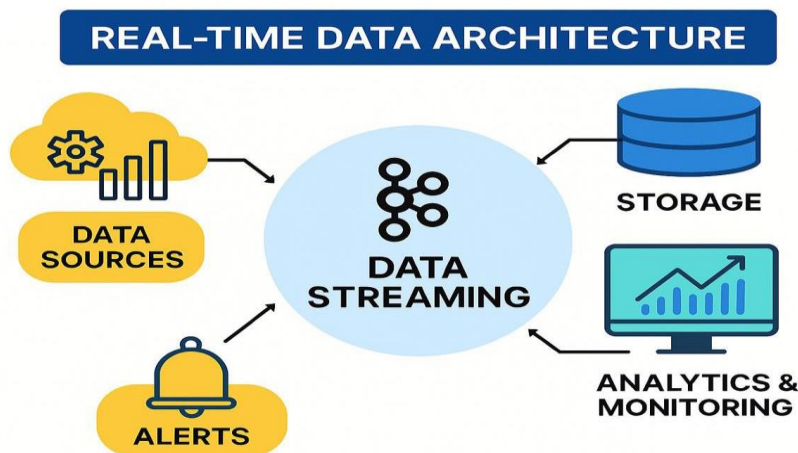


Fig 3: Real-Time Data Architecture

### 5.1. Data Sources

**Description:** Origin of raw data for real-time processing.

**Examples:**

- Core banking systems (transaction data).
- Market feeds (FX rates, interest rates).
- Payment systems and settlement platforms.

**Use Case:**

Capturing intraday liquidity positions from payment systems to monitor cash flow in real time.

### 5.2. Data Streaming

**Description:** Middleware that transports data continuously from sources to processing layers.

**Technologies:** Apache Kafka, AWS Kinesis, Azure Event Hub.

**Use Case:**

Streaming high-frequency transaction data to detect sudden liquidity outflows and trigger alerts instantly.

### 5.3. Storage

**Description:** Repository for structured and unstructured data.

**Types:**

- Hot Storage: In-memory databases for instant access (Redis, Memcached).
- Cold Storage: Data lakes for historical analysis (Hadoop, AWS S3).

**Use Case:**

Storing historical liquidity data for trend analysis and predictive modeling.

### 5.4. Analytics & Monitoring

**Description:** Real-time dashboards and predictive models.

**Functions:**

- Liquidity position tracking.
- Early warning indicators.
- Predictive forecasting using ML models.

**Use Case:**

Displaying real-time liquidity ratios and generating alerts when thresholds are breached.

### 5.5. Alerts

**Description:** Automated notifications for anomalies or threshold breaches.

**Channels:**

Email, SMS, system alerts.

**Use Case:**

Sending instant alerts to treasury teams when liquidity falls below regulatory limits (e.g., LCR threshold).

### 5.6. How Kafka Supports Streaming

Apache Kafka is a distributed event streaming platform designed for high-throughput, low-latency data pipelines. Here's how it works: Publish-Subscribe Model:

- Producers publish data (events) to Kafka topics.
- Consumers subscribe to topics and process data in real time.

**Key Features for Streaming:**

- Partitioning: Splits topics into partitions for parallel processing.
- Replication: Ensures fault tolerance and high availability.
- Retention: Stores events for a configurable time, enabling replay and batch processing.

**Streaming Integration:**

Kafka Streams API or tools like Apache Flink and Spark Streaming can process data in motion.

- Supports exactly-once semantics, critical for financial transactions.

### 5.7. Integration with Machine Learning

Kafka acts as the data backbone for ML-driven predictive analytics:

#### Data Ingestion for ML:

- Real-time transactions and market data flow into Kafka topics.
- ML models consume this data for continuous training or real-time inference.

#### Streaming ML Pipeline:

- Step 1: Kafka streams raw data to a processing layer (e.g., Spark, Flink).
- Step 2: Data is transformed, and features are extracted.
- Step 3: ML models (deployed in microservices or frameworks like TensorFlow Serving) consume the processed stream.
- Step 4: Predictions (e.g., liquidity shortfall risk) are sent back to Kafka for downstream systems (dashboards, alerts).

