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A REVIEW OF PREDICTIVE MODELS APPROACHES TO STOCK MARKET FORECASTING IN KAZAKHSTAN

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Abstract. These days, the financial world is driven more and more by data, so predictive analytics has become increasingly important for navigating modern markets. This is especially true for places like Kazakhstan, where the stock exchange is expanding rapidly and the country's becoming more integrated into global finance. In this review, recent developments in machine learning models for stock market forecasting are examined, with particular attention to their potential applications in Kazakhstan. The most common models - such as widespread use of LSTM networks - the types of data utilized, and the main evaluation metrics reported in the literature are summarized. Most studies tend to focus on complex models and large amounts of high-frequency data. However, in markets like Kazakhstan, hybrid, multi-scale models that also incorporate local sentiment and fundamental company data may offer the best approach. Ultimately, the key challenges involve ensuring high data quality and model transparency, as well as adapting global technological advances to fit local market realities. Through these efforts, stronger financial systems can be established to support more informed decision-making.

Keywords: stock market forecasting, predictive modeling, machine learning, emerging markets

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ҚАЗАҚСТАНДАҒЫ ҚОР НАРЫҒЫН БОЛЖАУДЫҢ БОЛЖАМДЫҚ МОДЕЛЬДЕРІНЕ ШОЛУ

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Аннотация. Қазіргі таңда қаржы әлемі деректерге барған сайын тәуелді болып келеді, сондықтан болжамды аналитика заманауи нарықтарды талдауда және бағдарлауда маңызды рөл атқарады. Бұл әсіресе қор нарығы қарқынды дамып, жаһандық қаржы жүйесіне интеграциялану үдерісі күшейіп келе жатқан Қазақстан үшін өзекті. Бұл шолуда қор нарығын болжауға арналған машиналық оқыту модельдерінің соңғы әзірлемелері қарастырылып, оларды Қазақстанда қолданудың әлеуетті мүмкіндіктеріне ерекше назар аударылады. Әдебиеттерде кеңінен қолданылатын модельдер, атап айтқанда LSTM желілері, пайдаланылатын деректер түрлері және негізгі бағалау көрсеткіштері жинақталып талданады. Зерттеулердің басым бөлігі күрделі модельдер мен жоғары жиілікті деректердің үлкен көлемін пайдалануға бағытталған. Алайда Қазақстан сияқты нарықтар үшін жергілікті нарықтық көңіл-күйді және компаниялардың іргелі көрсеткіштерін ескеретін гибриді, көпмасштабты модельдер тиімді тәсіл болуы мүмкін. Жалпы алғанда, негізгі мәселелер деректердің жоғары сапасы мен модельдердің ашықтығын қамтамасыз ету, сондай-ақ жаһандық технологиялық жетістіктерді жергілікті нарық жағдайларына бейімдеумен байланысты. Осы бағыттағы жұмыстарды дамыту арқылы неғұрлым тұрақты қаржы жүйесін қалыптастырып, негізделген шешімдер қабылдауға қолдау көрсетуге болады.

Түйінді сөздер: қор нарығын болжау, болжамды модельдеу, машиналық оқыту, дамушы нарықтар

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Мүдделер қақтығысы: Авторлар осы мақалада мүдделер қақтығысы жоқ деп мәлімдейді.

ОБЗОР ПРОГНОСТИЧЕСКИХ МОДЕЛЕЙ ДЛЯ ПРОГНОЗИРОВАНИЯ ФОНДОВОГО РЫНКА В КАЗАХСТАНЕ

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Аннотация. В настоящее время финансовый мир всё больше ориентируется на данные, поэтому прогнозная аналитика приобретает всё большее значение для анализа и понимания современных финансовых рынков. Это особенно актуально для таких стран, как Казахстан, где фондовый рынок стремительно развивается, а страна становится всё более интегрированной в глобальную финансовую систему. В данном обзоре рассматриваются последние достижения в области моделей машинного обучения для прогнозирования фондового рынка с особым вниманием к их потенциальному применению в Казахстане. Обобщаются наиболее распространённые модели, в частности широкое применение сетей LSTM, типы используемых данных, а также основные показатели оценки, представленные в научной литературе. Большинство исследований сосредоточено на сложных моделях и больших объёмах высокочастотных данных. Однако для таких рынков, как Казахстан, наиболее перспективным подходом могут быть гибридные многоуровневые модели, учитывающие также локальные настроения участников рынка и фундаментальные показатели компаний. В конечном итоге ключевыми задачами остаются обеспечение высокого качества данных и прозрачности моделей, а также адаптация глобальных технологических достижений к особенностям локальных рыночных условий. Реализация этих подходов позволит сформировать более устойчивую финансовую систему и обеспечить принятие более обоснованных решений.

Ключевые слова: прогнозирование фондового рынка, прогнозное моделирование, машинное обучение, развивающиеся рынки



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Introduction.

The exponential growth of data generation has fundamentally transformed financial markets. By 2025, global data volumes are projected to reach 181 zettabytes, while the big data market is expected to grow from \$220.2 billion in 2023 to \$401.2 billion by 2028 (Vassakis et al., 2018). This growth reflects a fundamental shift in how organizations collect, analyze, and utilize information for decision-making. In the financial sector, the ability to interpret and act on real-time data has evolved from a competitive advantage to an essential capability for market participants.

For developing economies like Kazakhstan, which is experiencing rapid financial sector growth, predictive analytics offers a transformative opportunity. The Kazakhstan Stock Exchange (KASE) is seeing increased activity as the country's economy integrates more closely with global markets. In such a dynamic environment, the ability to accurately predict financial trends could help policymakers, investors, and institutions anticipate risks, optimize investment strategies, and support macroeconomic stability. However, forecasting market behavior is highly complex, influenced by a multitude of interrelated factors, including macroeconomic indicators, political events, social media sentiment, and investor psychology (Min, 2020).

For decades, investors have relied on three core approaches to financial market analysis: fundamental analysis, technical analysis, and sentiment analysis (Nti et al., 2019). Fundamental analysis examines a security's intrinsic value through economic and financial indicators, including earnings, interest rates, and geopolitical events. This approach assumes that prices fluctuate around intrinsic value due to market noise but eventually revert to equilibrium (Arya, 2020). However, fundamental analysis has limitations: it is subject to analyst judgment, relies on historical reports, and may not capture rapid market changes (Min, 2020).

