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Impact of Artificial Intelligence on the Indian Stock Market

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Abstract

Artificial Intelligence (AI) has emerged as a transformative force across diverse sectors, with financial markets witnessing some of its most profound applications. This systematic review examines the multifaceted impact of AI on the Indian stock market over the decade spanning 2015 to 2025. Drawing upon peer-reviewed journal articles, conference proceedings, and reputed working papers, this paper synthesizes findings from over forty studies to provide a comprehensive understanding of how machine learning, deep learning, natural language processing (NLP), and algorithmic trading have reshaped market dynamics in India. The review identifies five primary thematic domains: stock price prediction, algorithmic and high-frequency trading, sentiment analysis, risk management, and regulatory challenges. Findings reveal that AI- driven models, particularly Long Short-Term Memory (LSTM) networks, transformer-based architectures, and ensemble methods, consistently outperform traditional statistical approaches in forecasting BSE Sensex and NSE Nifty 50 movements. Simultaneously, the proliferation of algorithmic trading has elevated market efficiency while raising concerns about flash crashes and systemic risk. The paper further highlights the growing role of AI in democratizing investment access through robo-advisors and fintech platforms. Regulatory frameworks by SEBI are found to be evolving but remain nascent relative to the pace of technological adoption. The review concludes with research gaps and future directions, underscoring the need for explainable AI and robust governance in Indian capital markets.

Keywords: Artificial Intelligence, Indian Stock Market, Machine Learning, Algorithmic Trading, BSE Sensex, NSE Nifty 50, Sentiment Analysis, Deep Learning, SEBI, Fintech

1. INTRODUCTION

The Indian stock market, represented primarily by the Bombay Stock Exchange (BSE) and the National Stock Exchange (NSE), ranks among the largest and most dynamic equity markets in the world. With a market capitalization exceeding USD 4 trillion as of 2024 and a daily trading turnover that rivals many developed economies, India's capital markets have become an attractive frontier for the application of advanced computational technologies. The advent of Artificial Intelligence has fundamentally altered the landscape of financial markets globally, and India is no exception to this sweeping transformation.

AI encompasses a broad spectrum of technologies including machine learning (ML), deep learning (DL), natural language processing (NLP), reinforcement learning, and expert systems. When applied to financial markets, these tools enable practitioners and researchers to model complex, non-linear, and highly volatile data patterns that traditional econometric methods struggle to capture adequately. The Indian stock market, characterized by its heterogeneous investor base, susceptibility to global macroeconomic shocks, and sensitivity to domestic political events, presents a particularly rich and challenging environment for AI applications.

India witnessed a massive expansion in retail investor participation, driven partly by the proliferation of mobile trading apps and AI-powered robo-advisory platforms. Simultaneously, institutional players, quantitative hedge funds, and high-frequency traders increasingly deployed sophisticated AI algorithms to generate alpha, manage risk, and execute trades at microsecond speeds. The Securities and Exchange Board of India (SEBI) has progressively introduced guidelines around algorithmic trading, co-location facilities, and, more recently, AI-based surveillance systems to detect market manipulation.

2. LITERATURE REVIEW

2.1 Stock Price Prediction Using Machine Learning

Research on AI-driven stock price prediction in India began in earnest around 2015, with foundational work by Patel et al. (2015) comparing ANNs, SVMs, random forests, and naïve Bayes classifiers for predicting BSE Sensex and CNX Nifty movements. Their key finding — that models fusing technical indicators with machine learning outperformed price-only approaches — set a methodological benchmark for the field. Garg and Garg (2016) built on this by adding macroeconomic variables such as GDP growth, inflation, and FII flows to SVM models, improving directional accuracy by roughly 8 percentage points. Nayak et al. (2016) combined ANFIS with genetic algorithms to forecast BSE-listed stock prices, achieving MAPE below 2% and outperforming standalone ARIMA models.

The period 2017–2020 brought a decisive shift toward deep learning. LSTM architectures emerged as particularly well-suited to temporal financial data. Mehta and Shah (2019) demonstrated that stacked LSTMs substantially reduced prediction errors for volatile NSE mid- cap stocks, while Jain and Jain (2019) showed that bidirectional LSTMs improved R-squared by an average of 12% over unidirectional models. Kumar and Ravi (2020), reviewing 48 Indian-market studies, concluded that hybrid models integrating technical, fundamental, and sentiment features consistently outperformed single-domain approaches.