#### Use Case Example:

Predicting intraday liquidity risk: Kafka streams payment data → ML model predicts liquidity gap → Kafka publishes alerts to treasury dashboard.

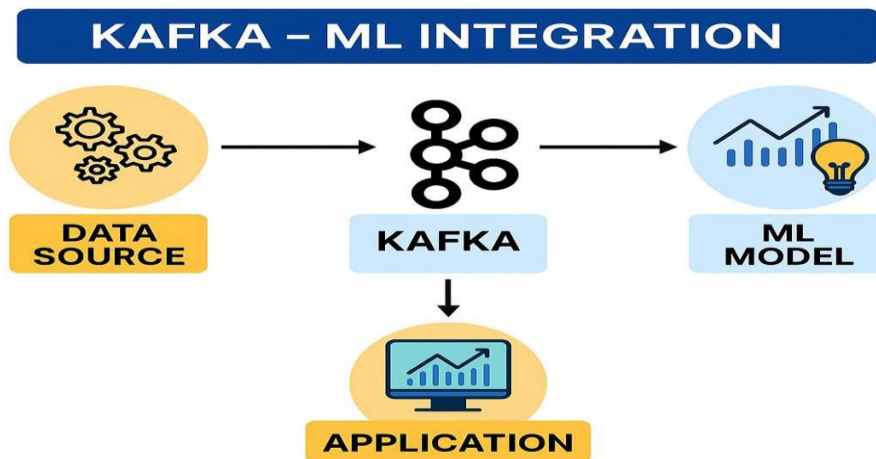


Fig 4: Kafka-ML Integration

## 6. Modeling Techniques for Liquidity Risk Prediction

Time-series models such as ARIMA and SARIMA are effective for short-term forecasting, while machine learning models like Gradient Boosting and Random Forest capture complex patterns. Deep learning models, particularly LSTM networks, excel in sequential data analysis for intraday liquidity prediction.

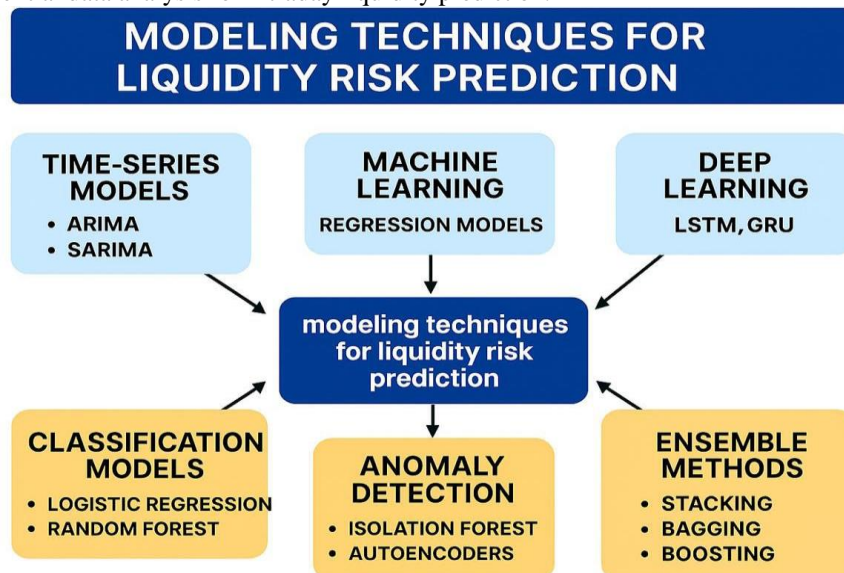


Fig 5: Modeling Techniques for Liquidity Risk Prediction

### 6.1. Time-Series Models

**Purpose:** Forecast liquidity positions based on historical patterns.

**Techniques:**

- ARIMA: Captures trends and seasonality in liquidity flows.
- SARIMA: Adds seasonal adjustments for periodic liquidity cycles.

