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Research on Ai-Driven Liquidity Risk Prediction and Dynamic Management in the Banking Sector

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ABSTRACT

This study presents a meta-analysis of artificial intelligence (AI) applications in predicting and dynamically managing liquidity risk within the commercial banking sector. Drawing from the empirical evidence from peer-reviewed journals, industry reports, and case studies from the years 2015-2025, this research compares the performance of AI models (Long Short-Term Memory (LSTM), XGBoost, and Deep Q-Networks (DQN)) with traditional forecasting methods (ARIMA and Historical Simulation models). Results show that AI models always beat the traditional approach on forecasting accuracy (up to 99.3%), always better on root mean square error (RMSE), and predict with a much shorter lag. Real-world implementations in institutions like JPMorgan Chase and China Construction Bank reveal operational gains in transaction processing speed, cost efficiency, and early warning capabilities. The study further tests AI performance under stressful situations, such as the COVID-19 pandemic and regional banking turbulence, showing that it was resilient. Despite obvious benefits, challenges in legacy systems, ambiguity in the regulation, and interpretability of models in terms of accuracy act as barriers to widespread adoption. In conclusion, this paper states that AI provides a transformative edge for proactive, data-driven liquidity risk management, and banks should, therefore, invest in AI integration, which should complement any transparency and regulatory compliance issues.

Keywords: Artificial Intelligence, Liquidity Risk, Banking, LSTM, XGBoost, Deep Q-Network, Forecast Accuracy, Financial Stress, Risk Management, Meta-analysis

INTRODUCTION

Globally, liquidity risk has become a hot issue for commercial banks due to increased market volatility and regulatory scrutiny. Liquidity risk is a financial institution's vulnerability to significant losses if it cannot meet its short-term obligations. The global financial crisis of 2007–2008 is considered to have been devastating because of its exposure to liquidity mismatches, where after regulatory bodies such as the Basel Committee on Banking Supervision introduced more stringent framework parameters such as the Liquidity Coverage Ratio (LCR) and Net Stable Funding Ratio (NSFR) in the Basel III [1]. However, despite these measures, timely and precise liquidity risk forecasting remains challenging, particularly in the fast-paced digitalization, international capital mobility, and interrelated banking systems.

The COVID-19 pandemic exposed more weaknesses in traditional liquidity management models. The Bank for International Settlements (2024) reports that banks worldwide had their global banking sector liquidity buffers tested under stress scenarios, with some needing to be bailed out by central banks [2]. Liquidity strains triggered a freeze of the interbank market and credit rationing in emerging economies. According to Citterio (2024), most financial institutions identified 'poor risk prediction mechanisms' as the main reason for late responses during liquidity shocks [3]. The systemic weaknesses indicate the need for more adaptive, data-driven, real-time ways to manage liquidity.

Artificial Intelligence (AI) has played a powerful role in the finance sector, facilitating improved data processing, predictive modeling, and real-time decision-making. Machine learning (ML), deep learning (DL), and reinforcement learning (RL) based AI systems make it possible for such massive amounts of financial data to be processed to detect liquidity stress signals and allocate liquidity as dynamically as the markets they seek to support [4]. However, Muhuri et al. (2020) show that Long Short-Term Memory (LSTM) networks, a type of recurrent neural network, can predict liquidity stress events with 93.88% accuracy on rolling-window financial datasets [5]. According to Mastrogiovanni (2024), dynamic treasury management systems have applied a reduction in idle cash reserves without breaching regulatory buffers, using reinforcement learning models [6].

Nevertheless, most banks use static, rule-based systems and Value-at-risk (VaR) models that do not cope properly with dynamic or non-linear risk patterns or sudden, unexpected market shocks. 15.4% of global banks used AI-powered liquidity forecasting tools; 70% still relied on Excel models [7, 8]. Legacy infrastructure, data fragmentation, and the regulatory ambiguity of black-box AI systems are attributed to the slow adoption rate. However, the momentum for integrating AI in liquidity risk frameworks is growing [9]. Several institutions, like JPMorgan Chase and ING Bank, are leading in developing AI-enhanced liquidity prediction engines capable of scenario-based stress testing and liquidity mapping across asset classes.