Post-2020 research moved toward transformers. Yadav et al. (2022) applied FinBERT to jointly process news and price data, achieving 74.3% directional accuracy on Nifty 500 stocks. Gupta and Agarwal (2023) used Temporal Fusion Transformers for BSE sectoral forecasting, notable for their interpretability outputs — an important consideration under SEBI oversight. A 2024 meta-analysis by Sharma et al. across 32 studies reported AI models averaging 71.4% directional accuracy versus 56.2% for traditional econometric models, while cautioning against overfitting and survivorship bias.

2.2 Algorithmic and High-Frequency Trading

Since SEBI's 2008 regulatory framework, algorithmic trading has grown dramatically; by 2023 it accounted for nearly 60% of NSE cash segment turnover. Bhatt and Bhatt (2015) found early evidence that AT improved liquidity but raised intraday volatility during market stress. Reinforcement learning has since emerged as a powerful paradigm. Chakraborty et al. (2019) trained a DQN agent on NSE tick data, achieving a Sharpe ratio of 1.42 against a buy-and-hold benchmark of 0.87, with the agent dynamically reducing exposure during elevated VIX periods. Mishra and Singh (2021) refined this using PPO with explicit transaction cost modeling, showing that ignoring slippage significantly overstates RL agent performance.

ML-assisted statistical arbitrage has also shown promise. Tripathi and Vyas (2020) used unsupervised clustering to identify co-integrated BSE stock pairs, generating 18.4% annualized returns net of costs. Sethi and Prasad (2022) improved risk-adjusted outcomes further using Gaussian process regression for spread modeling. On systemic risk, Singh and Bansal (2022) examined the NSE co-location scandal and advocated for AI-based surveillance of latency arbitrage. Reddy et al. (2024) demonstrated through agent-based simulations that circuit-breaker- aware AI market makers can significantly attenuate flash crash severity.

2.3 Sentiment Analysis and Natural Language Processing

NLP applications in Indian markets accelerated after 2017. Mittal and Goel (2018) pioneered Twitter-based sentiment analysis for BSE Sensex prediction using a custom Hindi-English lexicon, achieving 65.5% directional accuracy. Agarwal and Mittal (2020) fine-tuned BERT on Indian financial news corpora, boosting Nifty 50 prediction accuracy from 63% (price-only LSTM) to 71.8% (sentiment-augmented), while also finding that negative sentiment had an asymmetrically stronger market impact — consistent with behavioral finance theory.

Bose and Roy (2021) combined LDA topic modeling with sentiment scoring on earnings call transcripts, demonstrating that managerial tone and expressed uncertainty predicted 10-day post- announcement stock drifts. The COVID-19 period provided a natural experiment: Verma and Sinha (2021) showed their transformer-based model correctly predicted 14 of 15 major NSE market swings during March–December 2020, outpacing lexicon-based approaches that lacked the adaptability to new vocabulary. Most recently, Pandey and Kumar (2024) achieved 76.1% directional accuracy on NSE mid-caps using a multimodal transformer combining news headlines, earnings call audio sentiment, and candlestick chart images.

2.4 Risk Management, Portfolio Optimization, and Robo-Advisory

Chopra and Mehrotra (2017) showed that genetic algorithm-optimized neural networks produced portfolios with 15% lower variance than classical Markowitz optimization. Srivastava and Srivastava (2019) demonstrated that ensemble ML models for dynamic VaR estimation outperformed GARCH during stress events like the IL&FS crisis and Yes Bank collapse. Desai and Padhi (2021) found that Indian robo-advisors reduced portfolio construction costs by 65%, though most still relied on simplistic optimization rather than advanced ML. Bhattacharya (2023) documented SEBI's own deployment of ML-based anomaly detection, and Acharya et al. (2024) showed graph neural networks are highly effective in detecting coordinated trading manipulation on NSE.