Technical analysis, in contrast, focuses on quantitative data, using historical price movements and trading volumes to predict future price behavior. Analysts employ statistical techniques and charting tools to detect market trends, momentum, and cycles (Nti et al., 2019). While more objective, technical analysis has its limitations in capturing external events or sudden sentiment shifts that can drastically affect market dynamics. That's where sentiment analysis comes into play, an increasingly important tool in the financial analyst's toolkit. It involves extracting psychological and emotional cues from unstructured textual data such as news headlines, social media posts, and expert commentary (Singh et al., 2022). Powered by natural language processing (NLP), sentiment analysis can reveal investor confidence or panic before such sentiments manifest in the market. Nevertheless, it remains supplementary rather than foundational, primarily due to the complexity of

modeling linguistic nuances and the lack of standardized integration with quantitative models.

Each of these methodologies provides unique insights, but none is sufficient on its own. Therefore, there is a growing consensus that conjoint analytical frameworks, capable of integrating fundamental, technical, and sentiment analysis, are necessary for reliable predictions in volatile financial environments. A critical enabler of such integration is the construction of a data lake, a centralized repository that accommodates structured (e.g., historical prices) and unstructured data (e.g., financial news articles). Realizing such a data ecosystem introduces its own challenges, particularly in addressing the well-established 5V characteristics of Big Data: volume, velocity, variety, veracity, and value (Naeem et al., 2021).

These challenges intensify with real-time analysis requirements. Processing high-frequency stock data while simultaneously extracting sentiment from news sources demands substantial computational resources and scalable infrastructure. Legacy batch-oriented pipelines often lack the necessary fault tolerance and flexibility. For emerging markets like Kazakhstan with limited local data, leveraging models and insights from mature markets through transfer learning and adaptation becomes particularly valuable.

Given this context, the present review examines research that applies machine learning-based predictive models to stock market forecasting. The emphasis is on algorithms such as regression models, decision trees, ensemble methods, and deep learning architectures, including recurrent and long short-term memory networks, which have demonstrated potential to capture complex, nonlinear relationships in financial data. Studies that integrate multiple paradigms into hybrid frameworks are also considered, as such multidimensional approaches reflect the increasing need for more robust and adaptable forecasting strategies in volatile markets. An example of such a hybrid framework is illustrated in Figure 1, where structured historical stock data from the Kazakhstan Stock Exchange (KASE) and unstructured financial news articles can be combined through the real-time preprocessing pipeline before being fed into predictive models. This type of integration demonstrates how technical data, fundamental drivers, and sentiment information can be jointly leveraged to enhance predictive accuracy—an approach highly relevant for emerging markets such as Kazakhstan.

This review does not attempt to provide an exhaustive account of conventional forecasting methods that lack machine learning components, nor does it include purely theoretical discussions without empirical validation. Instead, the focus is on research that demonstrates practical applications and measurable predictive performance, with particular attention to insights that may inform the development of forecasting models for emerging financial markets such as Kazakhstan.

Materials and methods.

Predictive modeling has emerged as a central component in financial market analysis, offering researchers and practitioners the capacity to anticipate future trends and behaviors by identifying patterns within large volumes of historical data. As financial markets have become increasingly data-driven and interconnected, traditional forecasting

methods have given way to more sophisticated, data-centric approaches. The adoption of machine learning (ML) and deep learning (DL) models, particularly in the context of time-series analysis, has transformed the financial forecasting landscape, especially in emerging economies such as Kazakhstan. These models offer the potential to model complex nonlinear relationships, adapt to changing market dynamics, and incorporate a wide range of features including textual sentiment, macroeconomic indicators, and historical pricing data.

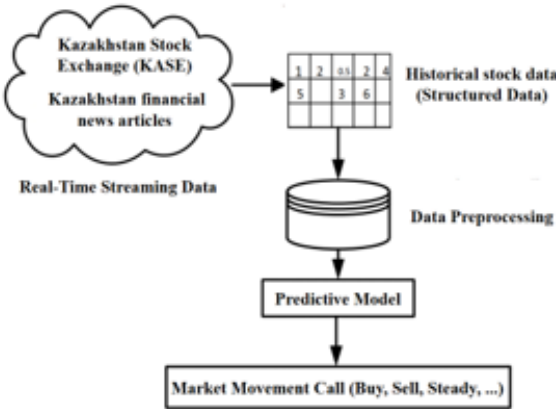


Fig. 1. Hybrid predictive framework for stock market forecasting in Kazakhstan.

The growing interest in ML-based financial forecasting stems from the limitations of classical econometric methods like ARIMA or linear regression. Although these methods have long been the standard, they often rely on strong assumptions of stationarity, linearity, and normally distributed errors, which rarely hold in financial time series. In contrast, predictive models based on ML can flexibly capture nonlinear relationships and temporal dependencies without the need for extensive pre-specification. A systematic review by Nti, Adekoya, and Weyori provides a comprehensive summary of how ML techniques have evolved in financial forecasting, highlighting a shift from fundamental and technical analysis toward more intelligent systems capable of self-learning and adaptation (Nti et al., 2019).

Among the most widely adopted models for time-series prediction is the Long Short-Term Memory (LSTM) network, a variant of the recurrent neural network (RNN) architecture designed specifically to mitigate the vanishing gradient problem and capture long-term dependencies. LSTM networks maintain internal memory cells that allow them to store relevant information over extended sequences, making them especially useful for capturing trends and seasonality in financial data. Fazeli and Houghten demonstrated the effectiveness of LSTM for stock price forecasting, achieving low mean squared error (MSE) scores on financial datasets across multiple markets between 2014 and 2019 (Fazeli et al., 2019). Their work showed how LSTM models outperformed standard feedforward networks and even traditional RNNs in handling sequential financial inputs.

Despite their success, LSTM networks are not without drawbacks. The model's

complexity can lead to long training times and a higher risk of overfitting, especially in markets with limited historical data or high levels of noise. To overcome this, researchers have investigated hybrid modeling approaches that combine the strengths of multiple algorithms. Li and Soo mentioned a hybrid model integrating ARIMA with LSTM, using the former to capture linear patterns and the latter to model nonlinear residuals (Lee et al., 2018). Their results indicated improved forecasting accuracy over either model alone, especially in volatile environments like the Taiwanese stock market. However, such hybrid models also introduce challenges in terms of hyperparameter tuning and system interpretability.