**Use Case:** Predicting daily or intraday liquidity gaps for treasury planning.

### 6.2. Machine Learning Regression Models

**Purpose:** Predict continuous liquidity metrics using multiple variables.

**Techniques:**

- Linear Regression: Simple relationships between liquidity and influencing factors.
- Random Forest Regression: Handles non-linear relationships and feature importance.
- Gradient Boosting (XGBoost, LightGBM): High accuracy for complex liquidity patterns.

**Use Case:** Estimating liquidity needs based on transaction volume, market volatility, and customer behavior.

### 6.3. Deep Learning Models

**Purpose:** Capture complex sequential patterns in large datasets.

**Techniques:**

- LSTM (Long Short-Term Memory): Ideal for time-series liquidity forecasting.
- GRU (Gated Recurrent Units): Efficient for sequential data with fewer parameters.

**Use Case:** Real-time prediction of liquidity stress during volatile market conditions.

### 6.4. Classification Models

**Purpose:** Identify risk scenarios (e.g., high risk vs. normal liquidity).

**Techniques:**

- Logistic Regression: Binary classification for liquidity breach risk.
- Random Forest / XGBoost: Multi-class classification for stress levels.

**Use Case:** Flagging accounts or counterparties likely to cause liquidity strain.

### 6.5. Anomaly Detection

**Purpose:** Detect unusual liquidity movements or patterns.

**Techniques:**

- Isolation Forest: Identifies outliers in liquidity flows.
- Autoencoders: Neural networks for anomaly detection in high-dimensional data.

**Use Case:** Detecting sudden liquidity outflows or abnormal transaction spikes.

### 6.6. Ensemble Methods

**Purpose:** Combine multiple models for better accuracy and robustness.

**Techniques:**

- Stacking: Combine predictions from different algorithms.
- Bagging & Boosting: Improve stability and reduce variance.

**Use Case:** Robust liquidity risk prediction under diverse market conditions.

### 6.7. Predictive Analytics Workflow

- Data Collection: Gather historical and real-time data from multiple sources.
- Data Processing: Clean, normalize, and transform data for modeling.
- Model Training: Apply ML algorithms (e.g., ARIMA, LSTM, Gradient Boosting).
- Model Deployment: Integrate predictions into dashboards and alert systems.

