© SEP 2026 | IRE Journals | Volume 10 Issue 3 | ISSN: 2456-8880
DOI: https://doi.org/10.64388/IREV10I3-1723436

# Application of Artificial Intelligence in Smart Share Trading: An Empirical Study of NIFTY 50 Using Machine Learning and Deep Learning

DR. A. SUKUMAR
*Department of Commerce PA, Sri Krishna Adithya College of Arts and Science, Coimbatore, India*

***Abstract- Artificial Intelligence (AI) is transforming financial-market analysis through automated data processing, pattern recognition, predictive modelling, sentiment analysis, portfolio optimisation and algorithmic trading. This study examines AI-based smart share trading with reference to the NIFTY 50 using a secondary empirical research design. The paper synthesises recent literature and documented NIFTY 50 empirical evidence while distinguishing reported results from results requiring fresh model estimation. Recent systematic reviews identify Support Vector Machines, Long Short-Term Memory networks and Artificial Neural Networks among frequently used approaches, while newer work increasingly examines attention-based architectures. The study distinguishes statistical prediction accuracy from practical trading performance and proposes evaluation using MAE, RMSE, MAPE, R², directional accuracy, ROC-AUC, Sharpe ratio and maximum drawdown, with transaction costs included in practical backtesting. A recent NIFTY 50 study reported substantially different errors across model architectures, illustrating the sensitivity of results to model design and evaluation. The paper proposes an integrated smart-trading framework combining market data, feature engineering, AI prediction, confidence filtering, risk management and human oversight. It concludes that AI can support market decision-making, but credible deployment requires data quality, leakage-resistant validation, realistic cost-adjusted testing, explainability and regulatory compliance.***

***Keywords - Artificial Intelligence; Smart Share Trading; NIFTY 50; Machine Learning; Deep Learning; LSTM; Algorithmic Trading; Stock Market Prediction; FinTech; Risk Management***

## I. INTRODUCTION

Artificial Intelligence has become an important research and application area in financial markets because modern trading environments generate large volumes of structured and unstructured data. Machine-learning and deep-learning models can process historical prices, volumes, technical indicators and, where available, textual or alternative data to identify nonlinear relationships. Reviews of the literature show that stock-market prediction research frequently uses Support Vector Machines, Long Short-Term Memory networks and Artificial Neural Networks, while historical closing prices remain a dominant input. Recent reviews also report a broad range of AI techniques and increasing use of deep-learning approaches in financial trading research.

The NIFTY 50 provides a useful Indian-market context for examining AI-enabled trading because it represents a diversified basket of large, liquid Indian equities and has extensive historical index data. The present paper focuses on the distinction between prediction and trading. A model may achieve a low forecast error without generating economically useful trading performance after transaction costs, turnover and drawdowns. Therefore, the paper proposes a framework in which predictive accuracy and financial performance are evaluated separately and jointly.

## II. STATEMENT OF THE PROBLEM

Stock-market movements are affected by nonlinear interactions, changing volatility, macroeconomic information, investor behaviour and unexpected events. Conventional forecasting techniques may not fully capture such relationships. AI methods offer flexible alternatives, but the literature remains heterogeneous in data sources, model architectures, validation procedures and performance measures.

A central problem is therefore not merely whether AI can forecast the NIFTY 50, but whether an AI-based prediction can be converted into a disciplined trading decision under realistic assumptions. In particular,

© SEP 2026 | IRE Journals | Volume 10 Issue 3 | ISSN: 2456-8880
DOI: https://doi.org/10.64388/IREV10I3-1723436

studies that rely mainly on prediction accuracy may not establish profitability, risk-adjusted performance or robustness outside the sample. This study addresses that problem by integrating prediction metrics, trading metrics, risk controls and chronological validation into a smart-share-trading framework.

## III. OBJECTIVES OF THE STUDY

1. To examine the application of AI techniques in stock-market prediction and trading.
2. To review the major machine-learning and deep-learning methods used in financial trading research.
3. To examine documented empirical evidence relating to the NIFTY 50.
4. To distinguish prediction accuracy from practical trading performance.
5. To develop a methodological framework for cost-adjusted and risk-aware AI trading evaluation.
6. To identify research gaps and suggest directions for future empirical work.

## IV. RESEARCH QUESTIONS

RQ1: What AI techniques are most frequently applied to stock-market prediction and trading?

RQ2: What data and performance measures are commonly used?

RQ3: What does published evidence indicate about model variation in NIFTY 50 forecasting?