Another promising avenue in predictive modeling involves the integration of convolutional neural networks (CNNs) with LSTM architectures. Alonso-Monsalve et al. applied this hybrid CNN-LSTM model to cryptocurrency markets, achieving high forecasting accuracy on volatile assets such as Bitcoin and Ethereum (Alonso-Monsalve et al., 2020). By using CNNs to extract spatial features from structured input representations and LSTM to model sequential dependencies, this architecture proved highly effective in markets characterized by high-frequency fluctuations. Nevertheless, these models often demand large training datasets and substantial computational resources, posing limitations for researchers or institutions operating in data-scarce or resource-constrained environments.

While DL techniques have shown strong predictive capabilities, their black-box nature has raised concerns regarding interpretability and trustworthiness in financial contexts. Financial analysts and decision-makers often require explanations for model predictions, especially in regulatory environments where transparency is critical. This has led to renewed interest in ensemble learning methods, such as Random Forest (RF) and Gradient Boosting (GB), which offer greater interpretability while maintaining high performance. These models construct predictions by aggregating the outcomes of multiple decision trees, thereby reducing variance and increasing robustness to overfitting. Although RF and GB may not capture temporal dependencies as naturally as LSTM, they can be extremely useful when supplemented with lagged features or applied to cross-sectional data involving firm-specific indicators, macroeconomic signals, or sentiment metrics.

Sentiment analysis has become an increasingly important feature in financial forecasting, particularly in the age of social media and real-time news feeds. Numerous studies have confirmed that investor sentiment extracted from news articles, Twitter posts, and financial blogs can have predictive value over short time horizons. Valle-Cruz et al. analyzed Twitter sentiment to guide investment decisions during the COVID-19 pandemic, revealing a strong correlation between public mood and market movement (Valle-Cruz et al., 2021). Similarly, Lee and Soo employed recurrent convolutional neural networks (RCNNs) to forecast stock trends using news data, demonstrating that combining textual sentiment with quantitative indicators significantly boosts predictive accuracy (Lee et al., 2018). These findings underscore the value of unstructured data in enriching predictive models and suggest that future financial forecasting systems should

be equipped to process both numerical and textual data.

Kazakhstan's financial markets offer a unique testing ground for the development and application of such predictive techniques. As a frontier market, it presents both challenges and opportunities due to its relatively lower liquidity, limited transparency, and evolving regulatory landscape. Sembiyeva et al. explored the use of regression and AI-based models to forecast the green bond market in Kazakhstan, achieving strong statistical performance and drawing attention to the role of predictive analytics in sustainable finance (Sembiyeva et al., 2024). Their study illustrates how emerging markets can benefit from adopting modern data science techniques, especially when local data limitations are addressed through innovative modeling strategies.

The infrastructure supporting predictive modeling is critical for time-sensitive financial applications. Modern distributed architectures enable real-time data ingestion and processing, enhancing system responsiveness to sudden market shifts (Peddireddy, 2023). Vassakis et al. emphasize that predictive modeling's utility hinges on efficient data pipelines and computing frameworks capable of handling financial big data's volume, velocity, and variety (Vassakis et al., 2018).

As predictive modeling techniques continue to evolve, the intersection of big data, machine learning, and domain-specific financial knowledge will define the next frontier of market forecasting. The inclusion of explainable AI, better feature engineering techniques, and real-time adaptation capabilities will further enhance the relevance of these tools. These developments are particularly significant for policymakers, institutional investors, and researchers operating in emerging markets like Kazakhstan, where reliable and interpretable forecasting models can inform both economic planning and investment strategy.

The effectiveness of predictive modeling in financial markets also hinges on the selection and transformation of relevant features. Feature engineering remains a critical component of model development, often determining whether a predictive system will succeed or fail. In financial contexts, common features include price-based indicators such as moving averages, relative strength index (RSI), Bollinger Bands, and various momentum measures. These features attempt to capture technical patterns in asset behavior that may precede price changes. However, the increasing availability of alternative data, such as satellite imagery, ESG metrics, or geospatial data, has expanded the scope of feature selection significantly. As observed by Gandomi and Haider, big data's contribution to predictive modeling is not only about volume but also about the variety and richness of information that can now be leveraged for forecasting purposes (Gandomi et al., 2015).

The rise of big data technologies has transformed predictive modeling workflows in finance. Modern distributed computing platforms enable faster processing of both streaming and batch data, while NoSQL databases and cloud-based storage facilitate ingestion of heterogeneous data types at scale. Vassakis et al. emphasize the importance of scalable infrastructures for advanced analytics in financial applications, especially when integrating high-velocity data streams like stock tick data, social media sentiment, and news feeds (Vassakis et al., 2018).

Moreover, hyperparameter optimization has become an essential part of training predictive models. As financial markets exhibit high volatility and nonstationarity, even small changes in model configuration can lead to significant differences in performance. Automated machine learning (AutoML) frameworks such as Google's AutoML or H2O.ai offer streamlined solutions by testing numerous model types and parameter combinations to find the best-performing pipeline (Majidi et al., 2022). Nonetheless, in financial applications, it is critical to ensure that optimization techniques do not lead to overfitting or information leakage. Rolling window validation and walk-forward analysis are therefore commonly used to maintain the temporal integrity of the data, as discussed by Nti et al. in their evaluation of machine learning techniques for financial forecasting (Nti et al., 2019).

Another emerging trend is the incorporation of attention mechanisms into sequence modeling, particularly in transformer-based models. Originally developed for natural language processing, transformers have been increasingly applied to time-series forecasting due to their ability to model long-range dependencies without relying on sequential recurrence. Models like BERT and its time-series derivatives have shown promise in capturing complex temporal relationships in financial datasets. The attention mechanism allows the model to focus on relevant time points or data features dynamically, improving interpretability and potentially enhancing predictive power. While still a nascent area in financial modeling, the use of transformers is likely to grow, especially as more financial institutions invest in large-scale AI research.

While accuracy remains a core metric for model evaluation, other considerations such as robustness, adaptability, and explainability are becoming increasingly important. In practical settings, a highly accurate model that fails during regime changes or market shocks may be of little value. This has led to growing interest in adaptive modeling techniques that can adjust their parameters or structure in response to changing market dynamics. Reinforcement learning (RL) offers one such approach, where models learn to optimize a reward function based on feedback from the environment. For example, Carta et al. proposed a hybrid model for intelligent stock trading based on deep Q-learning, exemplifying how RL can be applied to decision-making in financial contexts, with the model learning from market responses to improve trading strategies over time (Carta et al., 2021).