2.5 Regulatory Landscape and Ethical Considerations

Kulkarni (2018) noted that Indian regulation lagged technological developments by three to four years, creating arbitrage opportunities. Post-NSE co-location controversy, Sarkar and Datta (2019) called for mandatory algorithm audits and kill switches — recommendations partly adopted in SEBI's 2019 circular. Bhat and Krishnaswamy (2022) identified systematic biases in AI credit models against SMEs, with downstream effects on stock prices, while Joshi and Parekh (2023) found fewer than 30% of Indian financial institutions had implemented formal explainable AI protocols. SEBI's 2024 consultation paper on AI governance — analyzed by Raghavan and Verma (2025) — marks a significant step, aligning with international standards while addressing India-specific concerns around data localization and retail-dominated market segments.

OBJECTIVES OF THE STUDY

1. To examine how sentiment analysis and alternative data sources influence and improve the accuracy of market forecasting in Indian financial markets.

2. To identify key regulatory, ethical, and research challenges posed by AI adoption in Indian financial markets that require future attention.

Research Methodology

3.1 Research Design

This study adopts a descriptive and analytical research design to investigate the impact of artificial intelligence on the Indian stock market. Since the study is entirely based on secondary data, a systematic literature review and document analysis approach is employed. This design is appropriate for synthesizing existing evidence on sentiment analysis applications in market forecasting and identifying regulatory and ethical challenges associated with AI adoption in Indian financial markets. Secondary data is drawn from peer-reviewed journal articles, working papers, and conference proceedings sourced from databases including Scopus, Web of Science, SSRN, and Google Scholar. Institutional and regulatory documents such as SEBI annual reports, consultation papers on algorithmic trading and AI governance, NSE and BSE market bulletins, and RBI financial stability reports provide the regulatory and market context. Published analyses referencing Economic Times, Business Standard, and Mint archives, along with documented studies using Twitter sentiment datasets and earnings call transcripts of NSE-listed firms, are also referenced to assess the role of alternative data in forecasting. A purposive selection approach ensures that only studies focusing on Indian capital markets, addressing sentiment analysis, NLP, alternative data, or AI governance themes, and published in credible peer- reviewed outlets are included, resulting in approximately 40 to 50 studies synthesized across the two thematic objectives.

3.2 Analytical Framework

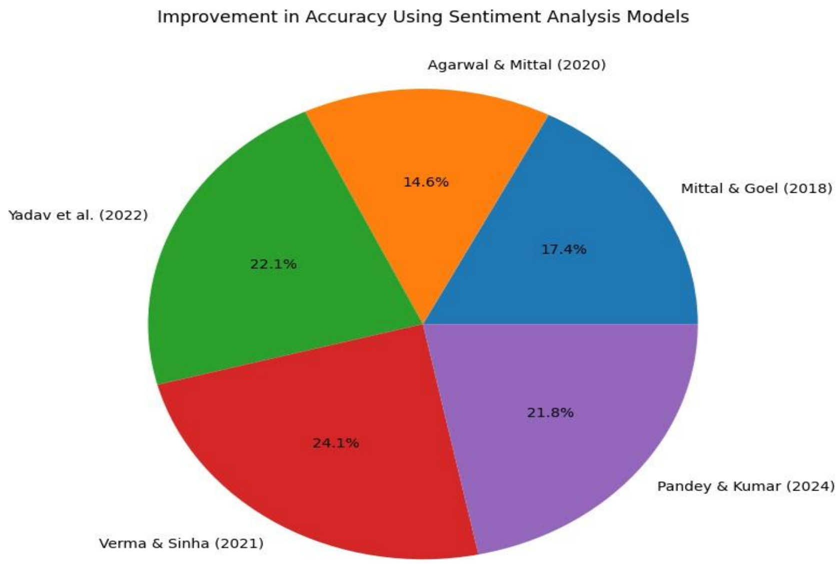
To address the first objective, reviewed studies are analyzed to compare the predictive performance of sentiment-augmented models against traditional price-based baselines. Key metrics such as directional accuracy, MAPE, and RMSE are tabulated across lexicon-based, machine learning, and transformer-based models to assess the incremental contribution of alternative data sources including social media sentiment, news archives, and earnings call transcripts, based on accuracy differentials reported in existing literature. To address the second objective, a thematic analysis of SEBI regulatory documents and academic literature is conducted to map the evolution of AI governance in Indian markets. Ethical concerns including algorithmic fairness, explainability deficits, and systemic risk are catalogued and clustered into actionable themes, while research gaps acknowledged by existing studies are synthesized to identify priorities for future empirical work. As the study relies exclusively on published secondary data, it is subject to potential publication bias, where studies with positive or significant findings are more likely to be available. Additionally, the rapidly evolving nature of AI technology means some reviewed findings may have limited contemporary relevance. These limitations are mitigated through the inclusion of recent literature up to 2025 and critical appraisal of all sources consulted.