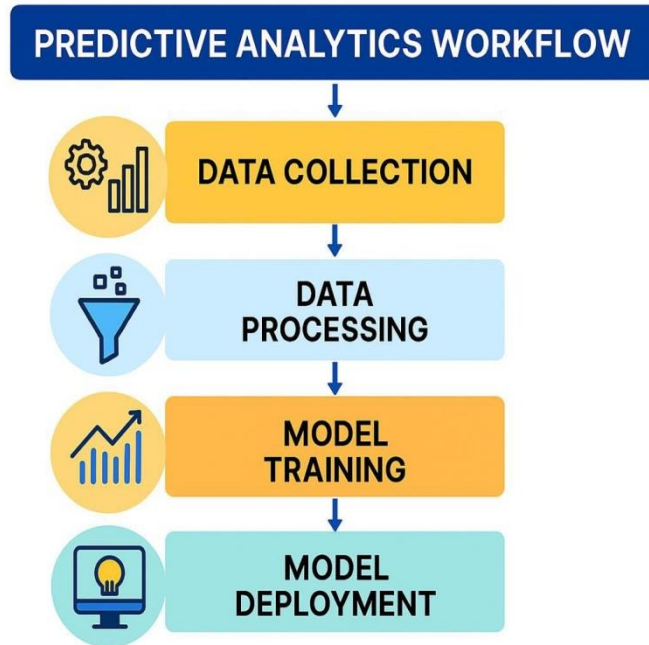


Fig 6: Predictive Analytics Workflow

### 7. Implementation Approach for Predictive Analytics in Liquidity Risk Monitoring

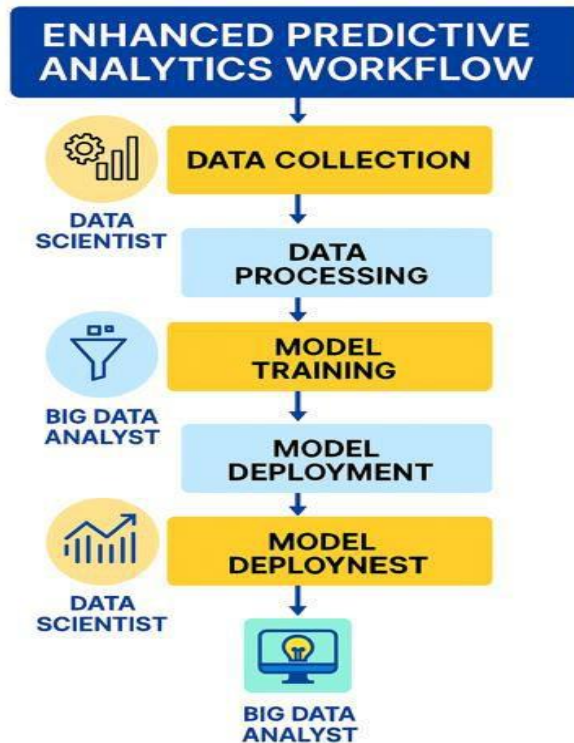


Fig 7: Enhanced Predictive Analytics Workflow

#### Step 1: Data Collection

##### Data Science Role:

- Identify relevant features (transaction volume, market volatility, customer behavior).
- Ensure data quality and completeness.

##### Big Data Analytics Role:

- Ingest large-scale, high-frequency data from multiple sources.
- Use distributed systems like Hadoop, Spark, or Kafka for scalability.

**Tools:** APIs, streaming platforms (Apache Kafka, AWS Kinesis).

### ***Step 2: Data Preprocessing***

#### **Data Science Role:**

- Perform data cleaning, normalization, and feature engineering.
- Apply statistical techniques for outlier detection.

#### **Big Data Analytics Role:**

- Use Spark or Flink for parallel ETL processing.
- Handle structured and unstructured data in real time.

**Tools:** Python (Pandas, NumPy, Scikit-learn), Spark MLlib.***Step 3: Model Development***

### ***Step 3: Model Development***

#### **Data Science Role:**

- Select appropriate algorithms (ARIMA, LSTM, Gradient Boosting).
- Build predictive models for liquidity risk.

#### **Big Data Analytics Role:**

- Train models on distributed clusters for large datasets.
- Use GPU acceleration for deep learning.

**Tools:** TensorFlow, PyTorch, Spark MLlib, H2O.ai.

### ***Step 4: Model Training & Validation***

#### **Data Science Role:**

Split data, tune hyperparameters, evaluate metrics (RMSE, Precision, Recall).

#### **Big Data Analytics Role:**

- Implement scalable training pipelines.
- Use MLflow for experiment tracking.

**Tools:** Grid Search, Bayesian Optimization, MLflow.

### ***Step 5: Real-Time Integration***

#### **Data Science Role:**

Deploy models for real-time inference.

#### **Big Data Analytics Role:**

Stream predictions using Kafka, Flink, or Spark Streaming.

**Tools:** Docker, Kubernetes, TensorFlow Serving, FastAPI.

### ***Step 6: Visualization & Alerts***

#### **Data Science Role:**

Build dashboards for liquidity monitoring.

#### **Big Data Analytics Role:**

Integrate real-time alerts into enterprise systems.

**Tools:** Power BI, Tableau, Grafana.

### ***Step 7: Continuous Monitoring & Retraining***

#### **Data Science Role:**

Detect model drift and retrain periodically.

#### **Big Data Analytics Role:**

Automate retraining pipelines using streaming data.

**Tools:** Airflow, Kubeflow, Spark.

## 8. Case Study / Simulation

### *Objective:*

Demonstrate how predictive analytics improves liquidity risk monitoring compared to traditional methods.