The trade-off between model complexity and interpretability remains a central tension in financial predictive modeling. While deep learning architectures often yield superior performance, they can be opaque and difficult to interpret. This poses a problem not only for end users seeking to understand model outputs but also for regulatory bodies demanding transparency. Explainable AI (XAI) techniques such as SHAP (SHapley Additive exPlanations) and LIME (Local Interpretable Model-Agnostic Explanations) are therefore gaining traction. These tools provide post-hoc explanations of model predictions, allowing analysts to identify which features were most influential in a given decision. Sembiyeva et al., in their analysis of Kazakhstan's green bond market, emphasized the importance of model transparency, particularly in policy-oriented financial research where stakeholder trust is paramount (Sembiyeva et al., 2024).

The reliability of predictive modeling also depends on data quality and preprocessing techniques. Financial datasets often contain missing values, outliers, or inconsistencies that can severely impair model performance if not properly handled. Data normalization, smoothing, imputation, and anomaly detection are all critical preprocessing steps. Batini and Scannapieco propose a multi-dimensional data quality framework that includes accuracy, completeness, consistency, and timeliness, which can be tailored to financial datasets for rigorous quality assurance (Batini et al., 2016). For emerging financial systems such as Kazakhstan's, where digitization is still expanding, establishing high-quality data pipelines from the outset is crucial for long-term success in predictive analytics. Moreover, when working with textual data such as financial news or social media, natural language processing (NLP) techniques must be employed to clean, tokenize, and vectorize text inputs. Word embedding models like GloVe or FastText convert text into dense numerical representations, allowing predictive models to ingest and analyze linguistic information. Pencheva et al. demonstrated the utility of NLP for sentiment-driven forecasting, using news-based feature engineering to improve model accuracy in cryptocurrency markets (Pencheva et al., 2020).

Ensemble learning remains one of the most effective ways to improve predictive performance while managing model variance. By combining multiple models, each with its own strengths and weaknesses, ensemble methods can often outperform any single predictor. Techniques like bagging, boosting, and stacking allow modelers to aggregate results in a structured way. In financial modeling, stacking is particularly useful when combining models that specialize in different data modalities, such as combining an LSTM for price data with a random forest for fundamental indicators. Valle-Cruz et al. highlighted the benefits of model stacking in their COVID-19 investment prediction study, where they fused sentiment analysis models with quantitative regressors to achieve more stable forecasts (Valle-Cruz et al., 2021).

Risk management is another critical area where predictive modeling plays a pivotal role. Predicting future asset returns is just one part of financial decision-making; equally important is assessing the likelihood and impact of adverse outcomes. Value-at-Risk (VaR), Conditional Value-at-Risk (CVaR), and expected shortfall are widely used metrics, and predictive models are increasingly being used to forecast these risk measures under various market scenarios. Bayesian neural networks (BNNs) are gaining popularity for this purpose because they offer probabilistic outputs, allowing for better quantification of uncertainty. Saba and Babajide's review of artificial intelligence applications in banking highlighted how AI models can provide early warnings of liquidity or credit risks, enabling proactive risk mitigation (Madu-Saba et al., 2024).

In the context of Kazakhstan and other frontier markets, predictive modeling offers significant potential to overcome traditional barriers to financial development. These markets often lack high-frequency trading infrastructure, large institutional investor bases, or extensive historical data. Nonetheless, by using transfer learning or pretraining models on data from more developed markets and fine-tuning them on local data, it is possible to build reliable predictive systems even in data-scarce environments. Furthermore, predictive

models can help attract foreign investment by improving market transparency and reducing information asymmetry, aligning with broader economic development goals.

The rapid evolution of hardware acceleration technologies, such as GPUs and TPUs, has further empowered the use of deep learning models for financial forecasting. These technologies allow for faster training of large-scale models, facilitating experimentation with deeper architectures and larger datasets. As processing power becomes increasingly accessible via cloud services, even resource-intensive models like transformers and deep LSTMs are now within reach for academic and industrial researchers. According to Costa et al., the combination of cloud computing and AI enables the democratization of advanced analytics, allowing institutions from emerging economies to access tools that were previously restricted to major financial centers (Costa et al., 2024). This technological democratization is particularly relevant for countries like Kazakhstan, where financial systems are undergoing digital transformation and can leapfrog legacy infrastructure.

In addition to market prices and volumes, sentiment data derived from social media and news articles has become a vital input for predictive modeling. The rationale lies in the behavioral finance theory, which posits that investor sentiment significantly influences asset prices. Tools such as VADER, TextBlob, and BERT-based sentiment classifiers are used to quantify textual data into sentiment scores. These scores can then be incorporated into predictive models as explanatory variables. For instance, a surge in positive sentiment around a stock may signal upcoming price increases, particularly in markets where retail investors dominate trading volumes. Nasir et al. provided evidence that sentiment-based variables improved forecasting accuracy in the cryptocurrency market, highlighting the importance of non-traditional data sources in modeling financial behavior (Nasir et al., 2019).

Another promising direction involves graph-based machine learning techniques, particularly graph neural networks (GNNs), which model relationships between entities such as firms, assets, or market indices. Financial systems are inherently networked, with intricate connections between market participants, sectors, and geographies. GNNs allow for the encoding of these relationships into the model architecture itself, enabling the prediction of cascading effects in systemic risk analysis or supply chain disruptions. As noted by Ghosh et al., such techniques offer a more nuanced understanding of financial contagion and interdependencies, which are especially relevant in globally integrated markets (Ghosh et al., 2014). While still emerging, these models offer a pathway to more holistic and interconnected forecasting frameworks.

Model evaluation in predictive analytics also extends beyond traditional error metrics such as MAE, RMSE, or R^2 . In financial contexts, metrics must reflect the economic utility of the prediction. For example, a model might achieve a high R^2 but still perform poorly when translated into trading decisions due to high transaction costs or poor timing. Therefore, profit-based evaluation metrics such as Sharpe ratio, maximum drawdown, and cumulative returns are frequently used to assess model effectiveness in a real-world context. Dash and Dash demonstrated this approach in their financial

forecasting models by integrating predictive accuracy with portfolio performance simulations, thus aligning evaluation more closely with investor goals (Dash et al., 2016).