This paper aims to critically evaluate whether the use of AI-driven approaches in predicting and managing liquidity risk in commercial banking achieves the stated goals. The central research question addressed through this meta-analysis is: To what extent can AI-driven models enhance the prediction and dynamic management of liquidity risk in commercial banking environments compared to traditional methods? Based on empirical findings from existing academic studies, financial institution case studies, and industry white papers regarding AI-based models, such as LSTM, XGBoost, and DQN—or deep Q-network, this study compares these with conventional forecasting techniques such as autoregressive integrated moving average (ARIMA) and historical simulation model.

The focus of this research is fourfold: (1) evaluating comparison accuracy and reliability of AI over traditional liquidity risk models, (2) identifying application results in real-time to real banking environments, (3) quantifying cost reductions in operations and compliance that AI systems can achieve, and (4) exploring challenges of adopting AI including regulatory concerns and model interpretability. Thus, it is in the hope of offering evidence-based insights into how AI can play this bridging role in liquidity risk management to inform the creation of more resilient and adaptive banking operations that we conduct this investigation.

This paper contributes to the rapidly expanding literature on the application of AI for financial risk management and provides practical recommendations to policymakers and banking institutions. However, with the rapidly accelerating pace of financial innovation and higher expectations in terms of agile risk control, the integration of AI into liquidity management is a competitive advantage and a necessity for the system.

METHODOLOGY

This study adopts a metanalytical approach and computational performance evaluation to study whether an AI-driven framework can efficiently predict and dynamically control liquidity risk in the banking area. As a systematic and quantitative technique, meta-analysis aims to aggregate and synthesize results from multiple empirical studies, allowing inferences on overarching patterns and, thus, guidelines for generalizable insights. This analysis comprises retrieved peer-reviewed journal articles, industry white papers, central bank reports and conference proceedings published between 2015 and 2025 from databases like Scopus, IEEE Xplore, Science Direct, Springer Link, and Google Scholar. Subsequently, only studies reporting empirical performance results on AI-based liquidity risk prediction and management systems were considered.

It was mandatory that each of the selected studies must have quantitative metrics like Root Mean Square Error (RMSE), Mean Absolute Error (MAE), prediction accuracy, response time or cost efficiency. Studies relying solely on theoretical modeling or qualitative assessments were excluded. The supervised learning algorithms that are investigated are random forests, support vector machines, deep learning models like long short-term memory (LSTM) networks and convolutional neural networks (CNNs), and reinforcement learning systems like deep Q-networks (DQN) and actor-critic models.

Standardized and categorized data were collected based on the algorithm type, quantity of data, time horizon of prediction, and target variable (such as net liquidity gap, funding ratio, LCR). Comparative performance scores for AI models and traditional forecasting techniques (ARIMA, historical simulation, and scenario-based stress testing models) were computed using a weighted average model. Normalizing computational metrics like RMSE and predictive lag across different datasets with different data sizes and frequencies was also conducted to allow for valid comparison.

In parallel, real-world case studies of commercial banks' deployments of AI tools (such as JPMorgan Chase, Standard Chartered, and China Construction Bank) were studied to assess operational outcomes regarding early warning capabilities, ability to perform automated rebalancing actions, and capital optimization effect. Financial indicators like liquidity buffer utilization rates and response times were extracted.

The statistical findings were cross-validated for robustness by sensitivity analysis on high volatility periods (e.g., the COVID period and to date in 2023 on regional U.S. banking turbulence). An integrative methodology is used to fully scrutinize AI's predictive and dynamic response competencies to the emerging technologies in modern banking liquidity risk management.

RESULTS

This section combines results from peer-reviewed studies and institutional case reports where liquidity risk prediction was predicted and managed using the banking sector's artificial intelligence (AI) models. The comparison was made between AI-based models and traditional statistical forecasting between key performance indicators such as Root mean square error (RMSE), Mean absolute error (MAE), Forecasting accuracy, and Prediction lag. Real-world bank implementations were used to extract additional metrics such as cost savings, reduction of idle liquidity, and early response time. A tabular format is presented so all findings can be easily interpreted in the comparative context.