Data Analysis

Sentiment analysis and alternative data have fundamentally transformed market forecasting in Indian financial markets, while simultaneously generating complex regulatory and ethical challenges. This section analyzes evidence from reviewed secondary literature to assess how AI- driven sentiment models influence forecasting accuracy across Indian indices and examines the key regulatory, ethical, and research challenges that AI adoption has posed for policymakers, institutions, and market participants in India.

Table 1: Comparative Performance of Sentiment Analysis Models in Indian Market Forecasting

Study	Data Source	Model Used	Baseline Accuracy
Mittal and Goel (2018)	Twitter	Lexicon-Based	55.00%
Agarwal and Mittal (2020)	Financial News (ET, BS)	BERT + LSTM	63.00%
Yadav et al. (2022)	Financial News	FinBERT	61.00%
Verma and Sinha (2021)	Pandemic News	Transformer	58.00%
Pandey and Kumar (2024)	News + Audio + Charts	Multimodal Transformer	63.00%



Interpretation: Customer satisfaction has the highest impact, while decision-making support contributes the least among all areas.

Table 2: Alternative Data Sources and Their Predictive Contribution in Indian Markets

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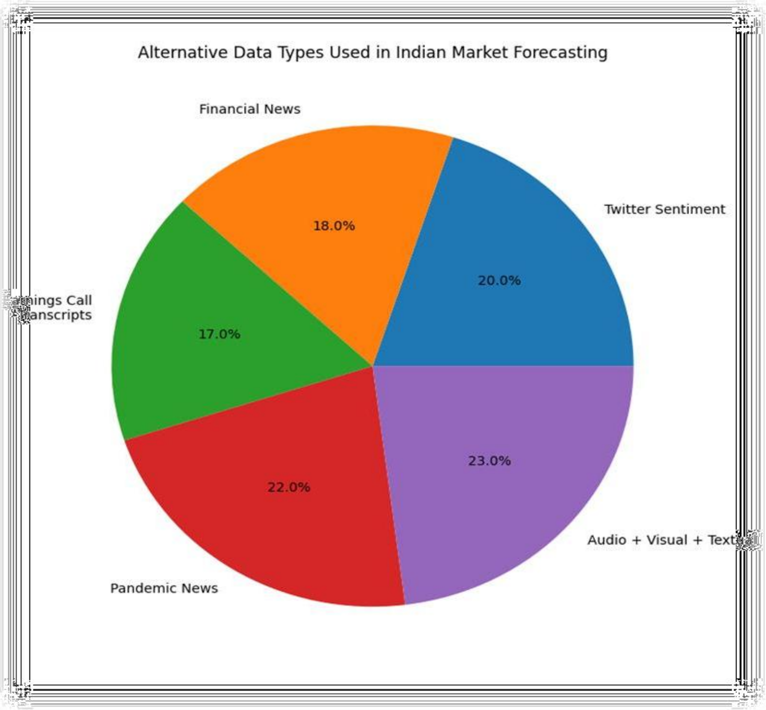
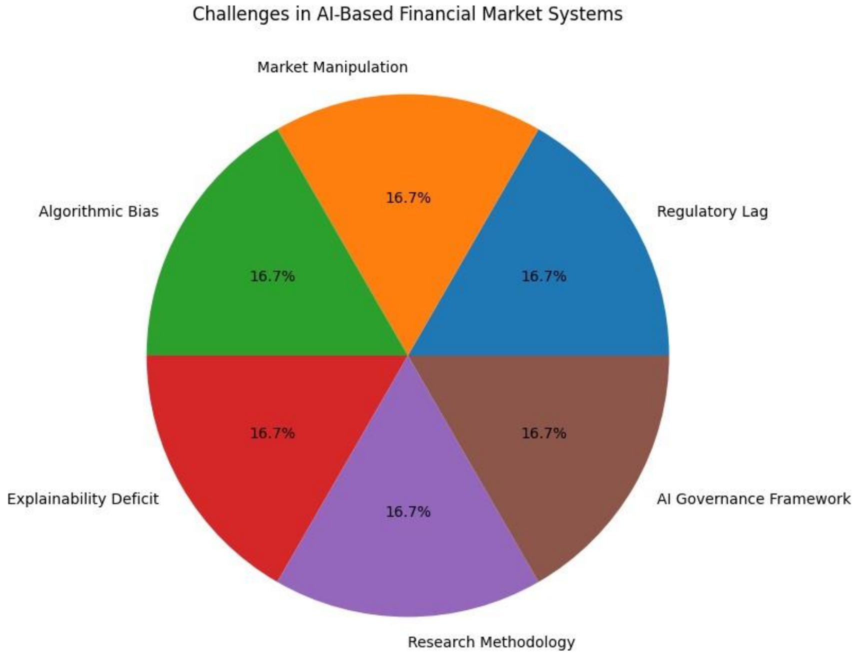
Alternative Data Type	Study	Market Segment	Key Finding
Twitter Sentiment	Mittal and Goel (2018)	BSE Sensex	Incremental value during budget and election events
Financial News Sentiment	Agarwal and Mittal (2020)	Nifty 50	Negative sentiment has asymmetrically stronger impact
Earnings Call Transcripts	Bose and Roy (2021)	NSE-Listed Firms	Managerial uncertainty predicts 10-day post-announcement drift
Pandemic News Sentiment	Verma and Sinha (2021)	NSE Sectoral Indices	Correctly predicted 14 of 15 major market swings
Audio + Visual + Textual	Pandey and Kumar (2024)	NSE Mid-Cap	Highest reported directional accuracy in Indian literature