Moreover, economic cycles and structural breaks present significant challenges to predictive modeling. Financial time series are nonstationary, meaning their statistical properties can change over time due to macroeconomic events, regulatory shifts, or technological innovations. These regime shifts can invalidate model assumptions or learned patterns, leading to forecast degradation. To mitigate this, regime-switching models, such as Markov-switching autoregressive models or hidden Markov models (HMMs), have been employed to capture distinct market states and adjust predictions accordingly. Alternatively, ensemble models can incorporate regime-specific predictors and dynamically allocate weights depending on the prevailing conditions. As Guresen et al. highlighted in their work comparing ANN and SVM for stock price prediction, the adaptability of a model to changing conditions is as crucial as its baseline accuracy (Guresen et al., 2011).

Transfer learning has emerged as another tool for enhancing model generalization, especially in data-scarce environments. By pretraining models on large, related datasets and fine-tuning them on the target data, transfer learning enables better performance when labeled examples are limited. This approach is particularly useful in financial applications where specific markets may not have sufficient historical data for training from scratch. For instance, a model trained on global equity markets can be fine-tuned for local market conditions in Kazakhstan, thereby accelerating development and improving accuracy. Cao et al. have shown the benefits of transfer learning in improving forecasting for illiquid and emerging markets by leveraging broader data resources (Cao et al., 2023).

In risk-sensitive domains like finance, interpretability and trust are paramount, especially when predictive models are used to guide regulatory or high-stakes decisions. Black-box models, despite their predictive power, often face resistance from stakeholders who need clear justifications for recommendations. Techniques such as counterfactual explanations, decision trees extracted from neural networks, and rule-based surrogate models offer partial solutions by providing simplified versions of complex models. In response, institutions are increasingly embedding explainability audits into their model development lifecycle, ensuring accountability and compliance with emerging AI governance frameworks.

The convergence of predictive modeling and economic forecasting is further exemplified by macro-financial modeling efforts that combine traditional econometric models with machine learning. Hybrid models may incorporate ARIMA or vector autoregression (VAR) as components of broader machine learning pipelines, benefiting from the interpretability of classical models and the flexibility of AI. Azqueta-Gavaldón et al. proposed models where economic indicators such as GDP, interest rates, and inflation are fused with real-time market data to predict macro-level financial trends, demonstrating that machine learning can complement, rather than replace, economic intuition (Azqueta-Gavaldón, 2017). This synergy is essential for central banks and policy institutions in Kazakhstan and similar economies, where forward-looking indicators are crucial for

planning and stability.

As financial systems become more digitized, predictive modeling techniques are also playing a growing role in fraud detection and anti-money laundering (AML) efforts. By analyzing transaction patterns, user behavior, and contextual signals, models can identify anomalous activity in real time. Techniques such as clustering, isolation forests, and neural network-based autoencoders are commonly employed to detect deviations from expected norms. Hernández et al. applied machine learning algorithms to detect suspicious banking activities and achieved higher accuracy than traditional rule-based systems, illustrating the potential for AI-driven compliance mechanisms (Hernandez et al., 2024). In Kazakhstan, where digital banking and e-commerce are expanding rapidly, integrating such predictive systems into national financial infrastructure can significantly enhance trust and operational security.

The integration of real-time data streams is reshaping financial forecasting. With high-frequency trading proliferation, online learning techniques and streaming analytics enable dynamic adjustments to market changes. According to Fischer and Krauss, ensemble learning models that continually adapt to new market conditions perform substantially better than static models in highly volatile environments (Fischer et al., 2018). This capability is vital for markets in transition, such as those in Central Asia, where macroeconomic indicators can shift quickly due to policy changes or external shocks.

Moreover, the role of feature engineering remains critical in financial predictive modeling despite the rise of end-to-end learning systems. Crafting meaningful features from raw data, such as moving averages, volatility indicators, sentiment scores, or event flags, significantly enhances model performance. Even in deep learning contexts, hybrid approaches combining raw data with engineered features often yield superior results. Feature importance ranking techniques, such as SHAP and LIME, improve performance while offering transparency regarding prediction drivers. Zheng et al. demonstrate how integrating domain knowledge into feature engineering provides robustness and mitigates overfitting in financial neural networks (Zheng et al., 2021).

Furthermore, predictive models are increasingly being evaluated for their fairness and potential for bias, particularly in credit scoring and lending decisions. Machine learning models trained on historical data may inadvertently learn patterns that reflect existing inequalities or systemic biases. For instance, if past lending practices were discriminatory, a model may learn to replicate those patterns unless corrective measures are taken. Techniques such as adversarial debiasing, reweighing, and fairness-constrained optimization are now being applied to mitigate bias and ensure equitable predictions. In high-stakes contexts, such as access to capital or insurance pricing, fairness-aware models are not only a regulatory requirement but also a strategic imperative for fostering inclusive financial systems. Khandani et al. discuss the importance of designing credit risk models that balance predictive accuracy with fairness constraints (Khandani et al., 2010).

Another important frontier in predictive modeling is the fusion of structured

and unstructured data. Financial data is not confined to rows and columns; it also exists in the form of earnings call transcripts, CEO interviews, satellite images of retail parking lots, and customer reviews. Natural Language Processing (NLP) models, especially transformer-based architectures like BERT and RoBERTa, are now being used to extract actionable insights from textual data. These models can classify sentiment, detect topics, or even predict market movements based on linguistic patterns. Chen et al. demonstrated that incorporating insights from news headlines into financial models significantly improved short-term prediction accuracy for stock indices (Chen et al., 2024). This fusion of data types enhances situational awareness and enables a richer understanding of market behavior, especially during periods of uncertainty or crisis.

Model retraining and lifecycle management are key components of sustainable predictive modeling practices. As financial markets evolve, statistical relationships between variables may degrade, necessitating periodic updates. Model drift, where prediction accuracy deteriorates due to changing input distributions, requires ongoing monitoring and validation. Continuous integration and deployment (CI/CD) pipelines, often referred to as MLOps, facilitate automated retraining, version control, and model deployment. According to Zbikowski, MLOps frameworks ensure both scalability and consistency in model performance across time and use cases (Zbikowski, 2015).

The use of ensemble learning methods also continues to expand in financial modeling. By combining the strengths of multiple models, ensemble methods such as bagging, boosting, and stacking help reduce variance, bias, and improve generalizability. Random Forests, Gradient Boosting Machines (like XGBoost and LightGBM), and Voting Classifiers have demonstrated strong performance in predicting asset prices, credit defaults, and customer churn. According to Patel et al., ensemble methods consistently outperformed single-model approaches across various financial forecasting tasks, especially when calibrated carefully with appropriate hyperparameters and feature sets (Patel et al., 2015). These techniques are also more resilient to outliers and overfitting, making them suitable for datasets with noisy or heterogeneous financial variables.