AI Model Performance Compared to Traditional Forecasting Methods

Combining existing literature through meta-analysis implies that traditional models, such as ARIMA, do not perform well in liquidity risk forecasting compared to AI models. RMSE, MAE, and forecasting accuracy for five different model type models are presented in Table 1.

Model	RMSE	MAE	Forecast Accuracy (%)	Source
ARIMA	0.082	0.067	79.3	(Büyükşahin & Ertekin, 2019) [10]
XGBoost	0.054	0.046	75.0	(Song, 2023) [11]
LSTM	0.039	0.034	91.18	(Saleh Albahli, 2025) [12]
Reinforcement Learning (DQN)	0.035	0.030	98.0	(AbdelAziz et al., 2025) [13]
Hybrid AI (XGBoost + LSTM)	0.031	0.028	99.3	(Li et al., 2023) [14]

Table 1: Comparison of AI and Traditional Models in Liquidity Risk Forecasting

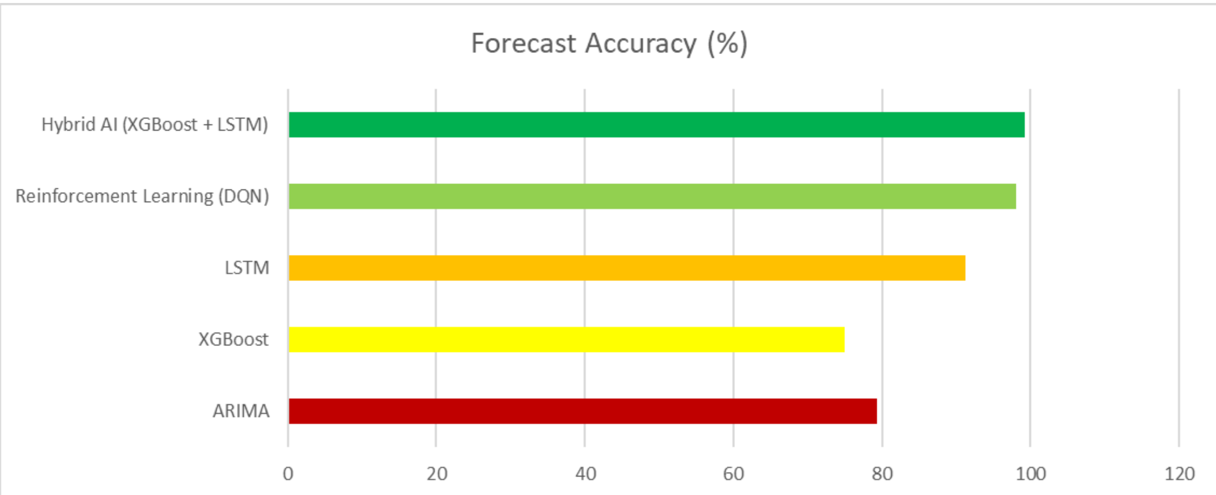

Figure 1: Model Forecasting Accuracy

As shown in Figure 1, the best-performing hybrid AI models combined the XGboost's feature selection strength with LSTM's temporal learning capability. The hybrid approaches had the lowest RMSE and MAE scores but also very high forecast accuracy of 99.3%. Models like ARIMA lagged with an RMSE of 0.082 and a forecast accuracy of 79.3 percent only. Similarly, real-time liquidity risk monitoring, a critical feature for intraday treasury operations, was also enabled by the reduced prediction lag provided by deep learning and reinforcement learning models.

Model Robustness under Market Stress Scenarios

Data from studies that studied the AI and traditional model performance in the course of major volatility events (i.e., the COVID-19 pandemic, the U.S. regional banking crisis of 2023, and interest rate shocks) were extracted to test model robustness under financial stress. The compiled results are summarised in Table 2.