### *Scenario*

- A bank processes high-volume intraday payments.
- Sudden market volatility increases liquidity outflows.
- Goal: Predict liquidity shortfall before it occurs.

### *Steps in Simulation*

#### *8.1. Data Collection*

- Transaction data: 1 million records (payments, settlements).
- Market data: FX rates, interest rates.
- Behavioral data: Customer withdrawal patterns.

#### *8.2. Data Processing*

- Clean missing values.
- Normalize transaction amounts.
- Feature engineering: Liquidity ratios, volatility indicators.

#### *8.3. Model Training*

- **Models Used:**
  - ARIMA for short-term forecasting.
  - LSTM for sequential intraday patterns.
  - Gradient Boosting for complex relationships.
- **Evaluation Metrics:**
  - Accuracy, Precision, Recall, RMSE.

#### *8.4. Simulation*

- Compare **traditional static model** vs.

### **Predictive model.**

Stress scenario: 20% increase in outflows within 2 hours.

### *Results*

#### **Traditional Approach:**

- Detection after shortfall occurs.
- Response time: 2 hours.

#### **Predictive Analytics:**

- Prediction 30 minutes before shortfall.
- Accuracy: 92%.
- Reduced regulatory breach risk.

### *Visualization*

- Graph: Predicted vs. Actual Liquidity Position.
- Dashboard: Real-time alerts triggered by ML model.

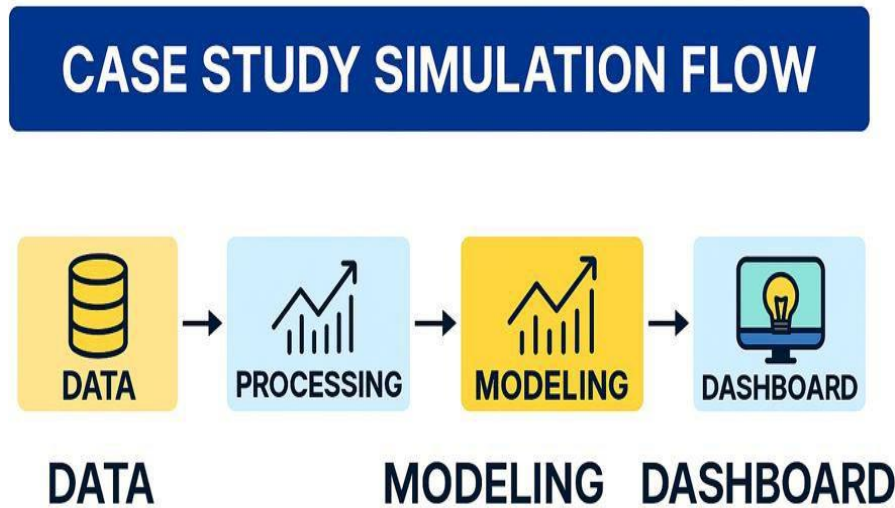


Fig 8: Case Study Simulation Flow

## 9. Benefits and Business Impact

### 9.1. Proactive Risk Management

- Benefit: Predictive models forecast liquidity gaps before they occur.
- Impact: Enables treasury teams to take preventive actions, reducing the likelihood of liquidity crises.

### 9.2. Real-Time Decision Making

- Benefit: Continuous monitoring and alerts through streaming data architecture.
- Impact: Faster response times (seconds vs. hours), improving operational resilience.

### 9.3. Regulatory Compliance

- Benefit: Automated stress testing and scenario analysis aligned with Basel III requirements.
- Impact: Minimizes regulatory breaches and associated penalties.

### 9.4. Cost Efficiency

- Benefit: Reduces manual intervention and reliance on static models.
- Impact: Lowers operational costs and improves resource allocation.

### 9.5. Enhanced Accuracy

- Benefit: Machine learning and deep learning models adapt to changing market conditions.
- Impact: Improves prediction accuracy, reducing false alarms and missed risks.