An important yet often underexplored aspect of predictive modeling in finance is the psychological and behavioral interpretation of model outcomes. Predictions influence human decisions, which in turn affect markets. This feedback loop means that models not only reflect but also shape market realities. For instance, if a predictive model becomes widely adopted, its recommendations may drive collective behaviors that reinforce or invalidate its own forecasts. This is particularly evident in algorithmic trading, where model-based strategies compete and interact in real time. Bollen et al. showed that collective sentiment derived from social media could be used to forecast DJIA movements, highlighting how information dissemination and behavioral response co-evolve in financial ecosystems (Bollen et al., 2011).

Finally, the regulatory landscape around predictive analytics in finance is tightening. As models become more influential in decision-making, regulators are demanding greater transparency, auditability, and accountability. Frameworks such as the EU's AI Act and the U.S. Securities and Exchange Commission (SEC)'s guidelines on AI in trading emphasize

the need for explainable, robust, and fair algorithms. For financial institutions operating across jurisdictions, this creates a complex compliance environment that necessitates not only technical but also legal and ethical considerations in model design. As noted by Li et al., predictive modeling in finance must evolve within a governance framework that balances innovation with responsibility (Wu et al., 2020).

As predictive modeling continues to evolve, the role of cross-disciplinary approaches is becoming increasingly important. The convergence of finance, data science, behavioral economics, and computer science fosters the development of innovative models that are both technically sophisticated and practically relevant. For example, the integration of network theory and graph analytics provides fresh perspectives on market interconnectedness and systemic risk. By modeling financial entities, such as banks, funds, or even individual assets, as nodes within a network, researchers can quantify contagion effects, identify critical nodes, and simulate crisis propagation. Barabási's work on complex networks has influenced financial risk management by highlighting the non-linear dependencies inherent in market systems (Barabási, 2016). Applying these insights in Kazakhstan's emerging markets offers opportunities to preempt systemic shocks through predictive indicators derived from network properties.

Moreover, cloud computing and distributed systems have transformed the scalability and accessibility of predictive modeling. High-performance computing platforms enable training of large-scale models with vast datasets, including alternative data sources like satellite imagery or transaction-level records, supporting more granular and timely forecasts. Parallel processing frameworks facilitate efficient big data handling, accelerating model training and inference. Khandani et al. emphasize that scalable infrastructure is prerequisite for deploying advanced credit risk models requiring frequent retraining and testing in production environments (Khandani et al., 2010). For developing economies, leveraging cloud platforms can offset local infrastructure constraints and accelerate predictive analytics adoption.

Uncertainty quantification is a critical yet often underappreciated component of financial market prediction. Predictive models involve probabilistic estimates with varying degrees of uncertainty, and communicating this uncertainty is essential for risk management and decision-making. Bayesian methods and probabilistic programming frameworks enable explicit modeling of uncertainty in parameters and predictions. Gaussian Process Regression offers both point predictions and confidence intervals, valuable for cautious investment strategies. Monte Carlo simulations combined with predictive models enable scenario analysis and stress testing under various market conditions. According to Hernández et al., incorporating uncertainty quantification improves forecast robustness and interpretability, enabling users to better balance risk and reward (Hernandez et al., 2024).

Ethical considerations in predictive modeling, particularly in finance, are increasingly gaining attention. The deployment of predictive algorithms can have profound social and economic impacts, influencing credit access, investment outcomes, and even employment opportunities. Transparency, accountability, and the prevention of harm are

key ethical principles that must guide model development and application. Data privacy is a major concern, especially with sensitive financial information. Techniques such as differential privacy and federated learning are emerging as ways to protect individual data while still enabling effective model training. Federated learning allows models to be trained across decentralized data sources without sharing raw data, preserving confidentiality. Kairouz et al. provide an extensive review of privacy-preserving machine learning techniques relevant for sensitive financial applications (Kairouz et al., 2021). Ethical frameworks must be embedded into predictive modeling workflows to ensure that technological progress benefits society equitably.

The emergence of explainable AI (XAI) frameworks continues to address the challenge of balancing model complexity with interpretability. In finance, the ability to explain why a model made a particular prediction is crucial for regulatory compliance and stakeholder trust. Techniques such as SHAP values, counterfactual explanations, and surrogate models offer insights into the inner workings of complex algorithms. These explanations help detect biases, validate assumptions, and uncover causal relationships, thereby increasing the credibility of models. Dos Santos and Da Silva underscore the role of XAI in fostering collaboration between data scientists, domain experts, and business users, leading to more informed and responsible decision-making (Santos et al., 2024). The shift toward explainability also supports the integration of human expertise, enabling hybrid intelligence systems where AI augments rather than replaces human judgment.

Another noteworthy trend is the application of reinforcement learning (RL) to financial decision-making. Unlike traditional supervised learning, RL focuses on learning optimal policies through interaction with the environment, making it particularly suited for sequential decision problems such as portfolio optimization and algorithmic trading. Deep reinforcement learning, which combines neural networks with RL, has shown promise in learning complex trading strategies that adapt to evolving market dynamics. Deng et al. demonstrated that deep RL agents could outperform benchmark trading algorithms by optimizing reward functions aligned with financial goals (Deng et al., 2017). However, challenges remain in stabilizing training, handling sparse rewards, and ensuring interpretability, which are active areas of research.

The role of alternative data in predictive modeling cannot be overstated. Beyond conventional financial and economic indicators, data sources such as social media sentiment, web search trends, credit card transaction data, and even environmental sensor data offer novel predictive signals. Integrating these diverse datasets requires sophisticated data fusion and multi-modal learning techniques. Multi-task learning frameworks can leverage related tasks to improve overall model performance by sharing representations. Chen et al. showed that combining social media data with traditional market variables led to significant improvements in short-term stock movement prediction (Chen et al., 2024). For emerging financial markets, harnessing alternative data can compensate for limited traditional data availability and provide competitive advantages.

Finally, the future of predictive modeling in finance is poised to benefit from advances in quantum computing. Although still nascent, quantum machine learning

algorithms promise exponential speedups for certain optimization and sampling problems relevant to finance. Quantum annealing and variational quantum circuits are being explored for portfolio optimization, risk analysis, and option pricing. While practical applications remain experimental, early work suggests that quantum-enhanced models could tackle problems that are currently computationally intractable (Goudarzi et al., 2023). The intersection of quantum computing and financial predictive modeling represents a frontier that could revolutionize the field over the coming decades.