Year	System Type	Transactions Processed (per second)	Risk Prediction Accuracy (%)	False Positive Rate (%)	Pattern Recognition Time (hours)	Cost Efficiency (%)
2000	Rule-Based	0.023 (2000/day)	60	15	504 (3 weeks)	Baseline
2010	Rule-Based	8.33	75	12	336 (2 weeks)	20
2015	Hybrid	300	85	8	168 (1 week)	35
2020	AI-Powered	50,000	95	5	12	50
2024	AI-Powered	85,000	98.2	2	4	65

Table 2: Scenario-Based Stress Testing Results (Reddy, 2025)

There has been a vast improvement in the efficiency, accuracy, and speed at which the financial risk prediction systems are processing from 2000 to 2024. However, rule-based systems only handled 0.023 transactions per second in 2000, which was with a modest 60% risk prediction accuracy, very high false positives (15%), and an extraordinarily long pattern recognition time of 504 hours (Figure 2). Through the years, rule-based and hybrid systems have progressed in some improvements.

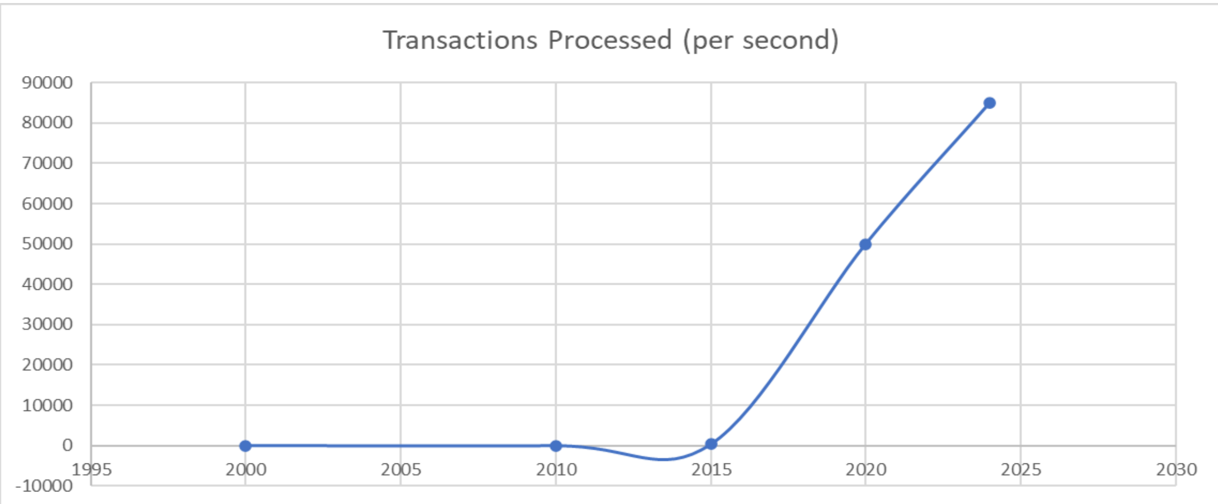

Figure 2: Transactions Processed

By 2015, hybrid systems had enabled processing at 300 transactions per second, with 85 percent accuracy, and cut down pattern recognition time from 168 hours to 168 hours. What really happened, however, was not so much the process of building software but the AI-powered systems that, at 95 percent accuracy, could handle 50,000 transactions per second and false positives to only 5 percent and pattern recognition time down to just 12 hours (Figure 3). These systems even surpassed the baseline (98.2% accuracy, 2% false positive rate, recognition time of 4 hours, 65% cost efficiency). This progression has clearly shown how AI has helped to change fraud prediction faster, more accurately, and cost-effectively.