RQ4: What methodological safeguards are required for credible AI-based trading evaluation?

RQ5: How can prediction models be integrated with risk management and human oversight?

## V. SCOPE OF THE STUDY

The study focuses on AI applications in share-market prediction and trading, with the NIFTY 50 as the principal Indian-market context. It covers machine learning, deep learning, technical indicators, forecasting, classification, algorithmic decision support and risk-aware backtesting. The study is primarily methodological and evidence-synthesis oriented. It does not claim to establish a live trading strategy or guaranteed profitability. Any future primary experiment should use a licensed, reproducible dataset and a pre-specified chronological train-validation-test design.

## VI. REVIEW OF LITERATURE

Chopra and Sharma (2021) reviewed AI applications in stock-market forecasting and identified methodological issues and research opportunities. Rouf et al. (2021) surveyed a decade of machine-learning approaches and highlighted the continued difficulty of forecasting dynamic and erratic stock-market data. Sonkavde et al. (2023) reviewed machine- and deep-learning models and discussed generic prediction and classification frameworks.

Lin and Marques (2024) systematically reviewed systematic reviews covering more than 379 studies and found SVM, LSTM and ANN among the most frequently used AI methods. They also observed that historical closing prices are a common data source and that accuracy is a dominant evaluation measure, while recommending broader data sources and improved evaluation standards. Dakalbab et al. (2024) reviewed 143 financial-trading articles, identifying 40 AI techniques; their review found technical analysis more frequently used than fundamental analysis and deep learning among the most frequently used approaches.
More recent NIFTY 50 evidence illustrates the rapid development of attention-based architectures. A 2026 FinTech study compared numerous models for NIFTY 50 close-price prediction and reported MAE values ranging from 124.70 for a BiGRU with fused attention architecture to 3010.03 for XGBoost in that study's experimental setting. These figures are study-specific and should not be interpreted as universal rankings because datasets, preprocessing, forecast horizons and experimental protocols differ.

## VII. RESEARCH GAP

The literature indicates several gaps. First, predictive accuracy is often emphasised more strongly than economic value after transaction costs. Second, many studies rely heavily on historical price series, while

© SEP 2026 | IRE Journals | Volume 10 Issue 3 | ISSN: 2456-8880
DOI: https://doi.org/10.64388/IREV10I3-1723436

multimodal data integration remains less mature. Third, market-regime robustness and chronological out-of-sample validation require greater emphasis. Fourth, explainability and human oversight are increasingly important when AI outputs influence financial decisions. Fifth, Indian-market studies are less numerous than the broader global literature. Finally, the relationship between model confidence, position sizing, drawdown controls and actual execution costs deserves more systematic investigation.

## VIII. RESEARCH METHODOLOGY

Research design: Secondary empirical and analytical research design.

Unit of analysis: NIFTY 50 index observations and published empirical studies relevant to AI-based financial prediction and trading.

Recommended primary experiment: Use daily NIFTY 50 data for a clearly licensed period, preferably a multi-year period ending before the manuscript submission date. A chronological split such as 2020–2023 for training, 2024 for validation and 2025 for testing can be used where complete, licensed data are available.

Candidate predictors: lagged returns; moving averages; exponential moving averages; RSI; MACD; volatility; momentum; high-low range; volume or turnover; and, where legally and technically appropriate, textual or sentiment variables.

Models: Logistic Regression, Random Forest, XGBoost, LSTM, GRU and attention-based sequence models. Models should be compared under identical information sets and forecast horizons.

Targets: Regression target $Y(t)=Close(t+1)$. Classification target $Y(t)=1$ if $Close(t+1)>Close(t)$, otherwise 0.

Validation: Random train-test splitting should be avoided for time-series forecasting because it can create information leakage. All preprocessing, feature scaling and hyperparameter selection must respect the chronological order of observations.

Evaluation: MAE, RMSE, MAPE and $R^2$ for regression; accuracy, precision, recall, F1 and ROC-AUC for classification; and cumulative return, CAGR, Sharpe ratio, Sortino ratio, maximum drawdown, turnover, number of trades and transaction-cost-adjusted return for trading evaluation.

## IX. ANALYTICAL PART

The analytical framework consists of five stages.

Stage 1—Data preparation: obtain a licensed historical NIFTY 50 dataset; sort observations chronologically; check missing values and outliers; and document all transformations.

Stage 2—Feature engineering: calculate lagged returns, moving averages, volatility and momentum indicators using only information available at the decision time.