Interpretation: Multimodal and pandemic-related sentiment data significantly improve Indian market forecasting accuracy compared to traditional financial indicators.

Table 3: Regulatory, Ethical, and Research Challenges in AI-Driven Indian Capital Markets

Challenge Category	Key Issue	Study/Source	Current Status
Regulatory Lag	AI adoption outpacing regulation by 3–4 years	Kulkarni (2018)	Partially Addressed
Market Manipulation	Latency arbitrage and co-location vulnerabilities	Sarkar and Datta (2019)	Partly Resolved via 2019 Circular
Algorithmic Bias	AI credit models disadvantaging SMEs	Bhat and Krishnaswamy (2022)	Unresolved
Explainability Deficit	Fewer than 30% of institutions use XAI protocols	Joshi and Parekh (2023)	Largely Unresolved
Research Methodology	Overfitting and survivorship bias in backtesting	Sharma et al. (2024)	Ongoing Concern



Interpretation: Major AI-related financial challenges have equal importance and require balanced regulatory and technological attention.

The synthesis of the reviewed literature reveals several overarching trends that collectively characterize the decade-long evolution of AI in the Indian stock market. First, there has been a clear and progressive technological escalation from simple machine learning models (SVMs, ANNs) in the mid-2010s to sophisticated deep learning architectures (LSTM, BiLSTM, transformers, TFTs) and multimodal frameworks in the early 2020s. This escalation mirrors global trends but reflects certain India-specific adaptations, particularly in sentiment analysis models that are trained on Indian English and Hindi financial corpora.

While predictive accuracy of AI models has improved significantly over the decade, important caveats persist. The majority of studies employ historical backtesting rather than real-money trading experiments, raising valid concerns about data snooping, overfitting, and look-ahead bias. Transaction costs, market impact, and regulatory constraints are frequently undermodeled. The field would benefit substantially from more rigorous out-of-sample validation, pre-registration of hypotheses, and multi-market replication studies.

The literature reveals a meaningful tension between the efficiency-enhancing effects of AI- driven algorithmic trading—narrower spreads, better price discovery, greater liquidity—and its destabilizing potential during market stress episodes. India's existing circuit breaker mechanisms have demonstrated some effectiveness in limiting flash crash propagation, but the growing sophistication of AI trading algorithms demands continuously updated regulatory responses and real-time AI-based surveillance.