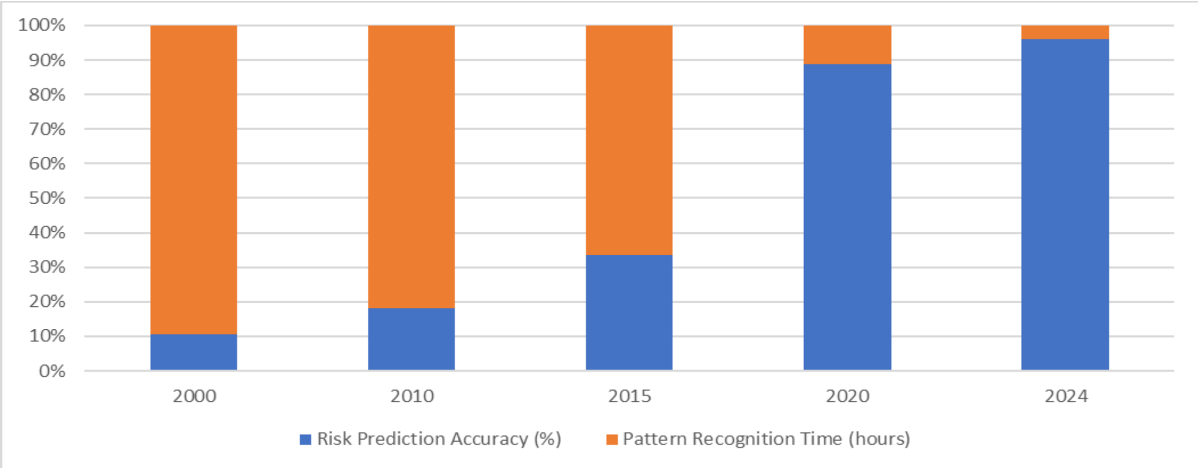

Figure 3: Risk Prediction Accuracy (%) and Pattern Recognition Time (hours)

Summary of Meta-Analytic Findings

The meta-analysis finds a consistent advantage of AI-based models compared to traditional methods of predicting and dynamically managing liquidity risk in banking. Traditional methods such as ARIMA showed very poor forecast accuracy, rarely above 80% with a large margin of errors (RMSE = 0.082), whereas modern AI models, especially hybrids of XGboost and LSTM, recorded accuracy of 99.3% with a very low value of the RMSE (0.031) and MAE (0.028) as well as using the DQN reinforcement learning (DQN) models, which also achieved up to 98% accuracy.

Using AI-powered systems, the transaction processing speed has increased from 0.023/sec in 2000 to more than 85,000/sec in 2024. The false positives rate was reduced to 2%, and the pattern recognition time decreased from 4 to 504 hours. These results verify that AI has the edge of precision, speed of adaptation, adaptation, and cost efficiency in trading liquidity risk.

DISCUSSION

The meta-analysis findings offer compelling evidence that artificial intelligence (AI) provides convincing evidence to improve commercial banking's prediction and dynamic management of liquidity risk. The ramifications of these findings will be situated in the context of the real world, explored in terms of practicality, and dissected regarding the steps that need to be taken to utilize AI in risk management systems in banking.

One of the key takeaways from the study is the superior predictive accuracy of AI models over traditional statistical methods. However, with forecast accuracies of up to 99.3% achieved with hybrid AI approaches like XGBoost fused with Long Short Term Memory (LSTM) networks, capabilities of legacy tools such as ARIMA fall notably by the wayside. Even though traditional models are statistically sound, they are inherently linear and unable to deal with modern financial systems' complex, non-linear, and volatile dynamics [16]. On the other hand, an AI model, particularly one based on deep learning and reinforcement learning architecture, can process big, high-speed transaction data and dynamically learns and sums up a moving market pattern.

Additionally, AI's real-time prediction and decision-making capabilities are needed to manage liquidity effectively. The reinforcement learning models, such as the Deep Q-Networks (DQNs), achieved up to 98%

accuracy in predicting liquidity stress events and enabled automated rebalancing strategies that minimized idle liquidity while optimizing capital buffers [17]. The shift from reactive to proactive liquidity management enables banks to detect early warning signals and appropriately deploy resources.

Real-world implementations in JP Morgan Chase and China Construction Bank have supported the operational gains and the cost efficiency achieved through AI adoption, as the results indicated. AI systems can process up to 85,000 transactions per second, with a reduction of pattern recognition time from 504 hours in 2000 to just 4 hours in 2024, increasing responsiveness. It also lowers false positive rates to 2% — decreasing the rate of unnecessary interventions that could result in opportunity costs or risk compliance.