Stage 3—Prediction: estimate benchmark statistical/machine-learning models and deep-learning models under a common experimental protocol.

Stage 4—Signal generation: convert predictions into signals only after defining a threshold and position rule in advance. For example, a classification model may generate a long signal when the predicted probability of an upward next-period movement exceeds a pre-specified threshold.

Stage 5—Backtesting: apply the signal to a realistic execution rule and subtract brokerage, exchange charges, taxes, slippage and other applicable costs. Report risk-adjusted performance rather than return alone.

The framework should be implemented with walk-forward or expanding-window validation wherever feasible. Hyperparameters should be selected using only the training and validation information. The final test set should remain untouched until model selection is complete.

© SEP 2026 | IRE Journals | Volume 10 Issue 3 | ISSN: 2456-8880
DOI: https://doi.org/10.64388/IREV10I3-1723436

## X. PUBLISHED NIFTY 50 EMPIRICAL EVIDENCE

A recent peer-reviewed FinTech study, "Capturing Short- and Long-Term Temporal Dependencies Using Bahdanau-Enhanced Fused Attention Model for Financial Data—An Explainable AI Approach" (FinTech, 2026), reports the following NIFTY 50 close-price results in its Table 1: BiGRU + Fused Attention MAE 124.70, RMSE 173.34, MAPE 0.58%, $R^2$ 0.9955; BiGRU + Bahdanau Attention MAE 192.30, RMSE 248.87, MAPE 0.89%, $R^2$ 0.9908; BiLSTM + Bahdanau Attention MAE 198.80, RMSE 250.38, MAPE 0.91%, $R^2$ 0.9906; LSTM + Bahdanau Attention MAE 405.53, RMSE 493.85, MAPE 1.82%, $R^2$ 0.9612; LSTM MAE 1472.77, RMSE 1526.47, MAPE 6.85%, $R^2$ 0.6518; Random Forest MAE 2855.10, RMSE 3709.02, MAPE 12.30%, $R^2$ −1.0560; and XGBoost MAE 3010.03, RMSE 3861.51, MAPE 13.01%, $R^2$ −1.2285. These values are reproduced as reported evidence from that paper and are not new estimates by the present study. They should be interpreted within that paper's dataset and methodology.

## XI. PROPOSED SMART TRADING FRAMEWORK

Market Data → Data Quality Checks → Feature Engineering → AI Prediction → Confidence Filter → Signal Generation → Position Sizing → Risk Controls → Cost-Adjusted Execution → Performance Monitoring → Human Review.

The framework separates the prediction layer from the decision layer. Prediction estimates direction or price; the decision layer determines whether the prediction is sufficiently confident to justify a trade. Position sizing can be constrained by volatility and maximum portfolio exposure. Stop-loss, maximum drawdown and daily loss limits can be specified before deployment. Human oversight should remain part of the governance process, especially when the system is used in a regulated market environment.

## XII. FINDINGS

1. AI has become a major research area in stock-market forecasting and financial trading.
2. SVM, LSTM and ANN are frequently reported in the stock-prediction literature.
3. Deep-learning and hybrid/attention architectures are increasingly prominent.
4. Published NIFTY 50 evidence demonstrates large variation in prediction error across model architectures within a given experimental setting.
5. Prediction accuracy alone does not establish practical trading usefulness.
6. Chronological validation is essential to reduce information leakage.
7. Transaction costs, turnover and drawdown can materially alter trading results.
8. Explainability and model governance are important when AI outputs influence financial decisions.
9. Reproducibility requires explicit disclosure of datasets, preprocessing, hyperparameters and trading assumptions.
10. Regulatory developments in India make governance and risk controls increasingly relevant to algorithmic trading.

## XIII. SUGGESTIONS

1. Use chronological train-validation-test or walk-forward validation.
2. Prevent look-ahead bias in every feature and scaling step.
3. Report both statistical prediction metrics and financial trading metrics.
4. Include realistic transaction costs and slippage.
5. Test performance across different market regimes.
6. Compare simple benchmarks with complex AI models.
7. Incorporate explainability methods such as SHAP where appropriate.
8. Establish position, exposure and drawdown limits before deployment.
9. Monitor model drift and define evidence-based retraining rules.
10. Align deployment practices with applicable SEBI requirements and broker/exchange controls.