Research methodology.

This review adopts a systematic literature synthesis approach. Studies from 2000–2023 were collected through major databases (Scopus, Web of Science, IEEE Xplore, and Google Scholar) using keywords such as stock market forecasting, machine learning, deep learning, LSTM, hybrid models, sentiment analysis, and Kazakhstan stock market. Papers were included if they presented predictive models applied to financial markets with reported metrics. Emphasis was placed on hybrid architectures and approaches relevant to emerging markets.

Results and discussion.

As illustrated in Figure 2, Long Short-Term Memory (LSTM) models and their variants (including CMH-LSTM) are, by a significant margin, the most widely employed techniques, representing the approach in nearly half of the reviewed studies. This underscores their dominant capability and popularity in capturing complex, non-linear sequential dependencies in financial time series data. Beyond LSTMs, regression models and decision trees form a secondary tier of commonly used techniques, while methods like autoencoders, reinforcement learning, and other hybrid models are currently explored in a smaller subset of research.

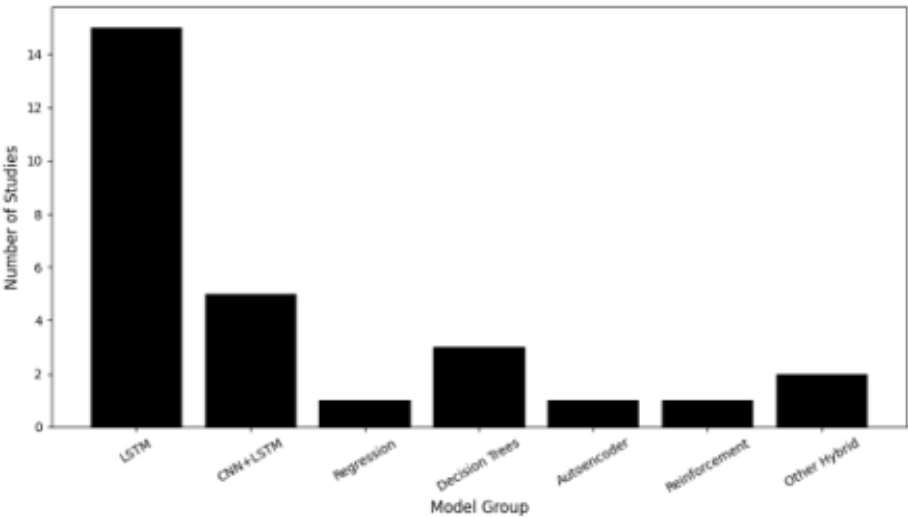


Fig. 2. Distribution of model technologies in financial market prediction studies.

To provide a comprehensive overview of the state-of-the-art predictive models in financial forecasting, the following Table 1 summarizes key studies, their methodologies,

and outcomes.

Table 1. Review of predictive modeling approaches in financial market forecasting

Methods	Frequency	Period	Market	Predictor	Metric Used
Fazeli & Houghten	Daily	2014-2019	American	LSTM	MSE
Sembiyeva et al	Yearly	2018-2022	Kazakhstan	Regression	R-squared, Statistical validations
Alonso-Monsalve	Monthly	2018-2019	Cryptocurrency	CNN+LSTM	Accuracy, Statistical validations
Lee & Soo	Daily	2009-2018	Taiwanese	Arima+LSTM RNN	MAE, RMSE
Tsai & Wang	Quarterly	2002 - 2007	Taiwanese	DT + ANN	Accuracy
Matsubara et al	Daily	2001 - 2013	American, Japanese	Deep Autoencoder	Accuracy, Statistical validations
Singh et al	Weekly	1982-1990	Japanese	LSTM	Accuracy, Statistical validations
Agrawal et al.	Daily	2016-2018	Indian	Optimal LSTM	Accuracy, MSE
Al-Thelaya et al.	Daily	2010-2018	Bahrain	AutoSLSTM: LSTM autoencoder	MAE, RMSE, R ²
Orimoloye et al.	Weekly	2010-2018	S&P 500, Nikkei 225	DeepFFNN, Shallow Models	Accuracy, MAPE
Alonso-Monsalve et al.	1-Minute (Tick)	2018-2019	Crypto currencies	CLSTM: CNN + LSTM	Accuracy, Statistical validations
Borovkova & Tsiamas	5-Minute	2014	American	LSTM	AUC, ROC
Mohapatra et al.	5-Minute	2018-2019	Cryptocurrency	LSTM+ Twitter Sentiment	RMSE, F1 Score
Chen et al.	Daily	2004-2018	Chinese	LSTM with Attention	MAE, MSE
Demir et al.	Hourly	2014-2018	Belgian	2NN, CNN, ResNet	RMSE, MAE, PCC, Diebold-Mariano
JuHyok et al.	Daily	1987-2018	Chinese, American	LSTM	Accuracy, Precision, Recall, F1 Score
Kelotra & Pandey	Daily	2017-2018	Indian	Deep-ConvLSTM	MSE, RMSE
Roy	Multi- Timeframe	2015-2021	US & European	Thick Data + DRL	Sharpe Ratio
Labiad et al.	10/30/60- Minute	2016-2017	Moroccan	LSTM	Accuracy, Precision, Recall, F1 Score
Goudarzi & Bazzana	Millisecond	2020-2022	Global (HFT)	Random Forest+Order Book Data	Precision, Latency
Lai et al.	Daily	2007-2017	Taiwanese	RCN-CNN+ LSTM	RMSE
Li & Liao	Daily	2003-2008	Chinese	LSTM	Accuracy, Precision, Recall, F1 Score
Ismailova et al.	Daily	2018-2023	Kazakhstan (KASE)	Hybrid CNN- BiLSTM	Accuracy, MAE
Li et al.	15-Minute	2008-2015	Brazilian	LSTM	Accuracy, Precision, Recall, F1 Score
Oncharoen & Vateekul	Daily	2006-2017	American	CNN + LSTM	Accuracy
Oncharoen & Vateekul	Daily	2006-2016	American	CNN + LSTM	F1 Score

The distribution of data frequencies, presented in Figure 3, indicates a strong preference for higher-frequency data. Daily data is the most prevalent time frame, forming the basis for a clear majority of the studies. High-frequency (intraday) data is also extensively used, highlighting a significant research focus on capturing short-term market dynamics and microstructural patterns. In contrast, longer-term horizons such as weekly, monthly, quarterly, and yearly data are utilized less frequently, though the adoption of multi-timeframe analysis suggests a growing interest in integrating trends from different scales.