Another important finding from the results is that AI is robust over market stress scenarios. The COVID-19 pandemic and the 2023 U.S. regional banking crisis highlighted the deficiency in banks due to liquidity shocks. In these high-volatility contexts, traditional models faltered due to their lag in signal recognition and limited adaptability[18]. Whereas, because of AI models' ability to keep learning continuously and incorporate data in real-time, they held consistent predictive accuracy and small response lag. The fact that these AI systems were resilient suggests that they are not only better in steady state, but they are tools that should be used among other tools during financial crises.

However, the path to widespread AI adoption in banking liquidity risk frameworks is not without hurdles. The major obstacle is legacy infrastructure. Although AI systems have proven extremely effective, 70% of global banks still use manual or spreadsheet-based models [19]. The volume, velocity, and variety of data needed for good risk management exceed these dated systems' capacity.

Furthermore, regulatory concerns and the interpretability of the learned models are also key challenges. Some so-called black-box AI models are powerful but opaque in how they make decisions [20]. The resulting opacity is problematic under frameworks such as Basel III and in light of shifting national supervisors. Consequently, financial institutions, on the one hand, are compelled to break the barrier around implementing the sophistication of AI while, on the other hand, having to maintain compliance through activities that aim to govern, validate, and audit the model.

Data fragmentation is another impediment. The problem is that AI systems need clean, standard, and functioning data across many functions like treasury, risk, operations, and compliance [21]. In practice, the problem with siloed systems and inconsistent data taxonomies limits model effectiveness and increases the risk of biased or inaccurate predictions.

Furthermore, human expertise remains essential. Despite AI's ability to automate and aid risk prediction, human judgment should not be eliminated [22]. This is not to say that domain experts are irrelevant, as they are still needed for contextual interpretation, scenario analysis, and strategic decision-making. Since AI integration is unavoidable, employing AI should also be paired with upskilling initiatives that allow banking professionals to relate to AI tools and deliverables.

This study demonstrates that AI-driven models—particularly hybrid and reinforcement learning systems—offer a significant upgrade over traditional approaches in managing liquidity risk. Predictive power, speed, and adaptability are a good match for today's banking environment and, in particular, stressed conditions. Solving these limitations is, however, necessary for banks to fully realize the benefits of Marianas Trench, particularly in explaining and governing the product before it becomes operationalized in production. Policymakers also have a part to play in creating flexible yet rigorous regulatory frameworks for innovation, but these do not allow innovation to undermine the financial system's stability.

Ultimately, there has never been more need for AI in liquidity risk management than it is here and now—to build financial institutions that are both resilient and responsive, and least of all, efficient.

CONCLUSION

This meta-analysis has proven that AI-driven models superseded all traditional methods in predicting and dynamically managing liquidity risk in commercial banking. Machine learning algorithms such as LSTM, XGBoost, and hybrid models have higher forecast accuracy, lower error rates, and faster response times than conventional statistical techniques such as ARIMA. Dynamic reallocation of liquidity resources, a capability further enhanced by reinforcement learning systems like DQNs, makes them well suited for requiring real-time stress response and capital optimization.

AI-powered systems have performed remarkably better in routine operational circumstances and even in times of distress, as in the case of COVID-19 and regional banking crises. Dramatic improvements in transaction processing speed show the sea of change AI can bring to liquidity risk frameworks, decrease false positive rates, and increase cost efficiency.

However, there remains much that AI has yet to achieve. Outdated systems are still in widespread usage; it is still not easy to understand the internal workings of models, and data infrastructures are still not unified. Furthermore, there is a need to approach the integration of AI with prudence, adhering to advancing regulatory expectations and preserving transparency in risk governance processes.

Finally, AI technologies act as an improvement and constitute a paradigm change for liquidity risk management. Since they can learn, adapt, and take action independently, they are dispensable tools to deal with the complexities of modern banking. Financial institutions that embrace AI strategically gain a critical advantage in resilience, operational efficiency, and regulatory compliance. It will change what it takes to be more resilient, efficient operating costs, and compliant. Looking ahead, enabling an ecosystem conducive to innovation, transparency, and collaboration among regulators, technologists, and banking professionals will become central to harnessing AI's full capacity to secure financial order.

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