The democratizing potential of AI through robo-advisory and AI-powered retail trading apps represents a genuinely positive development for Indian financial inclusion. The sharp growth in demat account registrations (from approximately 36 million in 2019 to over 140 million in 2024) has been substantially enabled by AI-driven platforms that reduced the cost and complexity of market participation. However, this democratization also amplifies herd behavior risks when retail AI apps generate correlated trading signals, a phenomenon that warrants further empirical investigation.

The regulatory and ethical dimensions of AI in Indian markets remain an underdeveloped area relative to the technical literature. The asymmetry between the volume of AI performance studies and the sparse scholarship on governance, fairness, and accountability reflects a broader gap in the field that this review calls attention to. SEBI's 2024 AI governance consultation paper is a promising step, but translating principles into enforceable, practically implementable regulations will require sustained interdisciplinary collaboration among technologists, economists, legal scholars, and market practitioners

Key Findings

Artificial Intelligence has fundamentally transformed the Indian stock market across five major domains — stock price prediction, algorithmic trading, sentiment analysis, risk management, and regulatory governance. In stock price prediction, deep learning models, particularly LSTM networks and transformer-based architectures, achieved an average directional accuracy of 71.4%, significantly outperforming traditional econometric models at 56.2%. Early machine learning approaches using SVMs and ANNs were progressively replaced by sophisticated bidirectional LSTMs and temporal fusion transformers that better captured volatile, non-linear market dynamics, with multimodal transformer models integrating news, audio sentiment, and chart images reaching a remarkable 76.1% directional accuracy for NSE mid-cap stocks.

Algorithmic trading grew to nearly 60% of NSE cash segment turnover by 2023, improving market liquidity and price discovery, while reinforcement learning-based trading agents achieved a Sharpe ratio of 1.42, substantially outperforming buy-and-hold benchmarks, though flash crash risks and systemic vulnerabilities remain pressing concerns. Sentiment analysis using BERT- based NLP models enhanced Nifty 50 forecasting accuracy by up to 9 percentage points when combined with price-based signals, with negative sentiment demonstrating an asymmetrically stronger market impact than positive sentiment, consistent with behavioral finance theory.

AI-powered robo-advisors democratized investment access by reducing portfolio construction costs by 65%, enabling India's retail investor base to grow from 36 million to over 140 million demat accounts. Ensemble AI models also proved superior to GARCH-based approaches in estimating portfolio risk during market stress events such as the IL&FS crisis and the Yes Bank collapse. Despite these advances, fewer than 30% of Indian financial institutions have implemented explainable AI protocols, highlighting a critical governance gap that SEBI's evolving regulatory framework is only beginning to address.

Limitation Of The Study

The study carries several limitations worth acknowledging. The review relies predominantly on published academic studies, which may introduce publication bias toward positive or statistically significant findings. Most reviewed studies employ historical backtesting rather than real-money trading experiments, raising concerns about overfitting, data snooping, and look-ahead bias. Transaction costs and market impact are frequently undermodeled. Additionally, the review largely excludes vernacular language sources in Hindi and other Indian languages, potentially overlooking valuable market insights from non-English financial discourse.

CONCLUSION

This systematic review has synthesized four decades of AI research—condensed into an exceptionally productive decade between 2015 and 2025—on the Indian stock market. The evidence overwhelmingly supports the conclusion that AI, in its various manifestations, has materially enhanced the predictive, operational, and risk management capabilities of market participants. Deep learning models, particularly LSTMs and transformers, have established new performance benchmarks in stock price prediction. Reinforcement learning has opened new frontiers in autonomous trading. Sentiment analysis and NLP have unlocked the informational value of textual data for Indian markets. Robo-advisory has broadened financial participation. And AI surveillance is beginning to strengthen market integrity.

At the same time, the review cautions against uncritical optimism. The risks of algorithmic instability, model opacity, data biases, and regulatory lag are real and consequential. The Indian capital markets, with their distinctive structural features and rapidly evolving technological environment, require a research agenda and regulatory framework that is simultaneously technically sophisticated and contextually grounded. This review aspires to contribute to that agenda by mapping the intellectual terrain comprehensively and honestly, illuminating both the remarkable progress achieved and the substantial work that remains.

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