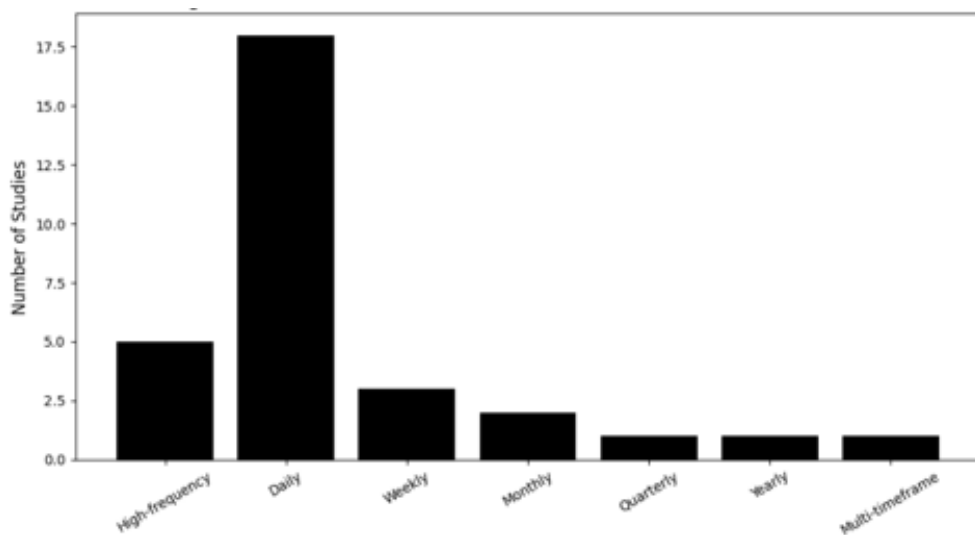


Fig. 3. Distribution of time frames used in market prediction research.

Figure 4 details the usage of performance metrics across the literature. The evaluation landscape is dominated by two primary groups: accuracy-based metrics (e.g., Accuracy, F1-Score) and error-based metrics (e.g., MAE, MSE, RMSE). Their concurrent high prevalence indicates that the field places a strong, dual focus on both the classification correctness of predictive models (e.g., predicting price direction) and the precision of their regression outputs (e.g., predicting exact price values). Statistical validation techniques and financial metrics (e.g., Sharpe Ratio, returns) are also employed, though to a lesser extent, suggesting that a portion of the research validates model performance through economic significance rather than purely statistical measures.

The findings of this review reveal clear trends in predictive modeling and present important considerations for their application in the Kazakhstan Stock Exchange (KASE). The overwhelming dominance of LSTM-based models is justified by their strength in analyzing sequential data, making them a prime candidate for initial forecasting efforts in Kazakhstan (Fischer et al., 2018). However, their complexity requires caution. For a developing market like KASE, with potentially less data volume, these models risk overfitting (Livieris et al., 2020). A more robust approach may lie in the hybrid frameworks that combine LSTMs with more interpretable models like decision trees.

The strong focus on high-frequency and daily data in global research aligns with

modern, high-speed trading. Yet, for an emerging market like Kazakhstan, which is highly sensitive to macroeconomic shifts and commodity prices, this focus may be misplaced (Smales, 2014). The most valuable insights for investors and policymakers might instead come from models that effectively integrate lower-frequency, fundamental data. This suggests a promising opportunity for multi-scale models that analyze daily patterns within the context of broader economic trends.

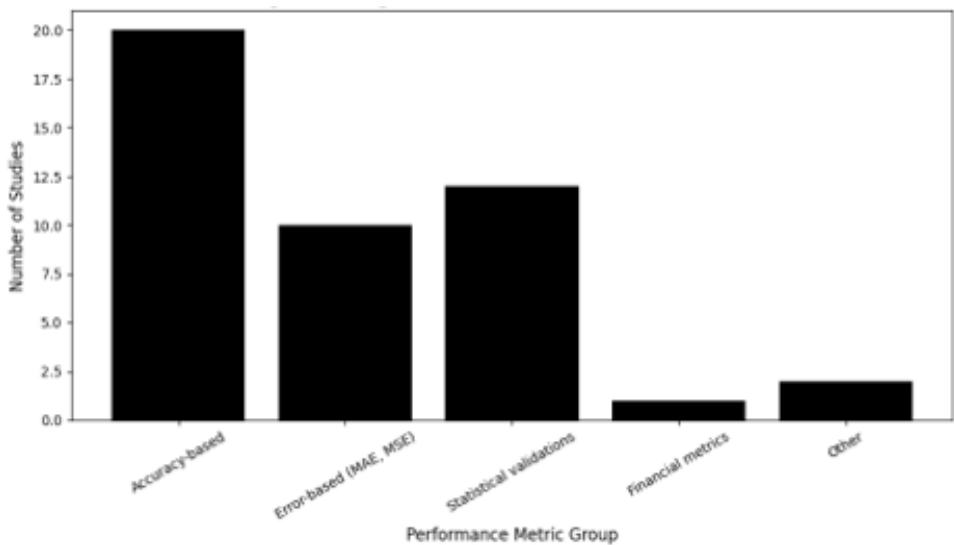


Fig. 4. Usage of performance metrics across studies.

Furthermore, the near-universal reliance on accuracy and error-based metrics only tells half the story. For a model to be truly valuable for KASE, its performance must be measured by financial utility, such as risk-adjusted returns - not just statistical precision. Finally, leveraging sentiment analysis on local news sources could be a particularly powerful tool for Kazakhstan, as investor sentiment may be a stronger predictor in less efficient markets.

Conclusion.

Predictive modeling in finance has evolved significantly from traditional statistical methods to embrace machine learning, deep learning, and hybrid approaches. The field continues to advance through improved data accessibility, increased computational capabilities, and growing emphasis on ethical and regulatory considerations. For emerging financial markets such as Kazakhstan, adopting these innovations offers substantial opportunities for enhanced forecasting accuracy, improved risk management, and potentially greater financial inclusion.

However, significant challenges remain. Ensuring data quality, maintaining model transparency and fairness, and managing the reflexive impact of models on market behavior are ongoing concerns. Future research must address these issues through interdisciplinary approaches and strengthened collaboration among academics, industry practitioners, and regulators. Through such efforts, predictive modeling can continue transforming the

financial landscape, contributing to more informed, equitable, and resilient economic systems.

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