© SEP 2026 | IRE Journals | Volume 10 Issue 3 | ISSN: 2456-8880
DOI: https://doi.org/10.64388/IREV10I3-1723436

## XIV. MANAGERIAL AND PRACTICAL IMPLICATIONS

For investors and financial institutions, the evidence supports treating AI as a decision-support component rather than assuming that predictive accuracy automatically translates into profitable trading. For researchers, transparent datasets, chronological validation and complete trading-cost assumptions improve reproducibility. For technology teams, monitoring, explainability, audit trails and fallback controls should be designed alongside the predictive model. For regulated participants, algorithmic-trading systems should be implemented consistently with applicable securities-market requirements.

## XV. LIMITATIONS

The present paper is primarily a secondary empirical and methodological study and does not claim a newly trained proprietary AI model. The reported NIFTY 50 performance figures are taken from the cited 2026 study and therefore depend on that study's data, preprocessing and experimental design. A full primary experiment using licensed data, transaction-cost assumptions and walk-forward validation is required before making claims about a deployable strategy. Market conditions also change over time, so historical performance cannot establish future performance.

## XVI. SCOPE FOR FURTHER STUDY

Future research can conduct a fully reproducible NIFTY 50 experiment using licensed data and walk-forward validation; compare price-only models with multimodal models incorporating news and sentiment; investigate transformers and other modern sequence architectures; examine regime-specific performance; study explainable AI and human-AI interaction; and evaluate portfolio-level allocation, execution costs and risk constraints. Research may also compare AI-generated signals with transparent benchmark strategies and examine robustness across different Indian market indices and asset classes.

## XVII. CONCLUSION

AI provides powerful tools for financial-market analysis, but smart share trading requires more than accurate prediction. The literature demonstrates rapid development from conventional machine learning to deep-learning and attention-based architectures. Published NIFTY 50 evidence also shows that model performance can vary substantially across architectures. Consequently, a credible smart-trading system should combine high-quality data, leakage-resistant features, chronological validation, prediction metrics, cost-adjusted trading performance, risk controls, explainability and human oversight. In the Indian context, these technical considerations should be accompanied by awareness of the applicable SEBI regulatory framework for algorithmic trading. The central research opportunity is therefore to move from isolated prediction experiments toward reproducible, risk-aware and economically meaningful AI trading evaluation.

## REFERENCES

[1] R. Chopra and G. D. Sharma, "Application of artificial intelligence in stock market forecasting: A critique, review, and research agenda," *Journal of Risk and Financial Management*, vol. 14, no. 11, Art. no. 526, 2021. MDPI

[2] F. Dakalbab, M. Abu Talib, Q. Nasir, and T. Saroufil, "Artificial intelligence techniques in financial trading: A systematic literature review," *Journal of King Saud University – Computer and Information Sciences*, vol. 36, no. 3, Art. no. 102015, 2024. ScienceDirect

[3] C. Y. Lin and J. A. L. Marques, "Stock market prediction using artificial intelligence: A systematic review of systematic reviews," *Social Sciences & Humanities Open*, vol. 9, Art. no. 100864, 2024. ScienceDirect

[4] N. Rouf, M. B. Malik, T. Arif, and S. Sharma, "Stock market prediction using machine learning techniques: A decade survey on methodologies, recent developments, and future directions," *Electronics*, vol. 10, no. 21, Art. no. 2717, 2021. MDPI

[5] G. Sonkavde, D. S. Dharrao, A. M. Bongale, S. T. Deokate, D. Doreswamy, and S. K. Bhat, "Forecasting stock market prices using machine learning and deep learning models: A systematic review, performance analysis and discussion of implications," *International Journal of Financial Studies*, vol. 11, no. 3, Art. no. 94, 2023. MDPI

[6] A. Chauhan *et al.*, "Capturing Short- and Long-Term Temporal Dependencies Using Bahdanau-Enhanced Fused Attention Model for Financial Data—An Explainable AI Approach," *FinTech*, vol. 5, no. 1, Art. no. 4, 2026.

[7] Securities and Exchange Board of India, "Safer participation of retail investors in Algorithmic trading," Circular No. SEBI/HO/MIRSD/MIRSD-PoD/P/CIR/2025/0000013, Feb. 4, 2025. SEBI

[8] Securities and Exchange Board of India, "Extension of timeline for implementation of SEBI Circular dated February 04, 2025 on 'Safer participation of retail investors in Algorithmic trading'," Circular No. SEBI/HO/MIRSD/MIRSD-PoD/P/CIR/2025/132, Sep. 30, 2025. SEBI

[9] NSE Indices, *NIFTY 50 and historical index data*. National Stock Exchange of India, n.d. NSE Indices