### 9.6. Competitive Advantage

- Benefit: Advanced analytics capabilities differentiate institutions in the market.
- Impact: Builds trust with stakeholders and enhances customer confidence.

### 9.7. Scalability

- Benefit: Cloud-based and big data solutions handle high transaction volumes.
- Impact: Supports global operations and future growth.

## 10. Challenges and Limitations

### 10.1. Data Quality and Availability

- Challenge: Incomplete, inconsistent, or delayed data can reduce model accuracy.
- Limitation: Requires robust data governance and integration across multiple systems.

### 10.2. Model Interpretability

- Challenge: Complex ML and deep learning models (e.g., LSTM) are often “black boxes.”
- Limitation: Regulatory bodies demand transparency in risk models, making adoption harder.

### 10.3. Infrastructure and Cost

- Challenge: Real-time streaming and big data analytics require high-performance infrastructure.

- Limitation: Significant investment in cloud platforms, storage, and compute resources.

#### **10.4. Regulatory Acceptance**

- Challenge: AI-driven models are not fully recognized by all regulators.
- Limitation: Institutions must maintain parallel traditional models for compliance.

#### **10.5. Cybersecurity and Data Privacy**

- Challenge: Streaming sensitive financial data increases exposure to cyber threats.
- Limitation: Requires strong encryption, access control, and compliance with data protection laws.

#### **10.6. Model Drift and Maintenance**

- Challenge: Market conditions change rapidly, causing predictive models to degrade over time.
- Limitation: Continuous retraining and monitoring are essential to maintain accuracy.

#### **10.7. Talent and Skill Gap**

- Challenge: Shortage of professionals skilled in data science, ML, and financial risk.
- Limitation: Institutions need to invest in training or hire specialized talent.

### **11. Future Directions**

#### **11.1. Blockchain Integration**

- Opportunity: Use distributed ledger technology for transparent and immutable transaction records.
- Impact: Enhances trust and reduces reconciliation time in liquidity reporting.

#### **11.2. Generative AI for Scenario Simulation**

- Opportunity: Apply generative models to create synthetic stress scenarios.
- Impact: Improves stress testing and risk preparedness without relying solely on historical data.

#### **11.3. Advanced Stress Testing**

- Opportunity: Combine predictive analytics with real-time macroeconomic indicators.
- Impact: Enables dynamic stress testing under evolving market conditions.

#### **11.4. Explainable AI (XAI)**

- Opportunity: Develop interpretable ML models for regulatory compliance.
- Impact: Increases transparency and trust in AI-driven liquidity risk frameworks.

#### **11.5. Integration with Cloud-Native Microservices**

- Opportunity: Deploy predictive models as scalable microservices.
- Impact: Improves flexibility, scalability, and cost efficiency for global operations.

#### **11.6. Real-Time Collaboration Platforms**

- Opportunity: Integrate predictive dashboards with collaborative tools (e.g., Teams, Slack).
- Impact: Enhances decision-making speed and coordination across treasury and risk teams.

#### **11.7. Quantum Computing for Optimization**

- Opportunity: Explore quantum algorithms for complex liquidity optimization problems.
- Impact: Potentially revolutionizes computational speed and accuracy for large-scale simulations.

### **12. Conclusion**

Predictive analytics represents a transformative approach to liquidity risk monitoring, enabling financial institutions to shift from reactive to proactive risk management. By integrating real-time data streaming, advanced machine learning models, and dynamic forecasting techniques, institutions can anticipate liquidity gaps before they occur, ensuring compliance with regulatory frameworks such as Basel III and improving operational resilience. The proposed framework demonstrates significant advantages over traditional methods, including faster response times, higher accuracy, and enhanced decision-making capabilities. While challenges such as data quality, model interpretability, and regulatory acceptance remain, ongoing advancements in Explainable AI, cloud-native architectures, and generative modeling promise to address these limitations.

Adopting predictive analytics for liquidity risk monitoring will not only strengthen financial stability but also provide a competitive edge in an increasingly volatile and interconnected global market.

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